Subjective and Projected Returns to Education

Nick Huntington-Klein\textsuperscript{a}

\textbf{Abstract}: There is significant heterogeneity over high school students in the wage and employment rate returns to education. I evaluate this heterogeneity using subjective returns derived from a data set of high school juniors and seniors in Washington State. Variation over observables in projected returns estimated using observed data is uncorrelated with variation in subjective returns elicited by directly asking students about their beliefs. These results mean that returns estimated using observed data are likely a very weak proxy for student beliefs.

Keywords: education; expectations; returns; subjective
JEL Codes: I21, I23, D81, D84, J24

\textsuperscript{a}Department of Economics, University of Washington, Box 353330, Savery 305, Seattle, WA, 98195-3330. Correspondence at nickck@uw.edu or (206) 915-5352. Research funds and support for this project have been provided by Collaborative Researchers for Education Sciences Training, Institute of Education Sciences Grant #R305B090012. Many thanks to Patrick Bajari, Robert Jensen, Eric Lin, Mark Long, Charles Manski, Ben Ost, Elaina Rose, William Zumeta, anonymous reviewers, and conference session participants for comments.
1 Expectations in Educational Choice

Human capital theory suggests that students make decisions about their educational attainment based on future returns. Models of educational choice must include assumptions about how students form expectations of future outcomes. Without such assumptions, preferences and expectations cannot be identified separately using observed choices, since there are many pairings of preferences and expectations that can generate given behavior (Manski, 2004; van der Klaauw, 2012). In practice, researchers build econometric models on the basis of these assumptions and generate forecasts to use as proxies for student expectations. However, if a researcher’s assumptions about expectations formation are false, estimates of preferences and demand will be biased. Without a strong literature on expectations formation, it is difficult to put much faith in these assumptions. In response, there has been growing interest in decision makers' stated, or “subjective,” expectations.

There is a growing literature on the measurement of subjective expectations data and their use in behavioral models. Subjective expectations data has been used to study intertemporal labor supply (Pistaferri, 2003), curriculum choice at the high school (Giustinelli, 2010) and college (Stinebrickner and Stinebrickner, 2014; Wiswall and Zafar, 2011) levels, teacher quality (Jacob and Lefgren, 2008), and a wide range of topics studied in developing nations, including agricultural, education, and labor choices (as reviewed in Attanasio 2009; Delavande et al. 2011).

In the context of the choice of the level of education, a number of studies examine one of the inputs relevant to the human capital model – students’ estimates of wages conditional on schooling level. These papers focus on reporting student estimates (Avery and Kane, 2004; Botelho and Pinto, 2004; Dominitz and Manski, 1996) or observing changes in estimates in
response to information or experience (Jensen, 2010; Oreopoulos and Dunn, 2013). The literature on the subjective returns of employment probability to education is more sparse (Attanasio and Kaufmann, 2012; Kodde, 1987; Varga, 2002). All of these studies expand understanding of the structure and importance of student expectations. However, they look at limited sets of educational counterfactuals, many (although not all) only comparing a high school degree to a bachelor’s degree, which offers a limited portrait of the options available to students\(^1\) and does not take into account the possibility of college dropout, which students in my analytic sample estimate occurs 37.5% of the time.\(^2\)

I evaluate high school students’ expectations of wages and the employment rate over six different levels of education (high school dropout, high school graduate, some college but no degree, two-year degree, four-year degree, and advanced degree). These expectations allow me to calculate how each student estimates the wage return to different levels of college attainment, and the change in the employment rate associated with degree attainment. I compare these subjective returns to projections calculated using observed data.

I focus on particular differences between students and demographic groups in their expectations. Heterogeneity in returns, at the group or individual level, are an important factor to study when determining whether or not projected returns estimated by a researcher are a good proxy for students’ stated subjective returns in models of educational choice. If subjective and projected returns are not correlated at the individual level, then the common practice of using projected returns as a proxy for actual student expectations will introduce bias to the analysis.

---
\(^1\) 53.9% of respondents aged 29-31 in the 2008-2010 American Community Survey have a highest grade completed that is not a high school degree or a bachelor’s degree.

\(^2\) Students in the APCAB (Assessing Perceived Costs and Benefits) sample used in this paper were asked to estimate the six-year completion rate at a generic four-year college. The mean estimate was 62.5%. This number is relatively accurate, compared to estimates of 63.3% (Washington) and 58.0% (national) using the Beginning Postsecondary Students Longitudinal Study cohort tracked from 2003/04 to 2009.
At the mean, students’ subjective wage returns are higher than my projected wage returns while employment rate returns match closely. However, for both wage returns and employment rate returns, heterogeneity in subjective returns across demographic and background characteristics is poorly aligned with heterogeneity in projected returns; for example, Hispanic students have a higher projected four-year degree wage return than white students, but Hispanic students expect lower returns than do white students. At the individual level, subjective estimates are uncorrelated with wage returns projected on the basis of background characteristics.

I additionally find that student plans for educational attainment relate positively to stronger subjective wage returns, and both subjective and projected employment returns. The fact that student choice is correlated with subjective returns indicates that students’ subjective reports are related to intended behavior, underlining the importance of avoiding poor proxies for expectations in the study of student choice.

In this study I find evidence that labor market returns projected using observed data are likely a poor proxy for students’ subjective beliefs. Differences between subjective and projected returns at the group and individual levels may harm inference in studies of educational choice that use projected returns as a proxy. These comparisons are made possible by subjective expectations data, the use of which has been growing in popularity in recent years to understand beliefs and choice in a growing number of domains.

2 Data

I make use of three data sources. Subjective data come from the Assessing Perceived Costs and Benefits of Post-High School Opportunities Survey (APCAB), a novel data set that I collected, which includes 1,224 high school juniors and seniors from King County, Washington. 56 students who skipped the subjective expectations questions were dropped, leaving 1,168
students in the final sample. Subjective expectations data are compared with observed data from Washington residents aged 29-31 in the 2008-2010 American Community Survey (ACS (WA)). To allow for disaggregation across background variables not available in the ACS, several analyses are also performed using the national sample of respondents aged 29-31 in the National Longitudinal Survey of Youth, 1997 Cohort (NLSY).

The APCAB survey was offered to juniors and seniors at thirteen high schools in King County, Washington. Subjects were surveyed between late April and early June, 2012, and were offered a $5 gift card in exchange for their participation. The survey was administered in two different settings. About half of the data come from environments where students were in a homeroom or assembly setting and were formally presented with the survey as an option. In these scenarios, the response rate was very high, over 95%. The rest of the data comes from more open environments, like a cafeteria during lunchtime. Response rates in this scenario depend on non-exact estimates of the number of present students, but were about 50%. Results are robust to the sample being limited to students in homeroom or assembly settings. The resulting sample does not appear to over- or under-represent students based on socioeconomic status, gender, or academic ability, as compared to school registration.³

I focus on three substantive questions drawn from this survey. Two ask for subjective expectations of full-time, full-year wages conditional on education level, and the third asks for subjective expectations of the non-employment rate conditional on education level. Following a short explanation of terms, the questions prompt:

³ Comparison school demographic profiles were taken from 2012 Washington State Report Card data at http://reportcard.ospi.k12.wa.us/.
What do you think the **annual salary** is for an average 30-year old full-time worker in Washington...

