The Impact of Identity and Self-perception on Labor Market Outcomes

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Abstract

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Economics

This dissertation explores the impact of perception on labor market outcomes in three contexts.

The first chapter uses NELS:88 data to examine the differential impact of subject specific self-perception on education choices and labor market outcomes. I find that test scores, grades and perception are all positive and statistically significant indicators of the years of education attained, and dissonance between the measures does not appear to affect investment in education. However, perception outperforms test scores when predicting later wages. These findings challenge the standard assumption that individuals have perfect information about their ability, and points to the importance of understanding self-perception in explaining future success.

The second chapter uses 2000 Census data to determine if there are country level differences in the returns to education for Hispanic males who migrated as adults. It also explores if similar country level effects are present in the returns to Hispanic males who migrated as children and in the returns to non-immigrant Hispanic citizens. We find that country level differences are evident in the returns to education for both adult and child immigrants. However, we do not find evidence of country level effects for Hispanic citizens; instead Hispanic citizens converge to a Hispanic mean, indicating that initial advantages for South American and Caribbean immigrants do not persist.

The final chapter uses a lab experiment to determine the impact of hair texture and style on labor market outcomes for African American women. The experiment is conducted by altering the photographs of African American women to show their hair in different styles. The photos are randomly paired with a short dossier. Study subjects are asked to use these dossiers to make hiring and wage decisions. I find that while hairstyle may not matter instances where ability is readily calculated, it may have an impact in situations where ability is more ambiguous.

JEL Classification: I26, J01, J15,

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Perceived Ability's Continuing Impact on Labor Market Outcomes

Chasya Hoagland*

June 18, 2015

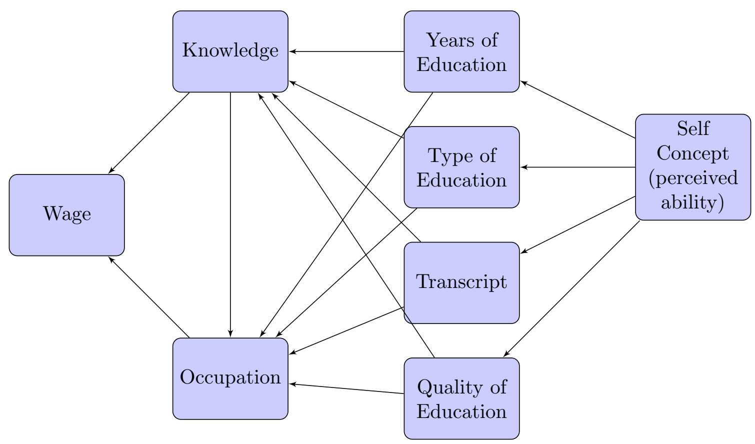
Abstract: Self-perception of ability is a key driver of educational and career achievement. However, the role that self-perception plays in the pursuit of education and career advancement has been largely ignored in human capital investment literature due to their anchoring assumption that individuals are fully informed of their abilities and optimally invest in education in order to maximize their expected life-time utility. This paper explores the differential impact of self-perception, relative to demonstrated ability, on education choices and performance outcomes. Using data from the National Education Longitudinal Study of 1988, I examine the impact of subject specific (math and English) self-perceived ability on investment in education and labor market outcomes, after controlling for test scores and grades. I also measure the impact of dissonance (when perception, test scores, and grades do not align) on these outcomes. I find that test scores, grades and perception are all positive and statistically significant indicators of the years of education attained, and dissonance between the measures does not appear to affect investment in education. However, perception outperforms test scores when predicting later wages. Interestingly, overestimating English ability is punished, but overestimating math ability is rewarded in terms of later wages. These findings challenge the standard assumption that individuals have perfect information about their ability, and points to the importance of understanding self-perception formation and their contribution in explaining future success.

How does a school, university, or for that matter an employer, know who the best, brightest and highest performing students will be? Many social scientist have dedicated lifetimes to better understanding this question. Therefore, it is unlikely that an eighth grade student will know how to choose which classes to take, or how hard to study, in order to best capitalize on his or her potential. Faced with uncertainty, perception of ability will be a key driver of educational and career achievement. Perception influences where college and job applications are sent, field selected, wage requested, and effort expended in the classroom and workplace. Nevertheless, the human capital investment literature understates the importance of perception by assuming that individuals are aware of their ability and invest in education in a manner that will maximize their expected utility. Test scores and grades are used in the literature as proxies for ability, with perception, at best, being inferred from these measures. The assumption that people are aware of their ability is not true empirically (Marsh, 1987; Steele & Aronson, 1995; Nguyen & Ryan, 2008; Good, Aronson, & Harder, 2008). This paper explores the impact of perception on labor market outcomes. I hypothesize that since students make education investment decisions based on their perceptions, perception may be a valuable indicator of achievement. I explore the impact of subject-specific perception on investment in education and labor market outcomes after controlling for test scores and grades. Finally, I examine if the magnitude of the dissonance (inconsistencies) between these measures influences wages and investment in education.

Test scores are often used as measures of student ability in a variety of settings. The benefit of using test scores to predict outcomes is that it is a standardized measure by which an entire sample can be compared. In general, test scores are positively correlated with years of education and labor market outcomes with or without controlling for years of education. Even high scoring high school dropouts earn persistently more than low scoring dropouts (Tyler, 2004). However, the impact of test scores on returns is indirect. Most tests estimate the stock of subject-specific knowledge instead of a student's true ability to learn. The subject-specific knowledge measured by test scores is not relevant in many professions. Several papers have indicated that even the cognitive skills indirectly measured through test scores are not the most important factor for employers when making hiring decisions (Bowles and Gintis (2002), Warren et. al. (2008), Rosenbaum (2001) and Bills(1988)). This distinction is relevant because firms principally care about a students ability to learn. Employers only indirectly value cognitive ability because it is an imperfect signal of the applicant's ability to retain and apply job-specific knowledge.

The relevance of test scores as a predictor of labor market outcomes is further complicated because many employers never see these test scores. Employers generally form expectations about an applicant's ability from his years of education, education type (major selection, quality of school), performance in school (measured through transcripts) and inferred education quality (which is not directly observed, but may be inferred from the reputation of the institution). Individuals invest in these four channels to maximize their expected utility. Traditional Economic models assume that workers are aware of their own ability level. It is unlikely that a middle school or high school student would be aware of their true ability without any job market experience. Therefore, students must invest based on their expected ability level.

Figure 1: The determinants of future wages



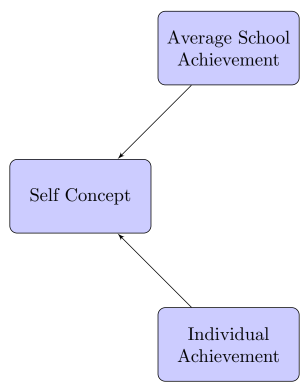
Although early test scores are correlated with one's perception of ability when making early human capital investment decisions, test scores have limited direct impact on perception. Students might not be aware of their test performance. Even if they are told their score, it may not significantly impact their perception of ability. Standardized test scores may not be as salient to the student as continuous classroom performance, which is largely captured by grades. Therefore, grades may also be a better predictor of performance than test scores. In addition, the student may, rightly or wrongly, have other reasons to believe that their test scores do not accurately capture their true ability.

Literature in the fields of psychology, behavioral economics, and labor economics build intuition about how performance may inform an individual's perception of ability and situations which might generate a systematic dissonance, or difference, between an individual's performance and their perceived ability. The key predictions of the relevant literature form an ambiguous picture of the ultimate impact of perception on labor market outcomes after controlling for performance. This ambiguity justifies the exploration of the specific impact of perception.

Big Fish, Little Pond

The Big Fish, Little Pond Effect (BFLPE) suggests that people infer their ability from their reference group. An individual with a given level of ability will believe that he is more talented if he is in a group with a low average ability (small pond) than if he is in a group with a high average ability (big pond). The inverse relationship between individual self-concept and average group ability is well documented. (Marsh and Hau, 2003). More importantly, these changes in self-concept have been shown to impact human capital investment. Davis (1966) demonstrated that the academic quality (mean scholastic aptitude) of a college has less of an effect on ultimate career choice than relative student performance (GPA). Marsh (1991) confirmed that academic quality, measured by the mean ability of the student body, had a statistically insignificant or negative relationship on a variety of outcomes, including a negative relationship with educational and occupational aspirations after controlling for ability.

Figure 2: The determinants of self-concept based on the Big Fish, Little Pond phenomenon

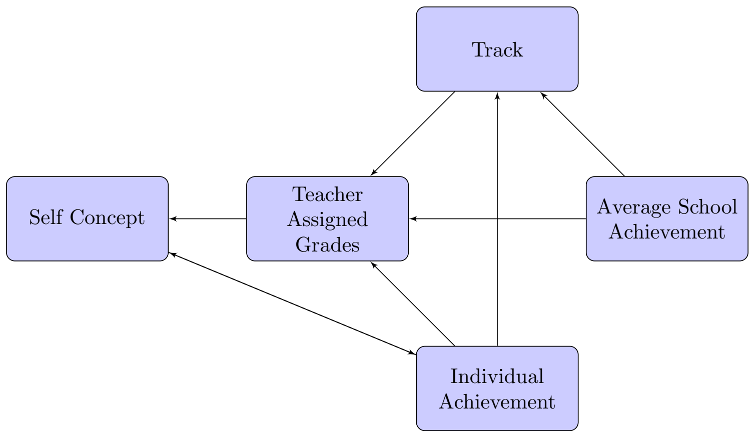


An illustrative rational for these results was given by Marsh (1990, 132–133):

> *"X was attending an academically selective high school, but she was doing poorly and not attending school regularly. A change in employment forced her parents to move and X changed to a new high school where students were not — on average — nearly as bright. Her parents were concerned that the change in schools would affect negatively her academic progress. Due to her poor academic performance in the last school, X was placed initially in classes with the least–able students in the new school. It quickly became evident, however, that she was a very able student. She had soon worked her way into the most advanced classes in this school and eventually became one of the best students in the school. Her parents noted that she was taking school more seriously and spending more time on homework in this new school. X herself told me that at the old school she had to work very hard to get just average marks, and that it was not worth the effort. If she worked hard at the new school, however, she could be one of the best — which was apparently worth the effort."*

This story illuminates a potential mechanism through which average school achievement influences self-concept.

Figure 3: The relationship between self-concept, grades and achievement based on the Big Fish, Little Pond phenomenon.



Being in a school with lower average student achievement may increase GPA, controlling for underlying ability (Marsh, 1987). Higher grades will increase a student's self-concept because they are doing better than observable peers. This is in part because students do not control for the average ability of their peers when forming their self-concept in this theory. Higher self-concept will lead to greater investment in education, which will result in greater achievement in the future.

Although this response is rational in isolation, it may not lead to the optimal investment in education. Literature on the impact of tracking on human capital accumulation is mixed. Some studies have shown that tracking increases human capital disparities between groups (Cahan et. al., 1996). These differences were partially attributed to the difference in curriculum between tracks as well as possible differences in the quality of teachers assigned to the lower level tracks. Ability-grouping literature has shown that student performance increases when a student is in a school with more talented peers (Hanushek et. al., 2003). Other papers have criticized the methodology used to separate the impact of track from innate student ability and other unobservable in the papers which find large differences in human capital accumulation due to tracking. These papers find that tracking has a much smaller, and perhaps statistically insignificant, impact. If tracking has no impact on the distribution of human capital accumulation, then the results from the BFLP hold. If tracking increases differences in human capital accumulation, then this may offset the positive effect of being in lower tracks.

Reconsider the illustrative example in the Marsh paper. Suppose that X had a friend Y, who had the same intrinsic ability and human capital accumulation as X at the time that she moved, but Y stayed at the selective high school. The BFLP literature demonstrates that X would be more likely to invest in education, attend college and select a competitive major. However, Y may have a higher level of human capital accumulation and be better prepared for higher levels of education.

Since the average ability in the groups diverges, it may be difficult to predict true ability relative to the entire population, even if students had an accurate measure of initial human capital. Since students do not observe the average ability of other classrooms, they have no effective way to compare their performance. This means that the negative impact of self-perception on human capital investment could offset the gain from the advance curriculum.

Although, the insight from the BFLP literature improves the current literature, it paints an insufficient picture of human capital accumulation decisions. It would predict that students who come from low ability schools would be over-represented in higher education, after controlling for ability, because they would have an inflated expected ability. This does not seem to be true empirically (Hardling, 2009 and Hoxby, 2013).

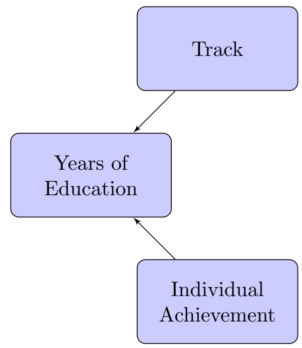
Keeping up with the Joneses

The Keeping up with the Joneses (KUWJ) model suggests that individuals get utility from their relative consumption rather than their absolute consumption choices. It predicts that a person would get more utility from a two car garage if their neighbors only had single car garages than if their neighbors had three car garages. Like the BFLP model, this model predicts that individuals feel worse about a given personal endowment when they are in a more successful cohort than when they are in a less successful cohort. However, it predicts that individuals will make the opposite investment decision in response to this feeling. If we assume that education can be viewed as a status symbol as well as an investment, this model would predict that a student would overinvest in education if he is underperforming in a high ability group. This is because he would not base his investment decision solely on his prospective returns to education, but would also consider the disutility of having a lower level of education than his peers. In this way, the KUWJ model offsets the BFLPE.