What do you think **YOUR** annual salary would be at **age 30** if you had a full-time, full-year job...

For each question, imagine 100 people in Washington who are 30 years old with the given level of education. How many of these 100 people would you expect to be **unemployed** today…

Following each prompt, the sentence concludes in six different ways for six levels of education, concluding with, for example, “who has some college experience but no degree” or “among 100 people who have some college experience but no degree” and allowed students to respond. See Appendix A for the full wording of these questions and more information about survey administration. Full survey text is available upon request.

For each of these education-conditional questions, students were asked to estimate the relevant wage or the non-employment rate (the probability of not being employed) for six different terminal amounts of education: No high school degree, a high school degree but no further, some college but no degree, a two-year college degree, a four-year college degree, and an advanced degree (including Master's degrees, PhDs, MDs, and JDs).

The two conditional wage questions differ in terms of their subject. One asks students to estimate wages for the typical 30-year-old in Washington State who is employed and has the specified level of education; these are referred to as Typical wages. The other asks students to
think about when they, personally, are 30 years old, have the specified level of education, and are employed in Washington; these are Self wages. The distinction between these two variables allows control for self-promotion effects and the theoretical distinction between the internal rate of return to education and the population wage return. In both cases, these are point estimates, intended to represent the central tendency of the underlying theoretical wage distribution.

Table 1 presents summary statistics for all three data sets and allows for demographic comparisons between data sets. Where the APCAB mean is tested against the observed-data mean, the standard deviation of the mean (as opposed to the standard deviation of the variable) is reported in parentheses. A racial difference that jumps out is the high percentage of nonwhites in the APCAB sample, higher than the ACS (WA) and NLSY percentages. APCAB students also have somewhat higher socioeconomic status proxy variables than those in the NLSY sample: there is a lower proportion of Free and Reduced Price Lunch (FRPL) students in APCAB, although some of this difference may be accounted for by the fact that the APCAB FRPL variable is a self-report of actual receipt of free or reduced price lunch, while the NLSY FRPL variable concerns being qualified for FRPL. Parental education rates are higher for APCAB respondents, which could represent some mix of geographical differences and cohort differences (APCAB students graduate high school about twelve years after the NLSY students do) as well as reporting error.

GPAs are higher by about half a point for APCAB students than for the NLSY sample. Much of this difference can likely be attributed to self-reporting in APCAB GPAs (Kuncel, Crede, and Thomas 2005 find that self-reported GPAs are strongly, although not perfectly, correlated with actual GPAs). The difference appears to be a level difference: the standard deviation of the mean of the self-reported GPAs is lower than that of the observed GPAs.

---

4 For all analyses in this paper, APCAB data are weighted according to survey response rate by school, and the ACS and the NLSY data are weighted according to supplied sample weights.
deviation for the variable itself (as opposed to the standard deviation of the mean) in both data
sets is about .62.

Table 1

Summary Statistics (Means and Standard Deviations of the Means)

<table>
<thead>
<tr>
<th></th>
<th>APCAB</th>
<th>ACS (WA)</th>
<th>NLSY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender: Female</td>
<td>.475</td>
<td>.489</td>
<td>.484</td>
</tr>
<tr>
<td></td>
<td>(.016)</td>
<td>(.007)</td>
<td>(.010)</td>
</tr>
<tr>
<td>Race: †</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>.683</td>
<td>.785***</td>
<td>.727***</td>
</tr>
<tr>
<td></td>
<td>(.114)</td>
<td>(.006)</td>
<td>(.008)</td>
</tr>
<tr>
<td>Black</td>
<td>.108***</td>
<td>.049***</td>
<td>.158***</td>
</tr>
<tr>
<td></td>
<td>(.10)</td>
<td>(.03)</td>
<td>(.06)</td>
</tr>
<tr>
<td>Asian</td>
<td>.190</td>
<td>.108***</td>
<td>.023***</td>
</tr>
<tr>
<td></td>
<td>(.13)</td>
<td>(.04)</td>
<td>(.03)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>.121</td>
<td>.144**</td>
<td>.128</td>
</tr>
<tr>
<td></td>
<td>(.10)</td>
<td>(.05)</td>
<td>(.06)</td>
</tr>
<tr>
<td>Other</td>
<td>.047</td>
<td>.021***</td>
<td>.025***</td>
</tr>
<tr>
<td></td>
<td>(.07)</td>
<td>(.02)</td>
<td>(.04)</td>
</tr>
<tr>
<td>Background:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Free/Reduced Lunch</td>
<td>.344</td>
<td>.478***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.15)</td>
<td>(.01)</td>
<td></td>
</tr>
<tr>
<td>Parent has Bachelor’s</td>
<td>.645</td>
<td>.295***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.16)</td>
<td>(.00)</td>
<td></td>
</tr>
<tr>
<td>GPA</td>
<td>3.36</td>
<td>2.84***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.21)</td>
<td>(.14)</td>
<td></td>
</tr>
<tr>
<td>Outcomes:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bachelor’s or Higher</td>
<td>.316</td>
<td>.334</td>
<td></td>
</tr>
<tr>
<td>Not employed</td>
<td>.240</td>
<td>.226</td>
<td></td>
</tr>
<tr>
<td>Salary ($, median)</td>
<td>41,313</td>
<td>35,000</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>1,168</td>
<td>7,179</td>
<td>2,773</td>
</tr>
</tbody>
</table>

Note: APCAB = Assessing Perceived Costs and Benefits, author-collected data. ACS (WA) = American Community Survey, Washington subsample. NLSY = National Longitudinal Survey of Youth. All numbers reported are means except Salary and N.
† For APCAB and ACS (WA), subjects are allowed to have more than one race. In the NLSY, white, black, and Asian variables are mutually exclusive. In all data sets, Hispanic status is allowed to overlap with the racial variables.
*/**/*** indicate averages significantly different from the APCAB sample at the 10%/5%/1% level.
Given these comparison groups it is possible to contrast subjective estimates of wages and the non-employment rate relative to projected estimates. In Table 2 Panel A I compare median salary conditional on education for both Typical and Self estimates against median salary in the ACS (WA) sample. In Panel B I make similar comparisons, contrasting mean non-employment rates conditional on education with ACS (WA) estimates.

### Table 2

**Absolute Salary and Employment Estimates**

#### Panel A: Annual Full-Time Salary ($, thousands)

<table>
<thead>
<tr>
<th></th>
<th>APCAB (Self)</th>
<th>APCAB (Typical)</th>
<th>ACS (WA)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>SD</td>
</tr>
<tr>
<td>No HS Degree</td>
<td>33.6</td>
<td>24.0</td>
<td>26.7</td>
</tr>
<tr>
<td>HS Degree</td>
<td>36.7</td>
<td>30.0</td>
<td>21.9</td>
</tr>
<tr>
<td>Some College</td>
<td>44.1</td>
<td>39.0</td>
<td>22.5</td>
</tr>
<tr>
<td>2-Year Degree</td>
<td>54.0</td>
<td>49.5</td>
<td>23.8</td>
</tr>
<tr>
<td>4-Year Degree</td>
<td>69.1</td>
<td>68.3</td>
<td>25.5</td>
</tr>
<tr>
<td>Advanced</td>
<td>90.5</td>
<td>97.5</td>
<td>27.9</td>
</tr>
</tbody>
</table>

#### Panel B: Non-employment Rates

<table>
<thead>
<tr>
<th></th>
<th>APCAB (Typical)</th>
<th>ACS (WA)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>No HS Degree</td>
<td>.484</td>
<td>.500</td>
</tr>
<tr>
<td>HS Degree</td>
<td>.432</td>
<td>.400</td>
</tr>
<tr>
<td>Some College</td>
<td>.382</td>
<td>.350</td>
</tr>
<tr>
<td>2-Year Degree</td>
<td>.337</td>
<td>.300</td>
</tr>
<tr>
<td>4-Year Degree</td>
<td>.285</td>
<td>.200</td>
</tr>
<tr>
<td>Advanced</td>
<td>.218</td>
<td>.100</td>
</tr>
</tbody>
</table>

Table 2 shows that subjective expectations of salary and the non-employment rate are high relative to current observed levels. In the case of salary, different student interpretations of how to incorporate inflation into expectations, or different projections of the inflation rate, may alter the comparison between subjective and observed wages for any given educational level. A focus on wage returns instead of wage levels, which are the same no matter what level of inflation is assumed, sidesteps this problem. Mean non-employment rates are a fairly consistent ten percentage points higher than observed data. In all cases, the variance of the difference is large, representing heterogeneity in wage and employment expectations across APCAB respondents. These comparative ratios and differences are shown directly in Appendix B Table B1.

I use the same data presented in Table 2 to calculate returns to degrees. Wages and employment rates conditional on one education level are compared to wages and employment rates conditional on another. These returns estimates, as calculated in the next section, are the basis for most analyses in the paper.

3 Calculating Returns to Degrees

This paper is interested in the returns of education in terms of wages and the non-employment rate, how estimates of those returns differ between subjective responses and effects derived from observed data, and how both the subjective returns and the differences between subjective and projected returns differ over student observables. I calculate the return to wages and the non-employment rate for each of four higher education outcomes: some college but no degree, two-year degree, four-year degree, and advanced degree, compared to the outcome associated with holding a high school degree and not attending college.
Students report their subjective expectations under each counterfactual attainment level. As such, the perceived return at each attainment level can be calculated for each student. For student \( i \), the returns to degree \( d \) for wages (\( W \)) and the non-employment rate (\( N \)) are

\[
\gamma_{di}^W = \ln(W_i|d) - \ln(W_i|HS) \tag{1}
\]

\[
\gamma_{di}^N = (N_i|d) - (N_i|HS) \tag{2}
\]

Where \( W_i|d \) is the expected wage conditional on having attained educational level \( d \) at age 30 in Washington State, \( N_i|d \) is the expected non-employment rate at age 30 in Washington State conditional on having attained educational level \( d \), and \( HS \) indicates that the terminal level of education is a high school degree. Note that \( N_i \) is a measure of “non-employment” that includes both unemployment and being out of the labor force.

Since counterfactuals are not observed at the individual level in the ACS and NLSY data, cross-sectional estimates are generated using sample averages of the outcomes of interest for workers aged 29-31.\(^5\)

\[
\gamma_{d}^W = \overline{\ln(W_i|d)} - \overline{\ln(W_i|HS)} \tag{3}
\]

\[
\gamma_{d}^N = \overline{(N_i|d)} - \overline{(N_i|HS)} \tag{4}
\]

Equations 3 and 4 show how I calculate projected student returns to education. For wages, only full-time, full-year workers are included. This method does not attempt to correct for endogeneity in schooling. The returns estimated in this way are intended to be comparable in interpretation to those estimated using APCAB data.\(^6\) I discuss the appropriateness of these comparisons in further detail in the next section.

---

\(^5\) In the ACS, employment is a binary variable indicating whether or not the subject is currently employed. In the NLSY, employment is measured as the fraction of weeks in the previous year for which the subject was employed.

\(^6\) An alternate method of estimating these is to regress the outcome of interest on an indicator of having attained \( d \), using a sample of only those who have attained exactly \( d \) or graduated high school but did not
4 Comparing Returns to Degrees

The goal of this paper is to make a meaningful comparison between estimates of returns to education based on subjective data and projected estimates of returns to education based on observed data. In this section I address the way in which these measures are comparable, how the similarity or difference between them can be interpreted, and what assumptions must be made about the subjective data in order for these comparisons to be meaningful.

The projected returns estimated using observed data in the ACS record differences across educational attainment in wages and employment for current workers in the state of Washington. This is to be compared to subjective data collected about the expected outcomes of the student (Self) or of the typical person (Typical). There are a number of issues that complicate the comparison of these measures.

One of these issues, relevant to the comparison between subjective Self estimates and projected returns, is selection into college. For Self data, each student reports their own expected outcomes under each counterfactual. The subjective estimates of returns calculated using Self data are then internal rates of return, and the average subjective return using Self data is the average internal rate of return over the sample. This internal rate of return is contrasted against the projected return, which is an observed premium that does not attempt to control for selection. The projected return can then differ from the subjective rate both because ability is correlated with educational attainment, and because there may be heterogeneity in the internal return to education. Students with higher returns may be more likely to pursue an education, driving up the projected return in relation to the average causal return over the whole sample.