Differentiation-Polarization Theory

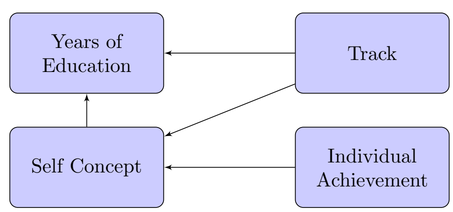
Differentiation-Polarization Theory suggests that an individual will make investment choices based on the group to which he belongs. Several studies have shown that divergent cultures emerge in different tracks.

Figure 4: The predictors of education quality based on the Keeping up the Joneses model.



Schools may implement a tracking system so that students are in classrooms with students of similar ability. Students in lower tracks, classes with lower average ability, develop increasingly anti-school attitudes over time and become increasing less concerned with academic achievement than the higher tracks. If the negative cultural strength in the lower track is strong enough, students in the lower track will underinvest in education compared to their true ability.

Figure 5: The predictors of self-concept based on Differentiation-Polarization Theory.

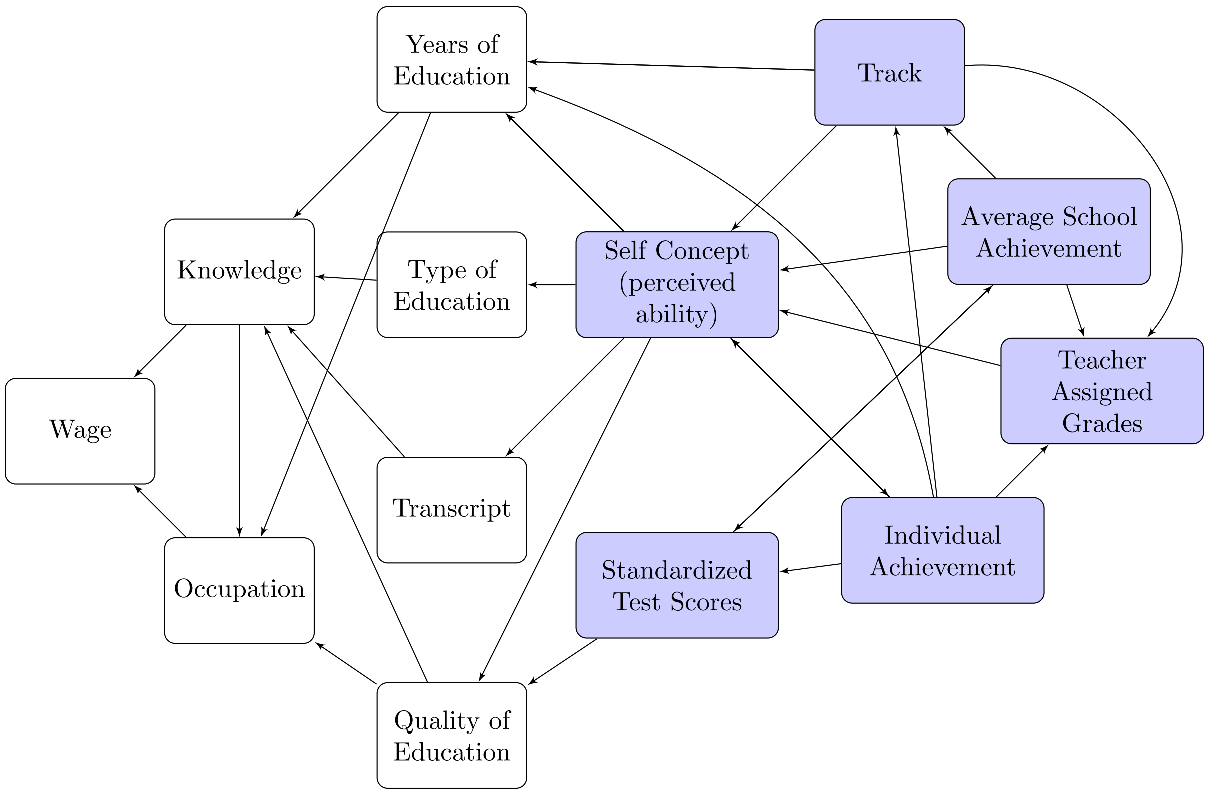


Discussion of hypothesized composite-theory relationships

The insights from the literature create a nuanced picture of the relationship between ”ability” and future wages. Figure 6 combines all of the channels through which early test scores, grades and self-perception impact investment in the employer observable characteristics based on the literature discussed in Figures 1 through 5.

Although past grades and test scores might limit quality of education that a student ultimately receives, the direct impacts of these signals are limited. Much of the literature suggests that individuals ultimately invest in education based on their perception of ability, which is informed by tests and grades. It is then possible that students who have a perception of ability which is very different from their test scores and grades will have different returns than individuals who have consistent ability measures. I hypothesize

Figure 6: Composite model of the determinants of the returns to educationl.



that individuals who have a perceived ability measure that is higher than their actual ability might receive negative signals as they compete with larger pools of students in high school or college and update their perception and ultimately under-perform in the job market. For example, a student who believes that he is good at math may decide to major in Engineering, but will not be as successful as other students in the major and will therefore receive lower wages. I test this by examining the possible impact of dissonance (differences) between the three ability measures on later outcomes.

Data Description

Restricted-access data from the Nation Education Longitudinal Study of 1988(NELS:88/2000) is used to analyze the impact of perception on later returns.The sample is restricted to all individuals working full time and most individuals working part time at the time of the fourth follow-up. Part-time workers who specifically stated that they did not want to work full time were excluded from the sample. There may be unobserved reasons for an individual to choose to work part time, such as continuing education or providing care for a dependent family member. They may have specifically chosen jobs which pay less than they could have otherwise made, given their education and ability level, for the increased flexibility. Therefore the wage data could be biased.

The drawback of this dataset is that the study participants are only in their mid-twenties at the time of the final survey; therefore, not all participants have finished their education investment at the time of the survey. If the omitted individuals have significantly different returns to education or responses to differences between their perceived and actual ability, then the results of the paper will be biased. The benefit of using NELS:88 data is that it is one of the few data sets which contains information about a student's perception of ability at the subject level, test scores, grades and some indication of labor market wages. Having all of these ability measures is critical because they offer different perspectives on the student's true ability. The data also shows that there is significant differences between these measures.

Description of the ability measures:

I focus on three early indicators of math and English ability. They include:

- Performance relative to all students in the sample (Test scores)
- Performance relative to similar peers (Grades)
- Self-perception (Response to the self-concept questions in the first follow-up)

Test Scores

Test scores are included as an imperfect measure of how a student performed relative to all other students in the sample. Test scores are measured using the Math and Reading scores in the NELS:88 Test Battery in the base year, which was administered when the students were in the eighth grade. The test was unspeeded[1] and low stakes for students and teachers. One concern is that the low stakes test may be less representative of true ability than a high stakes test because the students did not have an external incentive to ensure that they completed the test to the best of their ability. Cole and Osterlind (2008), however, showed that although there are differences in performance on high versus low stakes test, the difference is relatively small and should not meaningfully impact the reliability of test as a comparative measure. Segal (2012) found that low stakes test are still predictive of earnings after controlling for cognitive ability. This might imply that students with high cognitive skills who do not put in full effort on low stakes test may have other undesirable personality traits which will impact later wages. Since employers have indicated that knowledge stock is not directly important, the paper is not concerned with how accurately test scores specifically measure human

[1] A test is defined as unspeeded by the NELS if "nearly all test takers reached the three quarters point of the test, and at least 80 percent of the students answered the last item" (Rock et. al., 1991).

capital accumulation, as long as it has predictive power of later wages. It may, however, change the inference about what large differences between test scores and perception of ability truly mean.

Grades

Grades are included to measure how a student performed relative to similar peers (same teacher, same school, and many times, similar SES etc.). Although grades could be used to compare students within a classroom; they do not indicate how much a student has learned in a national sample. For example, an individual receiving a B in a college prep course might be better prepared to continue his education than a student who receives an A in a remedial course. In the initial survey, the grade variable measured the average subject letter grade from 6th grade until 8th grade. Using grades as an indicator is delicate because its meaning is less clear than the other two indicators. Grades not only measure subject comprehension but also the student's ability to to finish a task, manage deadlines, and other soft skills.

Self-Perception

The subject-specific self-perception measures are included as the most direct measure of what a student's perceived ability. The perceived mathematical ability variable was based on the following three variables in the first follow up:

- Math is my best subject[2]
- I have always done well in Math
- I am hopeless at Math [3]

The student's perceived English ability variable was based on the following three variables in the first follow up:

- English is my best subject [4]
- I learn quickly in English
- I am hopeless at English [5]

[2]Students may have a positive self-concept in a subject area without it being his "best" subject. To correct for this, I run the regressions without the variables "Math is my best subject" and "English is my best subject" included in the perception measure. It did not to significantly impact the results.

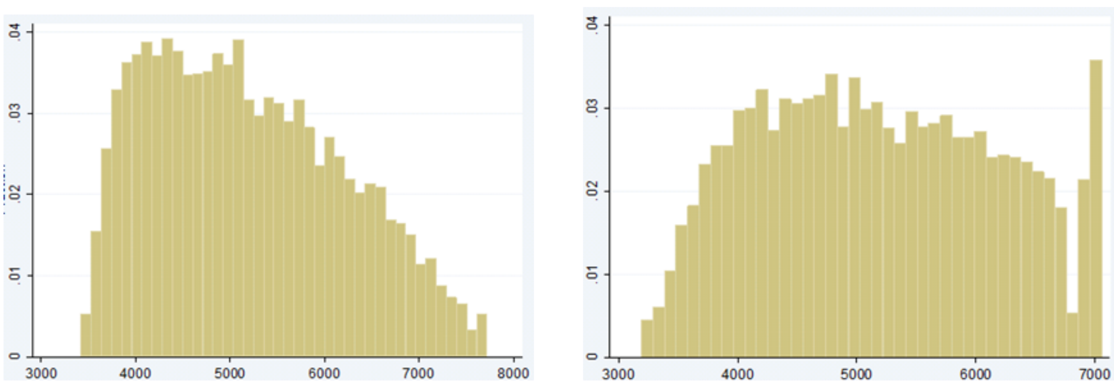
[3]Since the self-concept questions "I am hopeless at Math" and "I am hopeless at English" have a reverse effect on self-perception compared to the other perception measures, these scores were inverted so the ranking would be comparable to the other perception measures in the subject category.

[4]see footnote 2

[5]see footnote 3

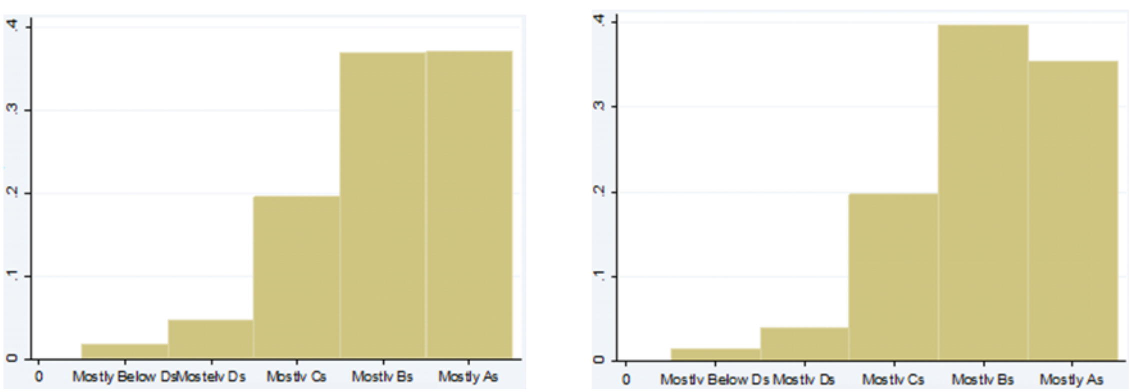
Figures 7- 9 consists of histograms representing the fraction of respondents in each response category for all of the ability measures. The figure shows that the distributions of the three measures vary significantly. Test scores have a positive skew with many students pooling around low to midrange scores. Grades tend to have a negative skew with over sixty percent of respondent receiving mostly B's or higher. The perception scores were in between the distribution of the grades and test scores.

Figure 7: Histogram of test scores



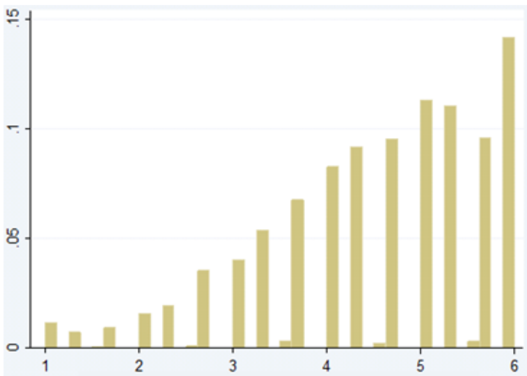
(a) Math Test Scores (b) English Test Scores

Figure 8: Histogram of average letter grades

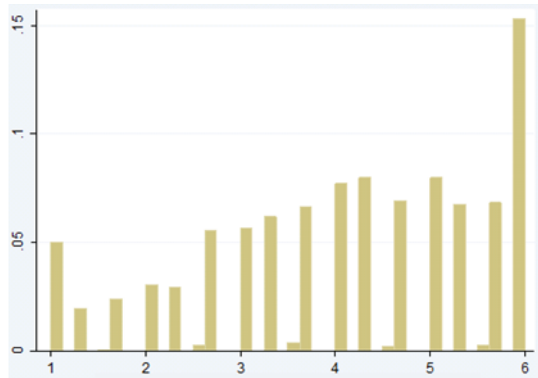


(a) Math Grades (b) English Grades

Figure 9: Histogram of average perception scores



(a) Perception of Math Ability



(b) Perception of English Ability

It is possible that the measures have ordinal consistency, even if they have different distributions. Table 1 presents the correlation between the variables of interest. Indicators within the same subject area have stronger correlations. Overall, the correlation between perception and test scores and grades is surprisingly low. There is only a moderate correlation between subject specific ability measures. Math and English ability measures are also weakly correlated for the grade and perception measures. This would allude to the possibility that students misperceive their ability or that the ability measures are capturing different capability aspects. Both explanations are relevant to the later analysis.

Table 1: Correlation between the ability indicators

	Math Test	English Test	Math Grades	English Grades	Math Perception	English Perception
Math Test	1.0000					
English Test	0.6897	1.0000				
Math Grades	0.4080	0.2750	1.000			
English Grades	0.3777	0.3851	0.3645	1.0000		
Math Perception	0.3339	0.1238	0.3823	0.1339	1.0000	
English Perception	0.2401	0.3256	0.1723	0.3516	0.0827	1.0000

Empirical analysis:

I estimate the impact of the three ability measures on the years of education obtained using the equation:

$$S_i = \beta_0 + \beta_1 A_i + \gamma' X_i + \varepsilon_i j \quad (1)$$

Where

S_i = years of education.

A_i is a vector of ability measures;(All of the ability measures were normalized to a 10 point scale so that they would be comparable)

X_i is a vector of control variables which includes age and its square, gender, childhood family income, mother's education, father's education, dummy variables for race and state of residency.

Table 2: Impact of ability measures on years of education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Math	0.207***			0.146***	0.174***		0.133***
Test	(0.012)			(0.013)	(0.013)		(0.013)
English	0.078***			0.058***	0.063***		0.048***
Test	(0.011)			(0.011)	(0.011)		(0.011)
Math		0.131***		0.088***		0.104***	0.075***
Grade		(0.009)		(0.010)		(0.010)	(0.010)
English		0.159***		0.110***		0.131***	0.093***
Grade		(0.010)		(0.011)		(0.011)	(0.011)
Math			0.091***		0.049***	0.050***	0.030***
Perception			(0.007)		(0.007)	(0.008)	(0.008)
English			0.137***		0.099***	0.092***	0.076***
Perception			(0.009)		(0.009)	(0.009)	(0.009)
Sample Size	6050	6130	6180	5960	6020	6000	5840
Adjusted R^2	0.3604	0.3456	0.3256	0.3805	0.3759	0.3599	0.3870

All ability measures were rescaled to a ten point scale.
Standard errors are in parentheses; ***=99% confidence, **=95% confidence, *=90% confidence

All of the ability measures have a statistically significant impact on the years of education obtained. Of all the ability measures, Math test scores have the strongest marginal impact on the years of education. English test scores have the smallest impact of all English measures. The reason for this large difference in the importance of math compared to English test scores is ambiguous. This could be because English grades more accurately reflect ability than test scores. It could also be that English test scores carry limited additional information after controlling for the other measures.Both perception measures are statistically significant, even after controlling for grades and test scores, and represent an improvement in the model.

Since the returns to human capital investment are of ultimate interest, I directly explore the impact that the three ability indicators on wages.

I estimate the returns to education using the following equation:

$$LnW_ij = \beta_0 + \beta_1 S_i + \beta_2 A_i + \gamma' X_i + \varepsilon_i j \tag{2}$$

Where

Ln $W_i j$ = the natural logarithm of income of respondent in 1999 from employment.

S_i = years of education;

A_i is a vector of ability measures;(All of the ability measures were rescaled to a 10 point scale so that they would be comparable) ;

Table 3: Impact of ability on earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	0.049***	0.046***	0.044***	0.044***	0.043***	0.043***	0.041***	0.041***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Math		0.015***			0.010*	0.006		0.003
Test		(0.005)			(0.005)	(0.005)		(0.006)
English		-0.008*			-0.009**	-0.0605		-0.007
Test		(0.004)			(0.004)	(0.004)		(0.005)
Math			0.013***		0.011***		0.006	0.006
Grade			(0.004)		(0.004)		(0.004)	(0.004)
English			0.006		0.008*		0.006	0.009**
Grade			(0.004)		(0.004)		(0.004)	(0.005)
Math				0.015***		0.014***	0.014***	0.014***
Perception				(0.003)		(0.003)	(0.003)	(0.003)
English				-0.001		-0.001	-0.003	-0.002
Perception				(0.004)		(0.003)	(0.004)	(0.004)
Sample Size		5700	5690	5730	5540	5570	5570	5420
Adjusted R^2		0.1135	0.1178	0.1181	0.1164	0.1162	0.1200	0.1187

For ease of comparison, all ability measures were rescaled to a ten point scale.
Standard errors are in parentheses; ***=99% confidence, **=95% confidence, *=90% confidence

Controlling for the three ability measures results in a slight decrease in the returns to education when compared to the regression without any ability measure controls. In every column, the math measures have a larger cumulative impact on wages than the English measures. This is probably because math skills are required in the top paying fields. Math test scores have a much smaller impact on wages than years of education obtained. The magnitude of the affect of math test scores is approximately the same as math grades and perception in models were only one ability category is included. Math test scores and grades are statistically insignificant after controlling for the individual's perception of math ability. This could be because much of the information captured by math test scores and grades are absorbed by years of education since they were shown to be better predictors of this measure (Table 2). Since it is possible that the primary impact of the three indicators could be through the years of education obtained, I run the regression excluding years of education to determine the total effect of the ability measures.

Table 4: Impact of ability on earnings without controlling for education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Math	0.024***			0.016***	0.013**		0.008
Test	(0.005)			(0.005)	(0.005)		(0.005)
English	-0.004			-0.007	-0.003		-0.005
Test	(0.004)			(0.004)	(0.005)		(0.005)
Math		0.019***		0.015***		0.011***	0.009**
Grade		(0.004)		(0.004)		(0.004)	(0.004)
English		0.013***		0.013***		0.011***	0.013***
Grade		(0.004)		(0.004)		(0.004)	(0.005)
Math			0.019***		0.017***	0.016***	0.015***
Perception			(0.003)		(0.003)	(0.003)	(0.003)
English			0.005		0.004	0.001	0.001
Perception			(0.004)		(0.004)	(0.004)	(0.004)
Sample Size	5700	5700	5730	5540	5570	5570	5420
Adjusted R^2	0.1017	0.1064	0.1068	0.1062	0.1061	0.1104	0.1095

All ability measures were rescaled to a ten point scale.
Standard errors are in parentheses; ***=99% confidence, **=95% confidence, *=90% confidence

When years of education is excluded from the model, math test scores are still insignificant in models which also include perception. Perception of English ability is also insignificant in the regressions excluding years of education. There is a marginal increase in the impact of English grades and math perception when the regression does not control for years of education. Math grades also become a statistically significant predictor of wages. Grades may be more important in models that do not control for the years of education because grades capture soft skills which will impact later success in school and on the job, such as deadline management and active listening. It may also be that grades in the 8th grade are usually used to determine a student's high school track. High school track can determine a student's level of college preparedness and possibly the quality of the college attended since many colleges use high school track in admission decisions.

Role of dissonance in later labor market wages

The previous section demonstrated that perception and grades are the most predictive of later earnings. It is important to understand the underlying reason for this result.

The results do not suggest that perception is a better indicator of ability than test scores. It simply shows that it is a better predictor of later wages. It is possible that perception and test scores are simply measuring the same thing. An individual with high self-perception may also have relatively high test scores. Just as English scores were not predictive of wages after controlling for math ability, math test scores may contain no additional information after controlling for perception. This could be because test scores are only a snapshot of a student's human capital accumulation, whereas perception is based on cumulative performance (even if it is biased by peer group). Therefore, test scores alone and perception alone would have a positive impact on wages, but test scores would be insignificant after controlling for perception.

It is also possible that perception matters more for later wages than early knowledge accumulation as measured through test scores. Suppose that an individual's perception of his ability is greater than their "true ability" and that his test score perfectly capture his underlying ability. If firms do not observe early test scores, but do observe investments made by a student based on his perception of ability, then this individual may be rewarded for his undeserved confidence. Individuals with high test scores are more likely to have a high perception of their ability, therefore test scores alone and perception alone would have a positive impact on wages, but test scores would be insignificant after controlling for perception.

Since the differences between the measures are the primary focus, all ability measures are grouped into pairs. In each pair, a comparative and perceived ability measure is identified. The comparative measure in the pair is the more objective measure of student performance relative to other students in the sample. The perceived measure best represents the student's assessment of his ability.

The classification of ability measures for all dissonance terms considered in the paper are shown in Table 5.

Table 5: Relationship between the three ability measures used in the paper

Term	Comparative Measure	Perceived Measure
Test vs. Perception	Test	Perception
Test vs. Grades	Test	Grades
Grades vs. Perception	Grades	Perception

Test scores are always considered an indicator of comparative ability because it is the only measure that shows how a student is performing relative to all other students in the sample. Perception is always considered a perceived measure of ability because it best captures how a student views himself. Grades can be considered a comparative or perceive measure. They are considered a perceived measure when analyzed with test scores because they only allow students to compare themselves to a small, unrepresentative group of students. It is considered a comparative measure when analyzed with perception because it shows how the student performed relative to other students in a given environment.

All of the dissonance measures were constructed to determine the difference between the comparative and perceived measure for all pairs. All comparative and perceived ability measures were rescaled to a 10 point scale.

The dissonance measures were of the form:

$$Dissonance_x, y, s = X_s - Y_s \tag{3}$$

where

x: transformed measure of comparative ability

y: transformed measure of perceived ability

s: subject(either Math or English)

If the dissonance measure is positive, the individual is "underestimating" his ability based relative to the comparative measure. If the dissonance measure is negative, the individual is "overestimating" his ability based on the comparative measure. The dissonance measure is adjusted because the simple transformation does not capture the fact that the dissonance most likely has a nonlinear impact on the model.

Test scores are a continuous measure while grades and perception are measured by discrete, aggregated categories. Therefore, small differences between scores probably do not cause meaningful distortion in human capital investment. As the difference between the scores grows, it is more likely to lead to distortion in investment. A dense measure was created to captures how much an individual's raw dissonance measure differs from the average dissonance in the sample. Individuals who are more than 2 standard deviations below the mean are given a dense dissonance score of -2. Individuals who are between 2 and 1 standard deviations below the mean are given a dense dissonance score of -1. Individuals who are within 1 standard deviation of the mean are given a dense dissonance score of 0. Individuals who are between 2 and 1 standard deviations above the mean are given a dense dissonance score of 1. Individuals who are more than 2 standard deviations above the mean are given a dense dissonance score of 2.

I estimate the returns to education using the following equation:

$$LnW_ij = \beta_0 + \beta_1 S_1 + \beta_2 C_i + \beta_3 P_i + \beta_4 D_i + \gamma' X_i + \varepsilon_i j \tag{4}$$

Where

Ln W_ij = the natural logarithm of income of respondent in 1999 from employment.

S_i = years of education;

C_i = comparative measure of ability;

P_i = perceived measure of ability;

D_i = dense dissonance measure;

Table 6: Impact of dissonance on years of education

	Test-Grades	Test Perception	Grades Perception
Math Dissonance	0.038	0.104	-0.031
	(0.063)	(0.063)	(0.066)
English Dissonance	-0.008	-0.014	0.088
	(0.064)	(0.063)	(0.066)
Math Test	0.137***	0.152***	
	(0.019)	(0.018)	
English Test	0.055***	0.065***	
	(0.017)	(0.017)	
Math Grades	0.099***		0.112***
	(0.018)		(0.017)
English Grades	0.105***		0.126***
	(0.018)		(0.019)
Math Perception		0.074***	0.047***
		(0.014)	(0.015)
English Perception		0.092***	0.091***
		(0.016)	(0.018)
Sample Size	5960	6020	6000
Adjusted R^2	0.3804	0.3759	0.3598

Standard errors are in parentheses; ***=99% confidence, **=95% confidence, *=90% confidence

None of the dissonance measures have a significant impact on years of education obtained by individuals in the sample. Individuals who have an inconsistent perception of their ability (test scores do not match perceived ability) do not invest in education any differently than those who have reinforcing measures of ability. It does not speak to the possibility that individuals with inconsistent perception measures may change the ways they invest in education in response to the difference. For example, they may choose to enroll in more/less aggressive courses, choose different majors, etc. It also points to the fact that many different types of intervention can increase the number of years that a student chooses to invest in school.

I then explore the impact of dissonance on earnings.