attend any college. This method produces identical results, but allows for the possibility of including controls for gender and race/ethnicity. No results change if these controls are included.
This issue of comparability suggests that Typical returns are more comparable to projected returns, since neither controls for selection. To elicit Typical returns, respondents were asked to think about the outcomes for the average person with a typical level of education in Washington State at age 30, which has a single correct answer that should match the overall mean of the observed data. While Typical returns avoid the issue of selection, the fact that there is a single “correct” answer across all students means that it does not make sense to compare demographic-specific subjective estimates. The correct Typical return estimated by a black student is the same as that estimated by a white student, even if their internal returns are different. Further, it is possible that different students have different ideas about who a “typical person” is. Because of this, differences between projected and Typical returns may be due only partially to differences in wage perceptions and partially to differences in demographic perceptions. However, even if the idea of the “typical person” varies among students, the comparison between subjective Typical and projected returns is valid as long as the average student in the APCAB sample has a realistic idea of who the “typical person” is.\footnote{Similarly, for Self estimates, students may have personal information not available to the researcher that is relevant to their return, which may be another reason for Self estimates to not match projected returns. However, comparisons of average returns can be considered valid as long as the average student within each group has unobserved personal information similar to the average person in the observed data.}

When making comparisons that are broken down by demographic characteristics, Self estimates represent internal rates of return unlike projected returns, but should include demographic differences. Since the subjective and projected returns are compared across demographics, selection bias is only a problem here to the extent that the difference between the projected return and the average causal return to education differs across demographic groups. It cannot be taken as given that all groups exhibit the same level of selection bias or heterogeneity in the returns. When discussing demographic-specific results, I make use of selection-corrected
demographic-specific returns to education found in the literature to support the conclusions
drawn from comparisons made between Self and observed data.

In practice, I report, in the paper or in appendices, the result of comparisons between
observed data and both Self and Typical subjective data for all analyses. Since the weaknesses of
these comparisons in general are not overlapping, the use of both strengthens the results. Self and
Typical returns estimates have very similar distributions (as seen in Section 5.1) and are
correlated across students (correlations between Self and Typical returns are .319, .446, .571, and
.705 for returns to some college but no degree, two-year degree, four-year degree, and advanced
degree, respectively). The close connection between the two measures suggests that students
think of the “typical person” as being somewhat like themselves, at least when it comes to
returns to education, and that students do not think the selection effect is very strong. Results are
robust to the use of either subjective measure.

Another issue facing comparability is the question of which feature of the wage
distribution is being reported by students. Unlike some other work (Attanasio and Kaufmann
2014; Dominitz and Manski 1996; Wiswall and Zafar 2015), APCAB data features only a point
estimate of the underlying wage distribution, rather than a subjective distribution with many
points of support. The necessary assumption here, in order to reasonably compare the subjective
estimates to those from observed data, is that the reported subjective estimate is, as instructed, a
central tendency of the distribution.

There is also the issue of comparisons across time, especially for subjective Self
estimates, in which students may be aware of current returns but are considering a future for
themselves where the returns to education have changed considerably. They may also be taking
business cycles and seasonality into account, which if applied to the observed data may change the projected return to which subjective returns are compared.

These issues of comparability across time pose some problem for comparisons between subjective and projected returns, but also highlight some of the issues in attempting to use projected returns as a proxy for student beliefs in the wider literature. For example, it is possible that student expectations of returns incorporate expected changes in returns in the future. However, the claiming that these future changes represent student expectations is tenuous without expectations data, and requires further assumptions about the way in which these predictions are made.\(^8\)

One final consideration, important given that this paper focuses on comparisons between subjective and projected returns rather than raw expectations of outcomes, is that of measurement error. Subjective reports are noisy representations of actual beliefs. Returns estimates, which involve the combination of two reports, are noisier. Classical measurement error will bias downwards any relationship between subjective and projected returns, and I discuss the implications of this further in Section 5.2. However, a focus on returns estimates rather than raw reports, which would presumably have less measurement error, is still worthwhile. The return, rather than the raw level, is the input of interest in the human capital model, and so it should be an object of interest. Additionally, as stated previously, raw reports may have less statistical noise but may also incorporate varying student perceptions about inflation or their own ability to earn unconditional on schooling. Returns estimates, as opposed to

---

\(^8\) Students do not appear to be making these predictions using prior trends, as the use of trend data does not make projected estimates of returns closer to subjective estimates. I estimate \(\gamma_{d, W}^{w} \forall d\) again using Washington residents aged 25-34 in the Current Population Survey data from 1997-2011. Over that 15-year time span, \(\gamma_{d, W}^{w}\) showed no statistically discernable upward trend. In the absence of an anticipated upward future shock, upward growth is too slow to predict an increase over the next 12 years which would significantly decrease the gap between average subjective and projected returns.
raw estimates of wage and non-employment rate levels, are noisier than raw estimates, but on the other hand avoid the above issues.

5 Results

5.1 Aggregate Returns

In Figure 1, I compare the subjective wage and employment rate returns to the projected wage and employment rate returns calculated using observed data. Each image relates to the return to a different attainment level (some college but no degree, two-year degree, four-year degree, and advanced degree). In each image, the kernel density plots of the subjective estimates are compared against the average estimated projected return, marked by a vertical line. There are two primary areas of interest to focus on in these graphs: the distributions of the subjective returns, and the relationship between the subjective and projected returns.

For both wage and non-employment rate returns, there is wide variation in student beliefs. The distribution of returns becomes less concentrated for higher degrees, possibly reflecting a higher degree of uncertainty about returns at these more remote levels. The means and medians of these distributions move in the expected directions – the average expected return for each degree is stronger than the average expected return for the degree below it. For example, the mean subjective expectation for the increase in log wages and the decrease in non-employment rate for a four-year degree are .736 and -.157, respectively. The mean returns for an advanced degree are 1.038 and -.228, respectively. However, there are still small groups of students who believe that attainment of higher education will lower their wages (the return is below 0) or increase the non-employment rate (the return is above 0). About 4.5% of students estimate that the Typical wage return to a bachelor’s degree is negative.
Figure 1

Panel A: Log Wage Returns to College ($\gamma_d^W$)

Panel B: Non-employment Rate Return to College ($\gamma_d^N$)

Note: Vertical line represents the projected return as calculated using ACS (WA) sample of Washington residents aged 29-31. A small number of outliers beyond the shown bounds of the graphs are dropped for clarity.
These subjective distributions can be compared (given the caveats in Section 4) to the average projected returns. For non-employment rate returns, despite the considerable level differences in non-employment rate estimates shown in Table 2, students at the mean make estimates of the non-employment rate return that match the projected return closely. On average, students estimate that the effect of some college but no degree or a two-year degree on the non-employment rate is about .020 smaller than the projected return, and about .005 larger for four-year and advanced degrees. While there is clearly a large amount of variation in subjective expectations of the return, on average, non-employment rate returns estimates generated using observed data appear to match student expectations.