Table 7: Impact of dissonance on earnings (controlling for years of education)

	Test-Grades	Test Perception	Grades Perception
Education	0.043***	0.043***	0.041***
	(0.005)	(0.005)	(0.005)
Math Dissonance	0.014	-0.054**	0.015
	(0.025)	(0.025)	(0.025)
English Dissonance	0.010	0.044*	-0.018
	(0.026)	(0.025)	(0.026)
Math Test	0.007	0.016**	
	(0.008)	(0.007)	
English Test	-0.011*	-0.015**	
	(0.007)	(0.007)	
Math Grades	0.014**		0.003
	(0.007)		(0.007)
English Grades	0.010		0.010
	(0.007)		(0.007)
Math Perception		0.004	0.018***
		(0.006)	(0.006)
English Perception		0.009	-0.007
		(0.025)	(0.007)
Sample Size	5540	5570	5570
Adjusted R^2	0.1161	0.1170	0.1199

Standard errors are in parentheses; ***=99% confidence, **=95% confidence, *=90% confidence

The dissonance between test scores and grades as well as grades and perception do not have a statistically significant impact on wages. Interestingly, the dissonance between perception and test scores is significant. The dissonance between test scores and perception have an opposite impact by subject. Individuals whose math test scores are greater than their perception of math ability are punished in terms of later wages, while individuals whose English test scores are greater than their perception of their English ability are rewarded. This is counterintuitive because math is seen as a more objective field. If someone did not have the prerequisite skills it should be much more difficult for them to successful progress in the next course. However, if an individual does not have confidence is his ability to perform well in math courses, he may not pursue technical fields, which will lower his earnings relative to individuals with the same test scores, but greater self confidence. English dissonance may have the opposite impact because an greater breadth of disciplines require writing skills.

Table 8 tests the impact of dissonance on earnings without controlling for education.

Table 8: Impact of dissonance on earnings (not controlling for years of education)

	Test-Grades	Test Perception	Grades Perception
Math Dissonance	0.015	-0.050**	0.014
	(0.025)	(0.025)	(0.025)
English Dissonance	0.009	0.044*	-0.018
	(0.026)	(0.025)	(0.026)
Math Test	0.012	0.022***	
	(0.008)	(0.007)	
English Test	-0.009	-0.012*	
	(0.007)	(0.007)	
Math Grades	0.019***		0.008
	(0.007)		(0.007)
English Grades	0.015**		0.015**
	(0.007)		(0.007)
Math Perception		0.007	0.019***
		(0.006)	(0.006)
English Perception		0.013**	-0.003
		(0.007)	(0.007)
Sample Size	5540	5580	5570
Adjusted R^2	0.1060	0.1169	0.1102

Standard errors are in parentheses; ***=99% confidence, **=95% confidence, *=90% confidence

The impact of dissonance is largely unchanged when years of education are omitted from the model Again, I find that dissonance is only significant in the model that contains perception and test scores and that the impact of math dissonance has the opposite sign of English dissonance. This is to be expected because the dissonance measure did not have a direct impact on the years of education in Table 6. When education is omitted, English perception has a statistically significant impact on wages. This may be because a minimum proficiency in English is required for certain levels of education.

It is possible that the reason that the impact of the dissonance is not consistent across education levels. I include an interaction to see if the dissonance variable impacts the returns to education for students in the sample. Table 9 examines the returns to education interacted with the dissonance measure.

Table 9: Impact of dissonance on returns to education

	Test-Grades	Test Perception	Grades Perception
Education	0.043***	0.044***	0.041***
	(0.005)	(0.005)	(0.005)
Math Dissonance	0.213**	0.166*	0.023
	(0.097)	(0.095)	(0.091)
Education*	-0.014**	-0.016**	-0.001
Math Dissonance	(0.007)	(0.007)	(0.006)
English Dissonance	0.067	0.081	-0.068
	(0.106)	(0.096)	(0.091)
Education*	-0.004	-0.003	0.004
English Dissonance	(0.007)	(0.007)	(0.006)
Math Test	0.008	0.016**	
	(0.008)	(0.007)	
English Test	-0.011*	-0.015**	
	(0.007)	(0.007)	
Math Grades	0.015**		0.003
	(0.007)		(0.007)
English Grades	0.010		0.010
	(0.007)		(0.007)
Math Perception		0.004	0.018***
		(0.007)	(0.006)
English Perception		0.008	-0.007
		(0.006)	(0.007)
Sample Size	5540	5570	5570
Adjusted R^2	0.1168	0.1177	0.1196

Standard errors are in parentheses; ***=99% confidence, **=95% confidence, *=90% confidence

Again, I find that only the dissonance between test scores and perception has a statistically significant impact on wages. Inclusion of the interaction term changes the sign of dissonance measure. Individuals who have test scores that are greater than their perception of math ability earn more, but they also receive a smaller return to education. This would suggest that either individual who have a perception of ability that is lower than their test scores are better informed about their actual ability or a lack of self-confidence can sabotage later performance.

Conclusion

My research found that ability matters, but not in the way that is typically portrayed in the literature. Knowledge accumulation is not the only relevant predictor of later labor market returns. Self-perception of ability is relevant even after controlling for grades and test scores. This suggests that there may be low cost ways to predict later performance. If studies cannot create a test to measure student ability, asking students about their ability might still provide relevant information.

It is to be expected that test scores strongly predict the years of education. However, it is interesting that wages are better predicted by math perception and grades than early test scores. It is also interesting the dissonance between the test and perception measures not only impacts wages directly, but also the returns to education. This would suggest that having a positive sense of self is critical, especially in the early stages of human capital investment.

Moving forward, I believe that it is important to understand why test scores had a relatively weak impact on earnings. In order to ensure that all children are equally prepared for the labor force, public schools have become increasingly reliant on using standardized tests to measure progress. However, the results of these tests are not as objective of a predictor of ability as we might have hoped. Even low stakes test scores may suffer from omitted variable biases when used to predict later outcomes if family characteristics and socio-economic status are not taken into account. We must then be cautious when interpreting test scores as a measure of student ability. We must also think more deeply about how ability might matter for later outcomes.

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Hispanic Returns to education

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Abstract: This paper examines variations in the returns to education experienced by Latino men in the United States, specifically the difference in returns by country of origin and citizenship status. Using 2000 Census data, we find that there are significant differences in the returns to education by country of origin for adult immigrants. This suggests that using ethnic dummies in research is inappropriate because measurements of the returns to education may be biased by the national composition on the immigrant population. We find that the country-level difference is much smaller for child immigrants. We also find that, while Hispanic identity continues to impact returns to education for later generations, there is no difference in returns by country of heritage.

Introduction

Our paper examines the comparative returns to education for Hispanic adult immigrants, child immigrants, and citizens by country of origin and ethnic identification.

Hispanic immigrants are not a homogeneous group. Immigrants vary in their transferability of human capital, level of education, quality of education, reason for migration and cost of migration. We determine if heterogeneity within Hispanic immigrant groups results in different labor market outcomes by analyzing country level variation in the returns to education in the United States. We also analyze if there are persistent country level effects for individuals who migrated as children and non-immigrants.

Previous studies have shown that a large part of the variation in returns to education for immigrants by country of origin can be explained by differences in English proficiency, undocumented status and the transferability of labor market experience (Borjas, 1982; Psacharopoelo et. al. , 2002; Duncan et. al., 2006; Passel and Cohn, 2009). Although immigrants may lose the ability to capitalize on their own human capital, they do not lose the ability to pass their knowledge onto their children.

We hypothesize that immigrant children and non-immigrant citizens from countries with lower initial returns to education will be able to "catch-up" to the general population. Immigrant children and non-immigrant citizens will be significantly less constrained because of access to education and human capital that is more readily accepted in the United States labor market (Bratsberg and Ragan, 2002). As expected, we find that individuals who migrated as children and non-immigrant citizens have increased returns to education. We also find that country level effects are not persistent in the non-immigrant, Hispanic population.

We also examine the assimilation process for individuals who came from countries with relatively high returns to education for adult immigrants. Immigrant children and non-immigrants from these countries may have an head start compared to individuals from countries where adult immigrants faced greater initial barriers. We examine if immigrant children and non-immigrants are able to capitalize on these initial advantages and converge to the national average. Literature has shown that groups tend to converge to their ethnic mean, rather than the national average. Research on the intergenerational human capital transmission for African Americans found that when slavery ended, the literacy and labor market outcome gap between descendants of slaves and free blacks closed within two generations. However, there was a persistent racial gap(Sacerdote, 2002). Similarly, we find that South Americans converge to a Hispanic mean. This suggests that there that there are persistent Hispanic effect that are independent of country level differences in preparation for the US labor market and whose source we cannot identify with Census data.

Methodology

Data

We use IPUMS data from the 2000 US census, restricted to Hispanic men between the ages of 25 and 65 who are currently not in school.

Hispanics are divided into three categories for analysis in this paper.

- Adult immigrants
  Individuals are defined as "adult immigrants" if they immigrated after they were 18 years old. This restriction ensures that these immigrants were considered legally adults when they arrived in the United States. It also means that they would not have been required to obtain any education in the United States.
- Immigrant Children
  Individuals are defined as "immigrant children" if they immigrated before they were 12 years old. Twelve was used as the cut off because this is usually the absolute minimum age for youth employment in any industry for a non-family business. It also ensures that these immigrants were required to attend at least some school in the United States. (US Department of Labor, 2011).
- Citizens (Non-immigrants)
  Individuals are defined as "citizens" if they are US citizens and do not have an immigration year. It does not include individuals who were born abroad because they may not have had all of their education in the United States, therefore differences in their returns may be due to differences in the type, quality, or transferability of education they received in the host county.

We focus on the country-specific effects for the top 10 sub-identifications of Hispanic adult immigrants in the sample[1]. We also include a catch-all for all other Hispanic immigrants.

Table 1 compares the average years of education for individuals over the age of 25 in the home country to the immigrant males in our sample [2].

[1] The top 10 sub-identifications include individuals of Mexican, Cuban, Salvadoran, Dominican, Guatemalan, Colombian, Ecuadorian, Peruvian, Honduran as well as unspecified Hispanic origin. Unspecified Hispanic consists of immigrants who identified themselves as Hispanic but did not specify a country of origin

[2] The mean year of education in the Country of ethnic origin was from Barro and Lee (2010) and includes all males over the age of 25 in the country of origin. All other mean education numbers were created using Census 2000 data

Table 1: Mean Years of Schooling by Country of Origin

Group Group	Mean in Country of ethnic origin[3]	Adult immigrants	Child immigrants	Non-immigrants
United States	13.17	-	-	-
Mexican	7.52	7.70	10.17	11.91
Dominican	5.90	10.34	12.01	12.42
Cuban	9.23	11.70	13.53	13.58
Guatemalan	4.31	8.09	11.12	12.37
Honduran	5.16	8.67	11.17	11.89
Salvadoran	6.23	8.10	11.17	11.68
Colombian	6.57	12.40	13.36	13.75
Ecuadorian	6.90	10.85	12.92	13.32
Peruvian	8.91	12.94	13.54	13.92

Adult immigrants from all countries, except for Mexico, have significantly higher levels of education than the mean level of education within the country of origin. Mexican adult immigrants have the lowest mean level of education, whereas South American adult immigrants have the highest mean level of education. As expected, US citizens of all ethnic origins have higher levels of education than adult immigrants of the same ethnicity, with child immigrants falling between these two groups.

Estimation Strategy

Returns to education are calculated using the following equation.

$$LnW_i = \beta_0 + \beta_1 S_i + \beta_2 O_i + \beta_3 O_i S_i + \gamma' X_i + \varepsilon_i j \tag{1}$$

- Where $\text{lnW}_i j$ is the natural logarithm of the weekly wage of immigrant i from country j divided by the respondents reported "usual number of hours worked per week";
- S_i is the level of education obtained by the immigrant (The education levels for Hispanics were not adjusted for reasons outline in the Appendix A);
- O_i is the country of origin of the immigrant;
- O_iS_i is an interaction term capturing the differential impact of country of origin on returns to education;
- X_i is a vector of control variables that includes dummy variables which control for age, square age, marital status, an indicator of whether health factors limited the individuals work ability, and the number of years in the United States since migration.

In all analyses, Mexican immigrants are the excluded immigrant category. People of Mexican origin are the largest subgroup in the adult immigrant, child immigrant and non-immigrant categories. Therefore, the country level effects for people of Mexican origin likely has the greatest impact on the Hispanic dummy variable and measure of returns to education in papers broad ethnic categories.

The first column in each table shows the returns to education for Hispanic immigrants when no country level effects are included. Column 2 includes dummies controlling for country of origin as well as the interaction between country of origin and years of education to capture the specific return to education by country of origin. Column 3 includes dummy variables to control for English speaking ability. Speaking English very well (but not only English) was used as the omitted category because it had a significant size in all three categories. Column 4 includes dummy variables to control for working in agriculture and construction. These variables partially control for legal status since undocumented immigrants are more likely to work in these two industries. Column 5 includes dummy variables for region of residency to control for diaspora effects that could impact wage. If immigrants from different countries tend to cluster in regions with different returns to education, it could bias the returns to education by country. Finally, Column 6 includes all other potential cohort effects including, year of immigration dummies, race dummies, and a dummy variable controlling for whether the immigrant was a naturalized citizen at the time of the census.

Adult Immigrants

We first determine the country level effects for adult Hispanic immigrants to create a baseline for other groups in our sample.