For wage returns the story is different. While the mean subjective and projected returns to some college are close, the average student expects to get a much bigger wage bump for any college degree than is found in the projected return. The average expected Typical wage return is 30, 32, and 43 percentage points higher than the projected return for two-year, four-year, and advanced degrees, respectively. In each case, about 85% of students estimate the Typical return to be higher than the projected return. Since these Typical estimates ask students to estimate the figures calculated in the observed data, the mismatch can be interpreted roughly as an error or lack of information on the student’s part. This result suggests that students are not aware of the population wage premium for higher education.9

Because Self and Typical estimates share nearly identical distributions, estimates of Self returns are similarly higher than projected returns. The difference between Self and projected

---

9 I run two robustness checks for this finding. First, it is possible that seniors, who are closer to the labor market than juniors, have better information about returns. However, there is no significant difference at the 95% level between the mean expected return for juniors and for seniors for any wage or employment return at any degree level. Second, it is possible that students are reporting returns for more localized areas such as King County or the surrounding Tri-County area, rather than all of Washington State. I re-estimate projected returns using the ACS data for these regions; regional returns are very similar to state-level returns.
estimates of wage returns to degrees suggests that estimates of returns made using observed data will have a difficult time matching student estimates of their own return, unless the correction to projected returns made by controlling for selection increases the return by approximately 30-40%, an amount larger than currently found in the literature on selection-controlled returns to education (see, e.g., Card 1999). Unlike the mismatch between Typical returns and projected returns, which can be interpreted as the inability of the students to match the data, this result points towards a difficulty in using the data to match the students. Additionally, the wide distribution of subjective returns suggests that any universal projected return to education will be unable to match student expectations of the return, no matter how that universal return is adjusted. In the next two sections, I evaluate whether projected returns that allow for heterogeneity across students are aligned with the heterogeneity present in student expectations.

5.2 Disaggregated Results

The subjective and comparison data sets are large enough that separate returns estimates can be produced for different subgroups. In this section I analyze the group-level match between subjective returns and projected returns, meaning comparisons of returns estimated using some subgroup of those in the APCAB (Self) data and those in the same demographic subgroup in the ACS (WA) or NLSY data. Analysis of returns at this level is crucial. As established in the previous section, projected wage returns are below subjective wage returns, and non-employment rate returns match closely. However, this result is not enough to conclude that projected returns are a bad proxy for wage returns but a good proxy for non-employment rate returns. If students who would be expected to have a high projected wage return also expect high wage returns, then projected wage returns are still a good proxy for subjective wage returns,

10 For demographic variables present in both the NLSY and the ACS, returns estimates are very similar in the two data sets.
since they will be highly correlated at the individual level. Conversely, if students who would be expected to have a high projected non-employment rate return expect low non-employment rate returns, then projected non-employment rate returns are not a good proxy for subjective non-employment rate returns.

Analysis from this point focuses on APCAB (Self) estimates, since these estimates should track demographic similarities in observed data. As mentioned in Section 4, comparison is not completely straightforward here since APCAB (Self) estimates represent the internal rate of return while projected estimates do not. I invoke estimates of selection-corrected returns in the literature and additional comparisons between APCAB (Typical) estimates and observed data to address this issue. Non-employment rate reports do not have a Self component and so estimates for the typical person are used.

To illustrate the analysis that will follow, Table 3 depicts differences in wage returns estimates broken down by gender. Women expect slightly higher returns than men, and with the exception of some college but no degree this is consistent with the projected return. So, the differences between subjective and projected wage returns are similar for men and women for non-advanced degree levels. We can then conclude that subjective and projected returns are aligned over gender, similar to what is found in Rouse (2004). This alignment is what one would expect if estimates were based on observations of labor market outcomes, albeit with an upward shift in the subjective return applied to all subjects at the population level.

Table 3 gives a detailed account of one demographic disaggregation. Keeping this example in mind, I demonstrate disaggregation over gender, race, GPA, FRPL, and parental education. Figure 2 Panel A presents a plot with the projected return for a four-year degree $\gamma_{4Y}^W$. 
estimated using observed data on the y-axis and the average of the subjective return $\gamma_{4W_i}^{W}$ estimated using APCAB (Self) on the x-axis. The comparison data set is the ACS (WA) for the

### Table 3

Mean Log Wage Returns to College Attainment by Gender

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th>Women</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Some College</td>
<td>Two-Year Degree</td>
</tr>
<tr>
<td>Subjective Return (Self)</td>
<td>.216</td>
<td>.426</td>
</tr>
<tr>
<td>Subjective Return (Typical)</td>
<td>.214</td>
<td>.439</td>
</tr>
<tr>
<td>Projected Return</td>
<td>.163</td>
<td>.167</td>
</tr>
<tr>
<td>Difference (from Self)</td>
<td>.053</td>
<td>.259</td>
</tr>
</tbody>
</table>

aggregate as well as for the disaggregation over gender and race\(^{11}\) and the NLSY for the disaggregation over GPA, FRPL, and parental education. In each case, the returns are de-meaned so the population-weighted average of the returns is 0. A 45-degree line passes through the “Origin” point, which represents the aggregated subjective and projected return. If a group’s point falls on this line, the difference between the subjective and projected returns for that group are the same as for the aggregated estimate.

\(^{11}\) For black workers, instead a national ACS sample is used due to the small number of black people at certain educational levels in the ACS (WA) sample.
For wages, we can see male and female falling roughly along the line, as demonstrated in Table 3, indicating that the subjective and projected returns are aligned over gender. However, other groups of disaggregated estimates do not fall along this line. In other words, the distance between subjective and projected returns differs by group, suggesting that the subjective and projected returns are not aligned over these groups and a population-level upward correction to projected estimates of $\gamma_{4\gamma}^W$ would not cause projected estimates to match subjective estimates.

Similarly, in Figure 2 Panel B, there is little apparent relationship between subjective and projected non-employment returns $\gamma_{4\gamma}^N$. In the cases of the split over parental BA status and GPA, the groups with higher subjective returns also have higher projected returns. However, in general the subjective and projected returns do not align.  

In the wage returns comparison, the subjective returns represent the average internal rate of return but the projected returns do not. As such, the lack of a relationship between subjective and projected returns in wages could be explained by the selection effect differing in strength across subgroups. While this is difficult to address in general, what can be found in the literature about demographic-specific selection-controlled returns to education supports the initial conclusion.

For example, in Figure 2 Panel A, projected wage returns for black students are larger than returns for white students, but the opposite is found with subjective returns. A higher average rate of return to a four-year degree for black students than for white students is found commonly in the literature (Henderson et al., 2011), even in the case of average internal rates of return over the population (Heckman et al., 2006). So in a comparison of subjective and average projected internal returns for white and black  

---

12 In Figure 2, returns to four-year degrees are shown. Returns to other degree levels, and for typical wage returns, can be found in Appendix B Figure B1. These other returns reiterate the findings in Figure 2: there is no strong relationship between subjective and projected returns at the subgroup level for any degree return.
Figure 2
Subsample Analysis

Panel A: Wage Return to a Four-Year Degree

Panel B: Non-employment Rate Return to a Four-Year Degree
students, the same result would be found. Similarly, the result found here that women have higher wage returns than men is also found in the literature (Brand and Xie 2010; Jacob 2002; Marcotte et al. 2014), although these studies do not address selection bias arising from the correlation between the internal rate of return and educational attainment. If the difference between the return for the marginal and average student varies greatly over these groups, this will threaten results. The general match over gender and white/black does not necessarily mean that the use of an average internal rate of return would leave the other subgroups unchanged, but they are suggestive and at least support the result for comparisons over gender and between white and black students. More generally, there is evidence in the literature that those who face more obstacles in going to college have higher returns (Brand and Xie, 2010). With parental BA status as an exception, this does not hold up in the subjective returns in Figure 2 Panel A. Whites, students with high GPAs, and students who do not receive FRPL all expect higher returns than others.

The analysis so far in this section does not take into account overlapping demographics. It is possible, for example, that while black students expect lower returns than white students, counter to the projected return, but that this problem may be resolved or lessened when looking at black men and black women separately. To allow for this, I generate individualized estimates of projected returns for comparison to the subjective returns, which are already calculated at the individual level. Additionally, this approach allows for a test of whether or not the subjective and projected returns are correlated at the individual level, which more directly addresses the use of projected returns as a proxy for subjective beliefs.

I generate individualized returns using observed data by allowing returns estimates to vary over background characteristics. Using an observed sample of high school graduates and
those with the educational attainment of interest, I regress the outcome (either log wages or non-employment) on the presented list of background controls, degree attainment, and the interaction between degree attainment and all background controls. The individualized projected return is generated using each APCAB student’s mix of background factors.

I plot the relationship between these projected returns and the reported subjective returns for a four-year degree in Figure 3. For both wages and employment, individualized subjective and projected returns are completely unrelated. The correlation between the individual-level projected and subjective returns is a statistically insignificant -.064 for wages and .052 for the non-employment rate.

This correlation is likely attenuated by measurement error in the subjective returns estimate. For wages, measurement error could imply an opposite sign if the error in the subjective returns estimate were correlated with the value of the return. For non-employment rate returns, a disattenuated correlation (Spearman, 1910) could imply a correlation more in the range necessary for an acceptable proxy. For this to happen, the reliability of the subjective return would need to be very low; the product of the reliabilities for the subjective and projected reliabilities would need to be about .01 to produce a disattenuated correlation of .5. Such low reliabilities would imply that, if the subjective and projected returns were equally reliable, about 90% of the variation in each return would be only noise.

Both figures use the NLSY as comparison data so as to allow for disaggregation across FRPL, parental education, and GPA, and focus on the return to a four-year degree. However, results are consistent for comparisons to the ACS (using only gender and race/ethnicity as background characteristics) and for returns to nearly all other degrees. Looking at all degree

---

13 The standard formula for the disattenuated correlation for two given variables is equal to the sample correlation of the variables divided by the square root of the statistical reliability of the first variable multiplied by the square root of the statistical reliability of the second variable.
levels, for either Self wages, Typical wages, or the non-employment rate, and using either the NLSY or the ACS, correlations are small and generally insignificant, with a notable exception of wage returns to advanced degrees, for which the correlation is about .11 depending on the measures used.

**Figure 3**

Scatterplot of Projected and Subjective Returns

Panel A: Wage Returns

Panel B: Non-employment Returns

The heterogeneity over observables exhibited by subjective returns estimates does not align with the heterogeneity over observables exhibited by projected returns estimates, either at the subgroup or individual level. At the available level of demographic detail, projected returns are not a good proxy for subjective returns.

**5.3 Educational Attainment Goals**

The lack of a relationship between subjective and projected returns to education naturally leads to the question of which of these seemingly orthogonal variables actually relates to decision-making. The goal in this section is not to develop a formal model of attainment as in

---

14 This lack of a relationship holds if projected returns estimates are taken using more localized ACS data from King County only or from the surrounding Tri-County area.
Attanasio and Kaufmann (2014), but rather to present a verification exercise. In any model of student choice in which students care about future earnings, returns should be related to student choice. If subjective returns do not correlate with student plans, then either students do not care about future earnings or the subjective returns are picking up something other than actual beliefs. In the second case the inability of projected returns to match subjective returns is not much of a concern.

Final educational attainment is not observed, but attainment is measured in two ways here. First, students were asked to state the final level of education they would like to attain. Consistent with other studies that elicit desired educational attainment, this variable is rather optimistic and students are likely to actually attain less education than they state (Avery and Kane, 2004; Choy, 2001). However, the variable gives us a measure of their desired final attainment, which should be consistent with their beliefs about the returns to education. Second, seniors were asked to report whether they were attending college the following fall, and which schools they were looking at or were registered for. These schools are coded as two or four-year institutions. This second measure is a more direct measure of student activity, but is noisy for other reasons – a student may change plans before the fall or may be planning delayed enrollment. A student attending a two-year school may not plan to finish their education there.

Table 4 shows pairwise correlations between measures of attainment and both subjective and projected returns. Projected returns are calculated on the individual level using the ACS data as in the previous section to allow for variation over all background characteristics; results are similar if the NLSY data is used instead. For subjective wage returns, Self returns are used, although results are similar if Typical returns are used instead.
Table 4

Correlation of College Decisions with Wage and Non-employment Returns

<table>
<thead>
<tr>
<th>Decision</th>
<th>Subjective Return</th>
<th>Projected Return</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Some College</td>
<td>2-Year Degree</td>
</tr>
<tr>
<td>Desires Any</td>
<td>.111**</td>
<td>.127***</td>
</tr>
<tr>
<td>Desires 4Y+</td>
<td>.080**</td>
<td>.078*</td>
</tr>
<tr>
<td>Attending Any</td>
<td>.023</td>
<td>.116**</td>
</tr>
<tr>
<td>Attending 4Y</td>
<td>.063</td>
<td>.073</td>
</tr>
</tbody>
</table>

|                   | Some College      | 2-Year Degree    | 4-Year Degree  |
| Desires Any       | -.004             | -.043            | -.109***       | -.103** | .029  | -.125*** | -.150*** | -.165*** |
| Desires 4Y+       | -.002             | -.039            | -.010          | -.015   | -.096*** | -.131*** | -.161*** | -.206*** |
| Attending Any     | -.004             | -.043            | -.109***       | -.103** | .029  | -.125*** | -.150*** | -.165*** |
| Attending 4Y      | -.028             | -.021            | -.066          | -.107*** | -.113*** | -.221*** | -.167*** | -.294*** |

Note: “Desires Any” and “Desires 4Y+” indicate that the student’s desired attainment level is, respectively, of any college degree or of a four-year or advanced degree. “Attending Any” and “Attending 4Y” was asked only of seniors and indicates, respectively, that they are attending any college in the following fall, or attending a four-year college in the following fall. */**/*** indicates statistical significance at the 10%/5%/1% level.