We find that there are statistically significant differences in the returns to education by country of origin. Column 1 demonstrates that Hispanic immigrants as a whole receive a 3.8 percent increase in wages for every additional year in school. When country level effects are added in Column 2 it shows that there are statistically significant regional differences in the returns to education for adult immigrants. It also shows that the Hispanic term may be biased by the lower returns for Mexican immigrants. All other Hispanic groups, except for Central Americans, have greater returns to education, however their returns to education are obscured because they make up a relatively smaller portion of the overall Hispanic immigrant population.

Immigrants from South America have the largest difference in returns to education. Immigrants from the Caribbean also have greater returns to education. This is consistent with distance decay migration theories, which say that the greater the distance between two countries, the less likely it is for individuals to migrate. We would expect that only individuals with high expected returns are likely to migrate because they expect

Table 2: LOG WAGE DETERMINANTS FOR ADULT IMMIGRANTS BY COUNTRY OF ORIGIN

	(1)	(2)	(3)	(4)	(5)	(6)
Education	0.038***	0.031***	0.054***	0.052***	0.052***	0.050***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dominican		0.026	0.047	-0.002	-0.041	-0.040
		(0.033)	(0.033)	(0.032)	(0.033)	(0.033)
Dominican*		0.006**	0.003	0.007**	0.007**	0.007**
education		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Cuban		-0.090***	-0.017	-0.073**	-0.071**	-0.112***
		(0.032)	(0.032)	(0.031)	(0.031)	(0.032)
Cuban*		0.013***	0.007***	0.011***	0.011***	0.013***
education		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Guatemalan		0.103***	0.088***	0.050*	0.044*	0.041
		(0.026)	(0.026)	(0.025)	(0.025)	(0.025)
Guatemalan*		-0.003	-0.004	-0.002	-0.002	-0.002
education		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Honduran		0.057	0.045	-0.002	-0.007	-0.006
		(0.040)	(0.039)	(0.039)	(0.039)	(0.039)
Honduran*		0.001	0.000	0.003	0.003	0.003
education		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Salvadoran		0.136***	0.120***	0.076***	0.073***	0.066***
		(0.021)	(0.021)	(0.020)	(0.020)	(0.020)
Salvadoran*		-0.003	-0.004*	-0.001	-0.001	-0.001
education		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Colombian		-0.069	0.003	-0.044**	-0.074	-0.101**
		(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
Colombian*		0.021***	0.011***	0.014***	0.015***	0.017***
education		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ecuadorian		0.018	0.034	-0.014	-0.062	-0.077
		(0.049)	(0.048)	(0.048)	(0.048)	(0.048)
Ecuadorian*		0.006	0.002	0.005	0.007	0.008*
education		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Peruvian		-0.245***	-0.161**	-0.202***	-0.230***	-0.240***
		(0.071)	(0.070)	(0.070)	(0.070)	(0.070)
Peruvian*		0.036***	0.024***	0.027***	0.028***	0.028***
education		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Not Specified		0.018	0.022	-0.002	-0.006	-0.015
		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Not Specified*		0.009***	0.005***	0.007***	0.007***	0.007***
education		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
All other countries		-0.053*	0.026	-0.019***	-0.033***	-0.049***
		(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
All other countries*		0.025***	0.013***	0.015***	0.016***	0.017***
education		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Country Dummies	NO	YES	YES	YES	YES	YES
English Dummies	NO	NO	YES	YES	YES	YES
Occupation Dummies	NO	NO	NO	YES	YES	YES
US Regional Dummies	NO	NO	NO	NO	YES	YES
Cohort Dummies	NO	NO	NO	NO	NO	YES
Sample Size	129316	129316	129316	129316	129316	129316
Adjusted R^2	0.0972	0.1046	0.1270	0.1378	0.1395	0.1450

Standard errors are in parentheses;***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence that their returns to education will offset their migration costs. We were unable to directly test the distance decay theory with this dataset.

The large increase in returns to education in column 3 are due to the fact that reference group was individuals who could Speak English very well, but did not only speak English. This is also consistent with previous literature which showed that much of the difference between the returns to education for Mexican and non-Mexican immigrants could be explained by differences in Engish speaking ability. Regressions including all US immigrants (See Appendix B) show that almost half of the Hispanic wage penalty can be explained by differences in English speaking ability.

Child immigrants

The previous section established three distinct patterns in the returns to education for Hispanic adult immigrants. South Americans (especially Colombians and Peruvians) perform significantly better than other Hispanic immigrant groups. Mexican and Central American immigrants seem to perform the worst in the United States labor market. Since this group makes up the largest proportion of immigrants, their returns seem to drive the low reported terms for Hispanic immigrants. Hispanic immigrants from the Caribbean fall somewhere in between these two groups.

We next look at the returns for immigrant children. All individuals categorized as Hispanic children in our sample immigrated before they were 12 years old, therefore they would have been required to complete at least a few years of education in the United States. As a result, their education should be more easily transferred to the US labor market. We would then expect these immigrants to have higher returns to education.

Table 3: LOG WAGE DETERMINANTS FOR IMMIGRANT CHILDREN BY HISPANIC IDENTITY OF AND LEVEL OF EDUCATION

	1	2	3	4	5	6
Education	0.063***	0.050***	0.062***	0.059***	0.057***	0.053***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Dominican		-0.287***	-0.199	-0.250**	-0.358***	-0.356***
		(0.127)	(0.126)	(0.126)	(0.127)	(0.126)
Dominican*		0.027***	0.018*	0.021**	0.025**	0.025**
education		(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Cuban		-0.579***	-0.467***	-0.517***	-0.533***	-0.536***
		(0.074)	(0.133)	(0.075)	(0.076)	(0.076)
Cuban*		0.060***	0.049***	0.052***	0.053***	0.050***
education		(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Guatemalan		-0.025	-0.011	-0.065	-0.105	-0.094
		(0.138)	(0.137)	(0.136)	(0.136)	(0.136)
Guatemalan*		0.008	0.005	0.009	0.010	0.010
education		(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Honduran		0.102	0.213	0.146	0.128	0.107
		(0.180)	(0.221)	(0.177)	(0.177)	(0.176)
Honduran*		-0.009	-0.020	-0.015	-0.015	-0.014
education		(0.015)	(0.015)	(0.015)	(0.015)	(0.014)
Salvadoran		0.187*	0.217**	0.165	0.166*	0.161
		(0.102)	(0.101)	(0.150)	(0.101)	(0.100)
Salvadoran*		-0.005	-0.010	-0.009	-0.008	-0.007
education		(0.005)	(0.009)	(0.009)	(0.009)	(0.009)
Colombian		-0.675***	-0.619***	-0.674***	-0.732***	-0.735***
		(0.165)	(0.200)	(0.163)	(0.163)	(0.162)
Colombian*		0.062***	0.055***	0.058***	0.060***	0.059***
education		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Ecuadorian		-0.366*	-0.210	-0.278	-0.419**	-0.427**
		(0.210)	(0.239)	(0.208)	(0.208)	(0.207)
Ecuadorian*		0.047***	0.033**	0.037**	0.044***	0.043***
education		(0.016)	(0.016)	(0.016)	(0.015)	(0.015)
Peruvian		-0.540*	-0.390	-0.413	-0.461	-0.514*
		(0.303)	(0.325)	(0.299)	(0.298)	(0.297)
Peruvian*		0.054**	0.039*	0.041*	0.045**	0.044**
education		(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Not Specified		-0.049	-0.037	-0.044	-0.048	-0.048
		(0.050)	(0.050)	(0.050)	(0.050)	(0.049)
Not Specified*		0.006	0.003	0.003	0.003	0.002
education		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
All other countries		-0.250**	-0.159	-0.209**	-0.250**	-0.247**
		(0.102)	(0.102)	(0.101)	(0.101)	(0.101)
All other countries*		0.034***	0.023***	0.026***	0.028***	0.027***
education		(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Sample Size	25,420	25,420	25,420	25,420	25,420	25,420
Adjusted R^2	0.1600	0.1742	0.1891	0.1981	0.2037	0.2107

The sample includes all citizens (Hispanic and non-Hispanic). However country level analysis is only done for the Hispanic groups of interest. In columns 1 and 2 all non-Hispanic immigrants are included in the excluded variable category. Standard errors are in parentheses; ***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

The baseline returns to education for Hispanic immigrant children is much higher than the return to education for Hispanic immigrant adults (6.3 percent versus 3.8 percent). Column (3) demonstrates that much of this difference in returns is due to differences in the English speaking ability between adult and child immigrants. When English ability is controlled for, the difference in returns is much smaller (6.2 percent versus 5.4 percent).

In the complete sample in column (6), country level effects for immigrant children are similar to the ones we found for adult immigrants. Mexican and Central American immigrant children have lower returns to education, which is offset by positive country level effects. This would mean that these immigrants are disadvantaged as they increase their education. South American and Caribbean immigrants have much higher returns for education even after controlling for English ability, occupation, diaspora effects, cohort effects and naturalization.

Citizens

We find that Hispanic citizens continue to receive more education than Hispanic immigrants. The country level grouping remains consistent, where Mexicans Americans and Central Americans have lower levels of education than South Americans. Like immigrant children, Cuban Americans have an education level that is closer to the South American average.

We would expect that Hispanic Americans would have the smallest difference in returns to education by country of origin. This is because these individuals would not be directly impacted by potential country-level human capital investment constraints or difference in human capital transferability.

Table 4: LOG WAGE DETERMINANTS FOR CITIZENS BY HISPANIC IDENTITY OF AND LEVEL OF EDUCATION

	1	2	3	4	5	6
Education	0.085***	0.082***	0.082***	0.079***	0.078***	0.078***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dominican		-0.298*	-0.334**	-0.377**	-0.496***	-0.478***
		(0.157)	(0.156)	(0.156)	(0.155)	(0.155)
Dominican*		0.028**	0.033***	0.035***	0.038***	0.038***
education		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Cuban		0.042	0.067	0.041	0.003	0.010
		(0.083)	(0.083)	(0.082)	(0.082)	(0.082)
Cuban*		0.006	0.004	0.006	0.007	0.006
education		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Guatemalan		0.318	0.303	0.265	0.238	0.241
		(0.196)	(0.196)	(0.195)	(0.194)	(0.194)
Guatemalan*		-0.012	-0.010	-0.008	-0.009	-0.009
education		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Honduran		0.305	0.283	0.234	0.144	0.135
		(0.198)	(0.196)	(0.197)	(0.196)	(0.196)
Honduran*		-0.025*	-0.024	-0.021	-0.016	-0.014
education		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Salvadoran		0.349**	0.359**	0.340**	0.288*	0.291*
		(0.157)	(0.156)	(0.156)	(0.155)	(0.155)
Salvadoran*		-0.017	-0.018	-0.016	-0.015	-0.016
education		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Colombian		0.017	0.033	-0.016	-0.093	-0.085
		(0.187)	(0.187)	(0.210)	(0.185)	(0.185)
Colombian*		0.005	0.005	0.008	0.011	0.010
education		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Ecuadorian		0.488*	0.504*	0.475*	0.331	0.331
		(0.270)	(0.270)	(0.269)	(0.268)	(0.268)
Ecuadorian*		-0.019	-0.019	-0.017	-0.012	-0.012
education		(0.020)	(0.020)	(0.020)	(0.019)	(0.019)
Peruvian		0.408	0.466	0.422	0.323	0.325
		(0.295)	(0.294)	(0.305)	(0.292)	(0.292)
Peruvian*		-0.026	-0.030	-0.027	-0.024	-0.024
education		(0.021)	(0.020)	(0.020)	(0.020)	(0.020)
Not Specified		-0.112***	-0.101***	-0.098***	-0.067**	-0.061**
		(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Not Specified*		0.005***	0.003*	0.003	0.002	0.002
education		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
All other countries		-0.076**	-0.055	-0.093**	-0.199***	-0.198***
		(0.102)	(0.037)	(0.037)	(0.038)	(0.037)
All other countries*		0.011***	0.010***	0.012***	0.016***	0.016***
education		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Sample Size	112,271	112,271	112,271	112,271	112,271	112,271
Adjusted R^2	0.1305	0.1332	0.1386	0.1433	0.1505	0.1516

The sample includes all citizens (Hispanic and non-Hispanic). However country level analysis is only done for the Hispanic groups of interest. All 10 subgroups were included in the regression, but results were divided for display purposes. In columns 1 and 2 all non-Hispanic immigrants are included in the excluded variable category. Standard errors are in parentheses; ***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

We find that most of the country level variation disappears when we examine the difference in returns for non-immigrant, US citizens of Hispanic descent. do not have significant variation in their returns to education by country of origin. The only exception to this is the returns to Dominican Americans and Hispanics who are not from the top 10-subgroups. We also ran these regression including all non-immigrant Citizens (see Appendix D). What is most surprising is that the Hispanic term and the interaction term are statistically significant in the citizen sample. This is surprising because it was not statistically significant in the immigrant children sample. This would suggest that some groups may be converging to the Hispanic mean as they spend more time in the United States. It does not seem to be the case that these citizens came from cohorts which were more homogeneous.The distinction between the returns between Mexicans, Central Americans and South Americans was established in previous literature as well (Borjas, 1982). It is then unusual that Cuban American and South American children, who would be the adults in our current sample, were not able to capitalize on the relative advantage of their parents in the US labor market.

Conclusion

Our paper demonstrates that the returns to education are not homogeneous for immigrants from different countries of origin in the Hispanic community. Therefore, grouping immigrants by regions and ethnicities obscures the immigrant's actual experience. It may also be ill-advised to simply rely on country of origin for categorization. We also find that these country-level differences do not persist across generations. Over time, Hispanics converge towards a Hispanic mean instead of assimilating to the country average. This is disturbing because the families of these immigrants came in with varied experience, and points to some other persistent effect that is unobservable using Census data.