The subjective wage return to a college degree is correlated with the decision to pursue a college degree. The returns to four-year or advanced degrees are correlated with all types of planned attainment, and the return to a two-year degree is correlated with the plan to attain any level of college degree but not with the plan to attend a four-year college. The return to attending some college but receiving no degree is related to desired attainment levels but not whether a senior is planning to attending college in the following fall. Projected wage returns, on the other hand, are not strongly related to educational choice in the expected manner. The return to some college, a two-year degree, or a four-year degree is actually negatively correlated with attainment.
plans, although the return to an advanced degree is positively correlated with attainment plans. As the return to the non-employment rate is negative (more education leads to less non-employment), a negative sign on the correlation of attainment with the return to non-employment in Table 4 indicates that a stronger return is associated with more attainment, which is to be expected. Subjective returns are almost always negatively correlated with attainment plans, although the relationship is only significant between whether the student is attending college in the following fall and returns to four-year and advanced degrees. Projected returns are negatively and significantly correlated with student attainment plans in a consistent manner.

That both subjective wage and non-employment rate returns correlate with college plans (although the employment relationship is weak) is indicative that they may be involved in the decision making process. Notably, though, the projected non-employment rate returns also relate strongly. Attanasio and Kaufmann (2012) also find that decision-making correlates with both subjective and observed-data returns. There are a few possible reasons why projected returns might relate to decision-making even though the student does not appear to be aware of them. First, projected returns may contain some information that students know internally and are capable of responding to but not reporting. Second, it is possible that parents in groups with stronger projected returns have higher incentives to offer more encouragement that their children go to college. Even if students are not directly aware of the projected returns, they may be indirectly influenced by them in this way.

Student attainment plans are correlated positively and significantly with subjective wage returns expectations. The sign of the correlation between student attainment plans and subjective non-employment rate returns expectations is reassuringly negative, although the relationship is not strong. These correlations imply that the information being picked up by the data does relate
to the actual decisions that students make. That the subjective returns are related to student plans indicates that the projected returns are indeed missing something important by not being related to subjective returns.

6 Conclusions

What information does this paper give us about student expectations? We have a number of general results to contend with:

- Most students expect that the returns to education are large, positive for wages, and negative for the non-employment rate.
- On average, the subjective internal wage return is higher than the projected wage return, but subjective estimates of non-employment rate returns are about the same as projected returns.
- There is a lot of heterogeneity in subjective estimates for wage and non-employment rate returns. This heterogeneity does not align with heterogeneity in projected returns on an individual or subgroup level.
- Student anticipated educational attainment relates positively to subjective wage returns, negatively (and weakly) to subjective non-employment rate returns, and correlates with projected non-employment rate returns (more so than subjective non-employment rate returns) but not most projected wage returns.

These results can be used to evaluate some approaches to studying educational choice and policy geared towards changing student beliefs.
The mismatch between subjective and projected returns has important implications for the way that educational choice is studied. Models of educational choice commonly relate students’ responses to some measure of the return to attending school, usually projected using observed data. The strength of the students’ response is taken to be a measure of preference for future income. If subjective and projected returns do not align, then the estimated coefficient will be biased. We see students responding to projected returns both in choice models and in the correlational analysis in this paper. However, it does not necessarily follow that this response is evidence of a direct preference for future consumption. Response to projected returns could be mediated through parental influence, for example. Many studies of educational choice treat the preference for future consumption as a parameter of interest, since the perceived rate of earnings returns can be a policy lever. A bias in this coefficient is of importance to researchers and policymakers.

If projected labor market returns do not relate to stated expectations, then research on educational choice must take this into account. One clear approach is to collect subjective expectations data and include it as a predictor of student choice. This work is already being done in a number of contexts (e.g. Arcidiacono et al. 2011; Attanasio and Kaufmann 2012; Wiswall and Zafar 2015) but could be expanded. Currently, most researchers planning to use subjective expectations data in educational contexts must gather it themselves, but inclusion of these questions in standard large-scale surveys would aid research on education.

Another, more difficult, approach to improving research when observed labor market returns do not relate to stated expectations is to flesh out a usable model of expectations formation such that the econometric model underlying the projected returns better reflects the expectations formation process. If this is the case then subjective and projected returns will likely
be strongly correlated. However, since this paper finds subjective returns to be uncorrelated with projected returns, such a model would need to be based on something other than belief updating in response to observations of the labor market. A number of studies in disparate contexts have examined the impact of information on beliefs and how beliefs respond to information-based research interventions and experiential learning (Jensen 2010; Oreopoulou and Dunn 2013; Wiswall and Zafar 2015; Zafar 2011). Information sources and the provision of information do impact beliefs, but even with direct intervention the influence of information is limited, and so this cannot be the whole story. Unfortunately, subjective beliefs are difficult to explain. Using APCAB data, a regression of subjective individual returns on demographics, family encouragement, (endogenous) information sources, senior status, and attitude towards education yields some significant coefficients but explains very little of the variance, like the intervention studies failing to provide a full portrait of what generates expectations.\(^{15}\) Other explanatory sources are necessary, especially outside of an experimental context.

Beyond its implications for economic research, these results have policy implications as well. There is recent policy research interest in interventions designed to change students’ perceptions of returns (e.g., Hoxby and Turner 2013; Jensen 2010), as well as a recent policy intervention, in the form of the College Scorecard system. The aggregate analysis suggests a possible pitfall in policy approaches that attempt to “correct” student beliefs to match projected returns. In the sample setting, student estimates of wage returns are actually above projected wage returns. If informational interventions are effectively convincing such that student beliefs

\(^{15}\) Full results are available from the author. \(R^2\) values range from .02 to .08, depending on which return it is. The included list of covariates includes all background characteristics used in prior sections as well as controls for senior status, whether the student’s family wants and/or expects them to go to college, and whether they got information on college from (nonexclusive): parents, family, teachers, school staff, other adults, college events, friends, printed materials, college representatives, college visits, the internet, or TV and movies.
match projected returns, then for many students the intervention would have the effect of lowering expectations of wage returns from college. Given that these expectations correlate with student choice, and that experimental approaches suggest this relationship is likely causal (Jensen 2010; Wiswall and Zafar 2015), the intervention may have an adverse effect.
References