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Appendix A

It was suggested that we use statistical disrimination to adjust for potential measurement errors in the reported years of education in the census data. I have not done so because statistical discrimination is not the appropriate tool to adjust for measurement error in this case.

Hashimoto and Kochin outline two types of measurement error in their paper "A bias in the statistical estimation of the effects of discrimination." The first is error which "originates in the process of responding to questions and transcribing the responses." The second "originates in the imperfection of the schooling variable as a measure of true productivity characteristics".

In regards to the first source of error, error in transcribing or responding to questions in the survey, I believe that adjustment would be inappropriate. There is information in the census data which would suggest that individuals from any country would systematically misreport their years of education or wages. Therefore any error in reporting would most likely be exogenous to our model. I also disagree with the assessment in the paper that the direction of error can be estimated. Without having an estimate of the amount of error, adjustment can introduce additional bias into the model, and make results less reliable.

The second source of error, differences in the true measure of school quality, is the main focus of this paper. We already acknowledge that that some of the differences in returns to education stem from differences in school quality in the host country. However, we address this by looking at how the differences change as they spend additional time in the US, and are exposed to more uniform education quality.

Appendix B

Results for all adult immigrants (including non-hispanics)

Table 5: LOG WAGE DETERMINANTS FOR ADULT IMMIGRANTS BY COUNTRY OF ORIGIN

	(1)	(2)	(3)	(4)	(5)	(6)
Education	0.049***	0.072***	0.072***	0.073***	0.073***	0.071***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	-0.183***	0.298***	0.259***	0.256***	0.268***	0.215***
	(0.004)	(0.009)	(0.038)	(0.032)	(0.032)	(0.032)
Hispanic*		-0.042***	-0.026***	-0.027***	-0.026***	-0.025***
education		(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
Mexican			0.046***	0.097***	0.098***	0.109***
			(0.032)	(0.032)	(0.032)	(0.032)
Mexican*			-0.021***	-0.024***	-0.025***	-0.025***
education			(0.003)	(0.003)	(0.003)	(0.002)
Dominican			0.077*	0.076*	0.058	0.083*
			(0.046)	(0.046)	(0.046)	(0.046)
Dominican*			-0.016***	-0.016***	-0.016***	-0.015***
education			(0.004)	(0.004)	(0.004)	(0.004)
Cuban			-0.001	-0.004	0.027	0.003
			(0.045)	(0.045)	(0.045)	(0.045)
Cuban*			-0.011***	-0.011***	-0.011***	-0.011***
education			(0.004)	(0.004)	(0.004)	(0.004)
Guatemalan			0.159***	0.169***	0.169***	0.174***
			(0.041)	(0.041)	(0.041)	(0.041)
Guatemalan*			-0.026***	-0.027***	-0.028***	-0.028***
education			(0.004)	(0.004)	(0.004)	(0.004)
Honduran			0.106*	0.107**	0.118**	0.129***
			(0.052)	(0.052)	(0.052)	(0.051)
Honduran*			-0.021***	-0.022***	-0.022***	-0.022***
education			(0.005)	(0.006)	(0.005)	(0.005)
Salvadoran			0.180***	0.183***	0.188***	0.189***
			(0.038)	(0.038)	(0.038)	(0.038)
Salvadoran*			-0.025***	-0.026***	-0.026***	-0.026***
education			(0.003)	(0.003)	(0.004)	(0.003)
Colombian			0.001	-0.001	-0.015	-0.025
			(0.059)	(0.058)	(0.059)	(0.058)
Colombian*			-0.004	-0.004	-0.003	-0.003
education			(0.005)	(0.005)	(0.005)	(0.004)
Ecuadorian			0.071	0.067	0.041	0.037
			(0.060)	(0.060)	(0.060)	(0.059)
Ecuadorian*			-0.017***	-0.016***	-0.015***	-0.015***
education			(0.005)	(0.005)	(0.005)	(0.005)
Peruvian			-0.196***	-0.198**	-0.210***	-0.212***
			(0.081)	(0.080)	(0.080)	(0.080)
Peruvian*			0.012*	0.012*	0.012**	0.012**
education			(0.006)	(0.006)	(0.006)	(0.006)
Not Specified			0.058***	0.082***	0.081***	0.088***
			(0.004)	(0.004)	(0.004)	(0.004)
Not Specified*			-0.014***	-0.015***	-0.016***	-0.016***
education			(0.003)	(0.003)	(0.003)	(0.003)
Country Dummies	NO	NO	YES	YES	YES	YES
Occupation Dummies	NO	NO	NO	YES	YES	YES
US Regional Dummies	NO	NO	NO	NO	YES	YES
Cohort Dummies	NO	NO	NO	NO	NO	YES
Sample Size	271622	271622	271622	271622	271622	271622
Adjusted R^2	0.232	0.242	0.244	0.249	0.250	0.256

The sample includes all immigrants (Hispanic and non-Hispanic). However country level analysis is only done for immigrants from the top 10 Hispanic groups of interest. In columns 1 and 2 all non-Hispanic immigrants are included in the excluded variable category.Standard errors are in parentheses;***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

Table 6: LOG WAGE DETERMINANTS FOR ADULT IMMIGRANTS BY COUNTRY OF ORIGIN AND LEVEL OF EDUCATION

	all	≤ 12 years No Diploma	≥12 years	all	≤ 12 years No Diploma	≥12 years
Education	0.071***	0.072***	0.097***	0.071***	0.011***	0.097***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	0.312***	-0.186***	0.329***	0.215***	-0.066	0.186***
	(0.010)	(0.014)	(0.029)	(0.032)	(0.043)	(0.071)
Hispanic*	-0.044***	0.001	-0.036***	-0.025***	-0.001	-0.019***
education	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.005)
Mexican				0.109***	-0.139***	0.257***
				(0.032)	(0.042)	(0.081)
Mexican*				-0.025***	0.001	-0.029***
education				(0.002)	(0.005)	(0.006)
Dominican				0.086*	-0.132**	0.287**
				(0.046)	(0.057)	(0.140)
Dominican*				-0.015***	0.007	-0.026***
education				(0.004)	(0.007)	(0.010)
Cuban				0.003	-0.156***	0.310***
				(0.045)	(0.060)	(0.106)
Cuban*				-0.011***	0.006	-0.029***
education				(0.004)	(0.007)	(0.007)
Guatemalan				0.174***	-0.080	0.275
				(0.041)	(0.050)	(0.194)
Guatemalan*				-0.028***	-0.003	-0.028*
education				(0.004)	(0.050)	(0.194)
Honduran				0.129***	-0.111*	0.172
				(0.051)	(0.062)	(0.235)
Honduran*				-0.022***	0.001	-0.019
education				(0.005)	(0.008)	(0.017)
Salvadoran				0.189***	-0.071	0.394**
				(0.038)	(0.047)	(0.162)
Salvadoran*				-0.026***	0.001	-0.035***
education				(0.003)	(0.006)	(0.012)
Colombian				-0.025	-0.038	-0.109
				(0.058)	(0.077)	(0.123)
Colombian*				-0.003	0.004	0.003
education				(0.004)	(0.009)	(0.009)
Ecuadorian				0.037	-0.166**	0.547***
				(0.059)	(0.075)	(0.170)
Ecuadorian*				-0.015***	0.005	-0.048***
education				(0.005)	(0.009)	(0.012)
Peruvian				-0.212***	-0.249**	0.147
				(0.080)	(0.115)	(0.141)
Peruvian*				0.012**	0.018	-0.012
education				(0.006)	(0.012)	(0.010)
Not Specified				0.088***	-0.119***	0.108
				(0.034)	(0.044)	(0.097)
Not Specified*				-0.016***	0.003	-0.012*
education				(0.003)	(0.005)	(0.007)
Sample Size	271622	271622	271622	271622	271622	271622
Adjusted R^2	0.232	0.242	0.244	0.256	0.096	0.221

The sample includes all immigrants (Hispanic and non-Hispanic). However country level analysis is only done for immigrants from the top 10 Hispanic groups of interest. In columns 1 and 2 all non-Hispanic immigrants are included in the excluded variable category. Standard errors are in parentheses; ***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

Appendix C

Results for all child immigrants (including non-hispanics)

Table 7: LOG WAGE DETERMINANTS FOR IMMIGRANT CHILDREN BY HISPANIC IDENTITY OF AND LEVEL OF EDUCATION

	1	2	3	4	≤ 12 years (No Diploma)	≥12 years
Education	0.072***	0.092***	0.092***	0.091***	0.021***	0.098***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)
Hispanic	-0.114***	0.328***	0.088	0.124	0.043	-0.093
	(0.008)	(0.028)	(0.114)	(0.113)	(0.198)	(0.168)
Hispanic*		-0.034***	-0.007	-0.008	-0.005	0.007
education		(0.002)	(0.008)	(0.008)	(0.020)	(0.012)
Mexican			0.345***	0.420***	-0.034	0.023
			(0.113)	(0.112)	(0.191)	(0.180)
Mexican*			-0.041***	-0.045***	-0.005	-0.009
education			(0.008)	(0.008)	(0.019)	(0.013)
Dominican			0.045	-0.076	-0.259	0.249
			(0.186)	(0.168)	(0.278)	(0.294)
Dominican*			-0.013	-0.006	0.010	-0.027
education			(0.013)	(0.013)	(0.028)	(0.021)
Cuban			-0.287**	-0.297**	0.044	-0.088
			(0.133)	(0.132)	(0.263)	(0.189)
Cuban*			0.023**	0.024**	-0.005	0.009
education			(0.010)	(0.010)	(0.026)	(0.013)
Guatemalan			0.309*	0.308*	-0.015	0.285
			(0.178)	(0.177)	(0.252)	(0.473)
Guatemalan*			-0.032**	-0.033**	-0.023	-0.023
education			(0.014)	(0.014)	(0.027)	(0.035)
Honduran			0.413*	0.375*	0.009	0.523
			(0.221)	(0.211)	(0.291)	(0.517)
Honduran*			-0.048***	-0.044***	-0.027	-0.049
education			(0.017)	(0.017)	(0.032)	(0.038)
Salvadoran			0.539***	0.555***	0.143	0.279
			(0.151)	(0.150)	(0.226)	(0.341)
Salvadoran*			-0.047***	-0.049***	-0.013	-0.024
education			(0.012)	(0.012)	(0.023)	(0.026)
Colombian			-0.380*	-0.457**	-0.602*	-0.266
			(0.200)	(0.198)	(0.360)	(0.276)
Colombian*			0.024	0.028*	0.045	0.015
education			(0.015)	(0.014)	(0.036)	(0.019)
Ecuadorian			-0.038	-0.188	-1.087***	0.013
			(0.239)	(0.238)	(0.413)	(0.371)
Ecuadorian*			0.007	0.014	0.127***	-0.001
education			(0.018)	(0.018)	(0.043)	(0.026)
Peruvian			-0.251	0.279	-0.461	0.047
			(0.325)	(0.323)	(0.765)	(0.417)
Peruvian*			0.016	0.017	0.034	-0.006
education			(0.024)	(0.024)	(0.078)	(0.030)
Not Specified			0.284**	0.339***	0.009	-0.240
			(0.121)	(0.120)	(0.198)	(0.221)
Not Specified*			-0.035***	-0.038***	-0.015	0.009
education			(0.009)	(0.009)	(0.020)	(0.016)
Sample Size	55,604	55,604	55,604	55,604	12,910	42,694
Adjusted R^2	0.2074	0.2112	0.2172	0.2293	0.0811	0.1891

The sample includes all citizens (Hispanic and non-Hispanic). However country level analysis is only done for the Hispanic groups of interest. In columns 1 and 2 all non-Hispanic immigrants are included in the excluded variable category. Standard errors are in parentheses; ***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

Appendix D

Results for all non-immigrant citizens (including non-hispanics)

Table 8: LOG WAGE DETERMINANTS FOR CITIZENS BY HISPANIC IDENTITY OF AND LEVEL OF EDUCATION

	1	2	3	4	≤ 12 years (No Diploma)	≥12 years
Education	0.099***	0.100***	0.100***	0.094***	0.034***	0.098***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Hispanic	-0.037***	0.196***	0.351***	0.284***	0.220	0.310**
	(0.003)	(0.011)	(0.105)	(0.104)	(0.251)	(0.132)
Hispanic*		-0.019***	-0.021***	-0.018**	-0.017	-0.020**
education		(0.001)	(0.007)	(0.007)	(0.025)	(0.009)
Mexican			-0.108	-0.048	-0.169	-0.274**
			(0.106)	(0.105)	(0.252)	(0.134)
Mexican*			-0.001	-0.004	0.008	0.014
education			(0.007)	(0.007)	(0.025)	(0.009)
Dominican			-0.399**	-0.448**	-0.599*	-0.306
			(0.186)	(0.184)	(0.356)	(0.291)
Dominican*			0.029**	0.032**	0.041	0.023
education			(0.014)	(0.014)	(0.036)	(0.021)
Cuban			-0.091	-0.076	-0.178	-0.067
			(0.132)	(0.131)	(0.323)	(0.166)
Cuban*			0.007	0.006	0.022	0.006
education			(0.009)	(0.131)	(0.032)	(0.011)
Not Specified			-0.229**	-0.131	-0.126	-0.396
			(0.108)	(0.107)	(0.254)	(0.138)
Not Specified*			0.004	-0.000	-0.003	0.021**
education			(0.008)	(0.007)	(0.025)	(0.009)
Guatemalan			0.231	0.237	-0.018	-0.341
			(0.219)	(0.217)	(0.371)	(0.133)
Guatemalan*			-0.014	-0.015	0.021	0.025
education			(0.016)	(0.016)	(0.040)	(0.030)
Honduran			0.203	0.123	0.112	-1.355***
			(0.221)	(0.219)	(0.354)	(0.522)
Honduran*			-0.026	-0.018	-0.046	0.088**
education			(0.017)	(0.017)	(0.042)	(0.037)
Salvadoran			0.247	0.241	-0.194	0.235
			(0.186)	(0.184)	(0.326)	(0.411)
Salvadoran*			-0.018	-0.018	0.034	-0.018
education			(0.014)	(0.014)	(0.036)	(0.029)
Colombian			-0.087	-0.128	-0.273	-0.067
			(0.212)	(0.210)	(0.499)	(0.270)
Colombian*			0.005	0.007	0.025	0.003
education			(0.015)	(0.015)	(0.050)	(0.018)
Ecuadorian			0.446	0.385	-0.031	0.912**
			(0.286)	(0.283)	(0.578)	(0.397)
Ecuadorian*			-0.023	-0.020	0.006	-0.056**
education			(0.021)	(0.020)	(0.057)	(0.028)
Peruvian			0.316	0.266	1.059	0.335
			(0.308)	(0.305)	(0.854)	(0.384)
Peruvian*			-0.027	-0.025	-0.117	0.335
education			(0.021)	(0.021)	(0.854)	(0.397)
Sample Size	2,476,358	2,476,358	2,476,358	2,476,358	273,699	2,202,659
Adjusted R^2	0.1632	0.1634	0.1635	0.1784	0.0772	0.1607

The sample includes all citizens (Hispanic and non-Hispanic). However country level analysis is only done for the Hispanic groups of interest. All 10 subgroups were included in the regression, but results were divided for display purposes. In columns 1 and 2 all non-Hispanic immigrants are included in the excluded variable category. Standard errors are in parentheses; ***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

Hair Raising: The Substantive Impact of Style

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Abstract: This paper uses a lab experiment to determine the impact of hair texture and style on labor market outcomes for African American women. I test if the job applications of black women who wear their hair straight are viewed differently than women who wear their hair with its natural texture or in a perceived ethnic style (e.g. dreadlocks or braids). The experiment is conducted by altering the photographs of African American women to show their hair in different styles (straight, natural, deadlocked or close-cropped hairstyle). The photos are randomly paired with a short dossier, including some logic test results. Study subjects are asked to read through several of these dossiers or "resumes" and make hiring and wage decisions. I find that hairstyles may impact wages when other factors are difficult to analyze.

"***The most important thing I have to say to you today is that hair matters . . . Your hair will send significant messages to those around you. What hopes and dreams you have for the world, but more, what hopes and dreams you have for your hair. Pay attention to your hair, because everyone else will***".
-Hillary Clinton (Yale Commencement Speech, 2001)

Appearances matter in the labor market. Research in several disciplines has shown that beauty impacts an observer's perception of a person's intelligence, competence and general goodness (Rhode, 2010). Experimental and empirical studies have found that more attractive individuals tend to earn higher salaries. Applicants with "ethnic sounding" names and darker complexions are less likely to get job interviews than applicants with Anglo-Saxon names and lighter skin (Harrison and Thomas, 2009; Bertrand and Mullainathan, 2004). However, individuals do not have control over how pretty they are or their race. One physical characteristic which can be manipulated, but has been given little to no attention in Economic literature, is hair.

The importance of hair is especially salient for African American women. There is a perception that their hairstyle will become a liability if it does not conform to the cultural aesthetic of their workplace. Several black women have faced termination or punishment because of their hairstyle. Police officer Gina Mosley was fired because her Chief believed that her dreadlocks violated the requirement that officers present "a neutral and uniform image to effectively relate to all segments of the population they serve" (Lubbock, Avalanche-Journal, 2001). Vanessa VanDyke, a 12 year old girl, was frequently teased at school because of her afro-like hair style. The school responded to her request for intervention by threatening to expel her because her hair was a violation of the school dress code (since the bullying proved that her hair was "distracting") (Huffington Post, 2013). Tiana Parker, a seven year old girl, was expelled from her elementary school because her dreadlocks were a violation of the school dress code (Fox 23 Tulsa, 2013). Jessica Sims, a 12-year veteran, was discharged from the Navy for not cutting her dreadlocks or wearing a wig. Her discharge came one week after the defense Defense Department announced that dreadlocks and other natural hairstyles would be allowed (Myers, 2014).

African American women cannot conform to the straight hair aesthetic without spending significant time and/or money straightening their hair. Many hairstyles which better suit their natural texture, such as Afros, twists, and dreadlocks, are viewed as being either unkempt or political. This creates an increased economic burden by adding additional time and monetary demands.

I hope to understand the nature and magnitude of one part of this burden through an experimental study. I surveyed over 500 individuals through two different survey formats to determine if they rated resumes including photos of African American women with straight hair, differently than African American women with "natural" hairstyles.

I divide black hairstyles into four categories, straight hairstyles, twa(close-cropped) dreadlocks and/or braids, and (other) natural hairstyles. In general, natural hairstyles refer only to styles in which the natural hair pattern in not chemically altered, but I further exclude all hairstyle where the hair is physically altered to appear straight. A description of these hairstyles and their comparative costs is included in the appendix. I find that hairstyle had an impact on wages in the experiment when it was harder for hiring managers to determine who is truly the most capable.

Hair as a signal

"Because blacks are judged on their hair. I think basically the long, straight hair people are more favorable. The shorter, kinkier, nappier [the] hair, the less favoritism is shown. I've lived that, coming through school as a young girl I was dark, but I had long hair. I was put in with the little light [skin] long-haired kids. But the ones who had the short, measly, nappy hair, no matter what they looked like, they were always last, in the back."-Interview respondent, Raine (quoted in Banks,2000).

Many people use physical characteristics as a signal of an individual's character and ability, and employers are no different. A national survey conducted by Careerbuilder.com found that 29 percent of hiring managers would be less likely to extend a promotion to an employee with messy hair (Careerbuilder.com, 2011). White women are perceived to have different characteristics based on their hairstyle. For example a survey by Marianne LaFrance found that women with short, light hair are seen as confident, while women with medium-length, dark hair are seen as intelligent

(Critchell, 2002). Hair not only impacts how others see you, but how you see yourself. Women feel less intelligent, and are more self-conscious when having a bad hair day. This means that women may perform poorly when they believe that they have "bad hair" even if this opinion is not shared by others.

For black women, this extends beyond being a cosmetic issue because hairstyle is inextricably connected to issues of race and colorism. Saying that natural hairstyles are less professional than straight hairstyles is akin to saying that some skin colors are less "professional" than other skin colors. Historically hair texture is second only to skin color for racial identification (Rhode, 2010).

Women with different hairstyles might be treated differently in the labor market for several reasons.

1. Perceived Ability Effect

   Certain hairstyles are seen as a signal of lower ability. Employers take hairstyle into account and revise wages down based on the lower expected performance.

2. Preference Effect

   Employers prefer to pay workers differentially based on their appearance, but do not see hairstyles as a signal of ability.

3. Conformative Effect

   Employers believe that hairstyle is a signal of one's willingness to fit into the company culture.

Hair texture should exogenously be a fairly weak signal of ability. It is less expensive for an individual to straighten their hair or wear a wig for the interview than to change their race, physical attractiveness or remain unemployed. Therefore, it would be difficult to prevent individuals from hiding their "true type" during an interview process so that they could obtain the job (although true hairstyle would affect subsequent promotion opportunities). In addition, more affluent African American women are more likely to wear their hair in natural styles, such as dreadlocks, twists and braids because they have the influence and power to do so. Individuals who are trying to increase their standing may be more likely to wear their hair in a straight style because they believe that conforming to the mainstream aesthetic will help them advance (Etcoff, 1999; Banks, 2000).

It is also arguable that, exogenously, hair is a weak signal of an individual's willingness to fit into the company culture. The cost of maintaining braided and straight hairstyles increases when there are fewer black women in a geographic area. It is harder to find stylists who have experience working with black hair. Since dreadlocks and (non-braided) natural hairstyles require less maintenance, individuals who live in predominantly white areas should be more likely to wear their hair in natural styles. Natural hair may then just as likely be a signal of being more acculturated.

The exogenous signal of hair goes against cultural expectations of what hair signifies. The "black is beautiful movement" in the 1960s tried to encourage black individuals to embrace their natural features, including hair texture. This in itself is not a radical belief, and helped African Americans to fight internalized racism. However, natural hair became associated with radical views, in part because of its connection to the more radical individuals and ideologies in the black power movement.[1]

Black women continue to believe that hair sends a signal to others. We surveyed 49 black women through mechanical turk to determine what signal they believed that various hairstyles send to others in the workplace. Women were asked to rate straight, dreadlocks, braids, natural and twa (close-cropped) hairstyles in 11 categories using a 7 point semantic differential scale.[2] the categories included:

- Professional—Unprofessional
- Down to earth— High Maintenance
- Assertive—Submissive
- Radical—Conventional
- Organized—Scattered
- Unintelligent—Intelligent
- Likable—Unlikable
- Quarrelsome— Agreeable
- Trustworthy— Untrustworthy

[1]African Americans believed that it would be hypocritical to espouse a message of black equality and continue to conform to a white aesthetic of beauty, so many people in the black power movement wore natural hairstyles.

[2]For example, when rating hairstyles as Professional—Unprofessional, a score of 1 would be the most professional, a score of 7 would be the most unprofessional and a score of 4 would be neutral.

- Extroverted—Introverted
- Competent—Incompetent

The survey found that black women believe that women with straight hair are perceived most positively and women with dreadlocks are perceived least positively on all characteristic pairs expect for "Extroverted-Introverted" and "Down to Earth- High Maintenance." Kruskal-Wallis rank test showe that these opinions are all 9 of the characteristics wre statistically significant. These characteristics are related to all three possible reasons for labor market differences. Responses for the 11 items and analysis are included in the appendix.

If black women perceive that hair is being used as a signal by others, then women may self-select hairstyles if they feel that it better reflects their "type". Alternatively, stereotype threat may cause black women with natural hair to perform less well because they expect to be treated differently.

Since the effectiveness of hair as a signal may depend on assuming that hair is being used as a signal, I believe that it would be inappropriate to use empirical data to determine if hairstyle is correlated with wages. Correlations between hairstyle and performance or wages may be due to women strategically choosing their hairstyles they might not have otherwise worn because they are trying to influence the way that others perceive them. If women believed that hairstyle did not send specific signals to others, they may choose different hairstyles and the current signals would be invalid.

I therefore focus on the impact of hairstyle on wage offers and employers' assessments of ability so that I can understand the exogenous impact of hairstyle. Using an experimental design allows me to also separate the impact of hair from the impact of other beauty markers. This format also allows me to distinguish between the perceived ability effect and the preference effect. Since the participants in the experiment did not have to interact with the applicants, and the applicants do not interact with other individuals in the hypothetical firm, I cannot test the conformative effect with this experiment.

Experimental Design

200 individuals were surveyed by CINT[3] to determine the impact of hairstyle on wages. The survey included a nationally representative group of individuals between the ages of 21 and 74. Demographic information about survey participants is included in Table 1.

Table 1: Demographics of Hiring Managers

Variable	Percent	Variable	Percent
Gender		**Household Income**	
Female	50.65	Over $200,000	2.03
Male	48.79	$150,000-$200,000	3.93
		$100,000-$149,999	11.78
Race		$75,000-$99,999	19.44
White	74.47	$50,000-$74,999	24.50
Black	7.72	$35,000-$49,999	12.20
Hispanic	11.91	$25,000-$34,999	7.90
Asian	5.67	$20,000-$24,999	4.16
		$10,000-$19,999	8.51
Employment Status		Less than $10,000	2.03
Full-time	74.32	Prefer to not say	2.93
Part-time	19.97		
Not in Labor Force /Unemployed	4.59	**Age**	
		21-24	8.88
		25-29	17.67
Education		30-34	17.53
High School Graduate	20.91	35-39	8.88
Some College	13.64	40-44	10.33
Associate's Degree	14.72	45-49	7.91
Bachelor's Degree	30.34	50-54	7.67
Graduate Study	19.83	55-59	9.67
		60-64	6.56
		65-69	1.44
		70-74	2.88

Survey participants were led to believe that they were participating in a labor market study to determine if employees or employers were better able to predict applicant productivity and set optimal wages. Participants were told that in a previous study, individuals assigned to role of applicants were given the opportunity to do a trial puzzle. Applicants then completed as many

[3]CINT is a third party online market research firm hired by Survey Gizmo to implement the survey.

puzzles as possible during a 20 minute work period.

All participants in this study were assigned the role of a hiring manager in the mock firms. They competed against eight other participants assigned the role of a hiring manager to create the most profitable firm by ”hiring” applicants from the previous study.

Hiring managers offered 7-9 applicants wages based on their resume information and also guessed the number of puzzles that the applicant would be able to finish during the work period. Applicants were hired by the hiring manager who offered them the highest salary for the work period among the group of 9 competing hiring managers. Their firm earned $1 for each puzzle solved during the work period by applicants hired.