http://dx.doi.org/10.1037/0033-295X.102.4.684


http://dx.doi.org/10.1016/S1574-0692(06)01007-5

http://dx.doi.org/10.1016/j.econedurev.2011.05.002


http://dx.doi.org/10.1016/S0272-7757(01)00051-6

http://dx.doi.org/10.1086/522974

http://dx.doi.org/10.1162/qjec.2010.125.2.515

http://dx.doi.org/10.3102/00346543075001063

http://dx.doi.org/10.3102/00346543075001063

http://dx.doi.org/10.1111/j.1468-0262.2004.00537.x

http://dx.doi.org/10.3102/01623737027002157

http://dx.doi.org/10.1086/374965

http://dx.doi.org/10.1111/j.0038-4941.2004.00277.x


Appendix A: Survey Administration and Wordings

The APCAB survey was administered at thirteen high schools in three districts in King County, Washington. The surveyed schools varied in socioeconomic status of the student body, urbanicity, and enrollment size, from fewer than 90 juniors and seniors at the smallest school to over 1,000 at the largest. The survey was voluntary and was offered to a subset of the students at each school in non-purposively selected school periods and classrooms. Students were offered a $5 gift card in exchange for their participation. The survey was administered using paper and pencil, and there was always a representative available to answer student questions about the survey. Wage expectations were elicited using a method similar to that used by Betts (1996). Students were informed of what was meant by “annual salary” and the structure of the question. Then, for each level of education, they were presented with a line of 39 numbers, representing $12,000 per year to $120,000 per year in increments of $3,000 per year, with the additional options “Less than $12,000” and “More than $120,000.” Students were also allowed to indicate that their answer was between two listed numbers. In analysis, these intermediate estimates were coded as being halfway between the circled numbers, “Less than $12,000” was coded as $9,000, and “More than $120,000” was coded as $123,000.\(^\text{16}\)

The introduction for the two questions reads:

Now I want you to think about **ANNUAL SALARIES**. For this survey, an annual salary is defined as the amount of money someone would make in a **year** from all of their employment if they worked full-time (at least 35 hours per week) and full-year

\(^{16}\) For the Typical salary, fewer than .1% of respondents were subject to these cutoffs for any education level other than “No HS Degree” and “Advanced Degree.” The same number for the Self salary is fewer than .38% of respondents. For both Self and Typical, about 1.5% of respondents experienced a cutoff for the “No HS Degree” option, 1.75% for the “Advanced Degree” option.
(at least 50 weeks of the year). For all of the following questions, think about someone who is 30 years old and is working full time and full year (at least 35 hours per week, 50 weeks of the year). Please answer ALL of the following, even if you are unsure. To give a sense of perspective, a person who earns $15 per hour and works full-time and full-year will have an annual salary of about $27,000.

For each question, circle the annual salary closest to what you think it is. If you think the answer is between two of the listed salaries, circle both of those salaries. All listed numbers are in thousands of dollars.

For example, if you want to answer “$30,000,” circle “30.” If you want to answer “$31,000,” circle both “30” and “33.” Raise your hand if you are not sure how to write your answers to this question.

The two questions for the Typical person and the Self had additional specifying instructions:

What do you think the annual salary is for an average 30-year-old full-time, full-year worker in Washington...

What do you think YOUR annual salary would be at age 30 if you had a full-time, full-year job...

The sentence concludes in six different ways for the six types of education: “who does not have a high school degree?” / “without having a high school degree?” for no high school degree, and then “who has”/ “with a” “high school degree but without going to college?” “some
college experience but no degree?” “an associate's or technical degree (two-year college degree)?” “a bachelor's degree (four-year college degree)?” or “a Master's degree, PhD, MD (Doctor), or JD (Lawyer)?”

The question relating to the non-employment rate was worded similarly. Students were encouraged to think about 100 typical 30-year-old Washington residents with the specified level of education and asked to estimate how many of those 100 residents might be unemployed. This method of asking for frequency counts rather than eliciting an actual non-employment rate follows from the psychological literature suggesting that this method of asking about rates is more likely to generate realistic responses (Gigerenzer and Hoffrage, 1995). The exact wording is:

For each question, imagine 100 people in Washington who are 30 years old with the given level of education. How many of these 100 people would you expect to be

unemployed today...

The sentence concludes again in six different ways with “among 100 people who” have the given levels of education, described in the same way as for the wage questions.
## Appendix B: Additional Results

### Table B1

Subjective Wages and Non-employment Rates Relative to HS Degree

| Panel A: Ratio of Annual Full-Time Salary to Annual Full-Time Salary with HS Degree |
|---------------------------------|---------------------------------|---------------------------------|------------------|------------------|
|                                 | APCAB (Self)                    | APCAB (Typical)                 | ACS (WA)         |
|                                 | Mean   | Median | SD    | Mean   | Median | SD    | Mean | Median |
| No HS Degree                    | .968   | .786   | .890  | .907   | .750   | .891  | .813 | .683   |
| HS Degree                       | 1.0    | 1      | 0     | 1      | 1      | 0     | 1    | 1      |
| Some College                    | 1.294  | 1.222  | .510  | 1.323  | 1.212  | .731  | 1.156| 1.067  |
| 2-Year Degree                   | 1.649  | 1.517  | .717  | 1.663  | 1.538  | .741  | 1.213| 1.183  |
| 4-Year Degree                   | 2.244  | 2.050  | 1.155 | 2.312  | 2.083  | 1.229 | 1.622| 1.547  |
| Advanced                        | 3.051  | 2.714  | 1.726 | 3.257  | 2.889  | 1.816 | 1.965| 1.737  |

| Panel B: Difference Between Non-employment Rate and Non-employment Rate with HS Degree |
|---------------------------------|---------------------------------|------------------|------------------|
|                                 | APCAB (Typical)                 | ACS (WA)         |
|                                 | Mean   | Median | SD    | Mean | Mean | Median |
| No HS Degree                    | .056   | .060   | .185  | .081 | .081 | .080   |
| HS Degree                       | 0      | 0      | 0     | 0    | 0    | 0      |
| Some College                    | -.056  | -.050  | .143  | -.080| -.080| -.080  |
| 2-Year Degree                   | -.103  | -.100  | .218  | -.129| -.129| -.129  |
| 4-Year Degree                   | -.157  | -.180  | .277  | -.159| -.159| -.159  |
| Advanced                        | -.228  | -.230  | .327  | -.222| -.222| -.222  |

Standard deviations are omitted for the ACS results since these comparisons are not calculated at the individual level.
Figure B1

All Subsample Analyses

Typical Wage Return to Some College

Typical Wage Return to Two-Year Degree

Typical Wage Return to Four-Year Degree

Typical Wage Return to Advanced Degree

Self Wage Return to Some College

Self Wage Return to Two-Year Degree

Self Wage Return to Advanced Degree

Non-employment Rate Return to Some College
Non-employment Rate Return to Two-Year Degree

Non-employment Rate Return to Advanced Degree

Legend:  7 – Hispanic
         1 – Origin  8 – GPA above Median
         2 – Male    9 – Parent has BA
         3 – Female  10 – GPA below Median
         4 – White   11 – No Parent has BA
         5 – Black   12 – FRPL
         6 – Asian   13 – No FRPL