Firm profit = $1.00 x (# of puzzles completed by employees) - salaries given to employees.

Participants offered each applicant a salary between $0 and $45 for the 20 minutes of work. They also filled in their estimate for the number of puzzles they believed that each applicant would be able to complete in the 20 minute period. The puzzle estimate allowed me to distinguish between the perceived ability and the preference effects.

Participants were given the following information about each applicant.[4] They were also able to see an example of the type of puzzle the applicants completed in the previous study.

1. Year in school
2. Degree
3. Major
4. Extracurricular activities
5. Practice test time
6. graph showing how the “applicant’s” test time compared to other “applicants”.
7. Business profession photo of the applicant

[4] An image of the formatting and the specific value of all information included in the resume is included in the appendix.

The participants were unaware that there was no previous study. The applicants were randomly generated in order to determine if there were changes in wage offerings based on the applicants' hair style, gender and race.

Applicant photo generation

Nine facial images were generated to test for the impact of hairstyle. There were two white females, two white males, one Asian female, one Asian male and three black females. The black females had three different complexions so that I could see if complexion impacted wages, ability estimates or affected the impact of hairstyle.

The facial images for the "applicants" were selected from Face Place[5]. Faces were selected from this lab in order to for control for the head position and facial expression of the applicants. All faces had the same face angle and a neutral expression. The faces were then paired with a professional outfit and hairstyle to resemble a typical business portrait. [6] Each African American photo was additionally altered to have one of four hairstyles (although the specific hairstyle varied by face):

1. Braid/Dreadlock
2. Natural Hair
3. TWA (close-cropped)
4. Straightened

All hairstyles and photos used in the study are included in the Appendix. Natural hairstyles were divided into three groups because they may be differentially perceived by the general society. Historically, dress codes have more often labeled dreadlocks and braids as unprofessional. In addition, many of the cases in which individuals were reprimanded involved individuals wearing dreadlocks or braids. African American women also had different perceptions of how these hairstyles would be perceived in the workplace. The TWA was included because it is a common hairstyle for African American women, especially those who are transitioning from chemically treated hair or dread-

[5]Stimulus images courtesy of Michael J. Tarr, Center for the Neural Basis of Cognition and Department of Psychology, Carnegie Mellon University, http://www.tarrlab.org/. Funding provided by NSF award 0339122, a database created by the Tarrlab, formerly, at Brown University

[6]Most of the digital editing was completed by Chris Brown from Reel Magic Studios

locks to natural hair. It would be useful to know if there is a penalty or bonus to earnings when transitioning between hairstyles.

Photos were semi-randomly assigned to one of 12 resumes (So that each photo could be paired with a high ability, low ability and average ability resume). Participants saw each photo, but only 9 of the 12 resumes. No resume or face was seen more than once.

I expect that the preference effect will be larger in this experiment than the perceived ability effect. Due to the nature of the assignment, it is unlikely that hairstyle would impact an individual's ability to perform the task (unlike in some service positions where an individual's hairstyle may impact the way that company is perceived). The experiment is designed to minimize the magnitude of potential bias based on hairstyle, given the concrete nature of the task and the inclusion of trial time as a clear signal of ability. Therefore, this experiment is likely to underestimate the impact of hairstyle on wage offers in a real world situation. Small or statistically insignificant results in this paper would not automatically mean that there is no bias in real settings.

Results

The impact of hair was estimated using the following formula:

$$S = \beta_0 + \beta_1 A + \beta_2 D + \beta_3 H + \beta_4 P + \beta_3 M + \varepsilon \tag{1}$$

- Where S is the salary offered to "applicants";
- A is the applicant's resume information;
- D is the applicant's demographic information (captured in the photograph);
- H is the applicant's hairstyle;
- P is the hiring manager's estimate for the number of puzzles the applicant can complete within 20 minutes.
- M controls for the hiring managers fixed effects.

Participants had a difficult time estimating the number of puzzles than an applicant would be able to complete in 20 minutes. As a result, we found that hairstyle did not have an impact on the perceived ability of the applicants. We did, however, find some evidence of a preference effect since applicants with specific hairstyles were paid differentially after controlling for the respondents' puzzle estimates.

Table 2: Impact of hairstyle on wage offer

	(1)	(2)	(3)	(4)
Hairstyle				
(omitted: dreadlocks)				
Natural	1.975**	1.819**	1.997**	1.838**
	(0.915)	(0.924)	(0.911)	(0.920)
TWA	0.427	0.334	0.432	0.339
	(0.914)	(0.920)	(0.911)	(0.916)
Straight	0.725	0.633	0.606	0.514
	(0.916)	(0.918)	(0.912)	(0.914)
Applicant Demographics				
Race				
Asian	0.908*		0.852*	
	(0.469)		(0.467)	
Black	-0.280		-0.403	
	(0.759)		(0.756)	
Gender				
Female	0.986*		0.959*	
	(0.516)		(0.513)	
Photos				
(omitted: white female)				
Asian woman		0.099		0.016
		(0.682)		(0.679)
White Male (1)		-2.297**		-2.231**
		(0.966)		(0.962)
White Male (2)		-0.606		-0.656
		(0.995)		(0.991)
Asian Man		-0.935		-0.979
		(1.765)		(1.757)
White female (2)		-1.393		-1.432
		(1.781)		(1.774)
Black Female (dark)		-1.521		-1.664
		(1.786)		(1.778)
Black Female (medium)		-1.355		-1.529
		(0.993)		(0.990)
Black Female (light)		0.315		0.206
		(1.246)		(1.241)
Puzzle's estimate			-0.00037***	-0.00036***
			(0.0001)	(0.0001)
Hiring Manager FE	YES	YES	YES	YES
Sample Size	1685	1685	1685	1685
Adjusted R^2	0.6021	0.6039	0.6057	0.6074

Standard errors are in parentheses; ***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

Table 2 shows that hairstyles do impact labor market wages offered to applicants. The model also showed biases based on race, gender and hairstyle. Respondents tended to pay applicants they believed to be Asian almost \$1 more than white applicants, although there was not a statistically significant difference between black and white applicants. Women were also paid about \$1 more. However, the reason that women and Asians are paid more may be partially due to the fact that the two white male faces were more often assigned to the lower ability applications.

Surprisingly, in the general sample African American women with natural hair were given higher salaries than women with the other hairstyles. They earned approximately \$2 more, controlling for applicant and hiring manager fixed effects. This runs counter to my initial hypothesis that African American women whose hairstyle did not conform to the social norms would earn less.

Identification of subgroups

It is possible that the wage offers may be based on demographic characteristics of the respondents. For example, women may respond to hairstyle differently than men; there may be racial differences in the interpretation of hairstyle and race; there might also be generational differences. Millennials may have a different aesthetic than older generations. I test for demographic differences in the results in Table 3.

Table 3: Impact of hairstyle on wages (controlling for demographic characteristics of hiring managers)

	(Women)	(Men)	(White)	(Black)	(Hispanic)	(Asian)	(Millenials)	(Generation X)	(Baby Boomers)
Natural	-0.465	4.173***	0.996	5.488	8.702***	3.517	3.271**	2.103	-0.350
	(1.263)	(1.336)	(1.024)	(3.611)	(2.690)	(3.847)	(1.437)	(1.586)	(1.706)
TWA	-0.307	1.113	0.576	6.204*	0.797	-0.665	1.146	-0.249	0.227
	(1.244)	(1.339)	(0.989)	(3.433)	(2.711)	(4.788)	(1.490)	(1.456)	(1.801)
Straight	-0.923	1.538	-0.122	1.938	7.669***	-3.583	1.526	-0.043	-1.157
	(1.275)	(1.318)	(1.021)	(3.475)	(2.346)	(4.019)	(1.466)	(1.477)	(1.802)
Race									
Asian	0.841	0.791	0.666	-2.714*	2.409*	2.809	1.405*	0.361	-0.480
	(0.627)	(0.694)	(0.526)	(1.487)	(1.364)	(2.226)	(0.739)	(0.797)	(0.864)
Black	-1.202	0.319	-0.672	-6.299**	3.658**	-0.093	0.521	-0.739	-2.893**
	(1.031)	(1.112)	(0.854)	(3.139)	(1.854)	(3.324)	(1.240)	(1.247)	(1.376)
Gender									
Female	1.417**	0.306	0.239	3.302**	2.271	0.210	0.488	0.411	2.287**
	(0.690)	(0.763)	(0.579)	(1.561)	(1.557)	(2.412)	(0.809)	(0.884)	(0.940)
Puzzle's estimate	0.025**	-0.00037***	-0.00037***	0.214***	0.630***	1.586***	-0.00035***	-0.00041**	0.445***
	(0.011)	(0.0001)	(0.00009)	(0.054)	(0.114)	(0.324)	(0.0001)	(0.0018)	(0.057)
Hiring Manager FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sample Size	851	825	1252	142	194	94	751	577	348
Adjusted R^2	0.6661	0.5324	0.6229	0.6267	0.6504	0.7069	0.5141	0.6644	0.7330

Standard errors are in parentheses; ***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

The results in table 3 control for application fixed effects, but these results are not included in the table since they do not vary significantly from the results in the general sample, and this was not the primary focus of the paper.

Men were more responsive to changes in hairstyle than women. Men paid $4 more to individuals with natural hair than to individuals with other hair styles. This result has to be taken with a grain of salt because magnitude of the impact of the puzzle estimates was significantly smaller for male respondents. This could mean that men were not taking as much care in their survey response as women.

There were also significant differences in the impact of hairstyle by race/ethnicity. While white and Asian respondents did not pay individuals differentially by hairstyle, there was a significant impact for blacks and Hispanics. Black respondents paid applicants approximately $6 more when they wore a TWA (close-cropped) hairstyle. African Americans were the only demographic group who paid more to this hairstyle. Hispanics paid African American women with natural hair more, which was consistent with the general sample. However, the magnitude of the difference was much larger. They paid individuals with natural hair almost $9 more. This is a tremendous difference considering that all wages fell between \$0 and \$45. Hispanics were also the only group to pay individuals with straight hair more (almost \$8 more after controlling for application fixed effects).

Hairstyle only had a statistically significant impact on wage offers given by Millenials. Millienials gave women with natural hair more than individuals with other hair types. Race was statistically significant for Millenials and Baby Boomers. Baby boomers offered black applicants \$3 less while Millenials offered Asians more.

The Bureau of Labor Statistics Current Population Survey showed that in 2014, 38.6 percent of all individuals employed in management occupations were women. The survey also showed that all Blacks, Hispanics and Asians were underrepresented in management occupations. Therefore, it is most likely that the person making the final hiring decision is likely to a white male from either from Generation X or the Baby Boom. In our sample, this group was unlikely to show preference to a woman wearing a straight hairstyle. In fact, a woman with a natural hairstyle might have a slight advantage.

In most of the regressions, the hiring managers' estimate of the number of puzzles that the applicants would complete were statistically significant, but only had a small impact on wage offers. In the real world, some of these hiring managers would lose money for their company because the wages offered were too high based on the predicted number of puzzles or their own estimate of the workers' abilities. I test to see if the hiring manager's ability impacted the marginal affect of hairstyle on earnings.

Column 1 analyzes the difference in pay for individuals who had a lower salary offer than predicted by the number of puzzles completed (which would mean that the firm would make a profit from this applicant) and had predicted that the applicant would finish fewer than 240 puzzles (less than one puzzle ever 5 seconds). These participants offered significantly lower wages on average (\$14 on average compared to \$22 on average). They also were more likely to pay individuals with the TWA (close-crop) hairstyle more. This is actually consistent with the work by LaFrance, which found that white women with short hair were viewed as more powerful.

Table 4: Impact of hairstyle on wages (controlling for response characteristics)

	(1) profitable	(2) unprofitable	(3) wage below expected	(4) wage above expected
Natural	0.464	2.335***	1.802	2.221**
	(1.546)	(0.830)	(1.468)	(0.990)
TWA	4.034***	0.654	0.372	1.611
	(1.492)	(0.838)	(1.400)	(1.044)
Straight	1.770	0.396	1.508	0.590
	(1.622)	(0.827)	(1.505)	(1.003)
Race				
Asian	-0.230	-0.038	-0.015	0.850*
	(0.776)	0.432	(0.821)	(0.490)
Black	-0.451	-0.956	-0.384	-0.877
	(1.348)	(0.690)	(1.226)	(0.835)
Gender				
Female	-0.378	0.512	1.028	0.592
	(0.833)	(0.473)	(0.875)	(0.556)
Puzzle's estimate	0.285***	0.948***	-0.00032***	-0.00038***
	(0.024)	(0.043)	(0.0001)	(0.00013)
Hiring Manager FE	YES	YES	YES	YES
Sample Size	283	1391	510	1175
Adjusted R^2	0.8783	0.6898	0.7792	0.6633

Standard errors are in parentheses; ***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

Column 2 shows that for individuals who have a wage offer that is greater than their ability estimate (and would be losing money in this example), Natural hair has a positive effect on wage offers.

Columns 3 and 4 show the results for individuals whose wage offers were above and below the mathematical estimate for the number of puzzles completed based on the trial times. Individual who had a wage estimate that was lower than the trial time (which could be seen as the expected ability) did not vary wage offers by hair type, race or gender. Hiring managers who offered wages which were higher than the number of puzzles completed based on the trial times, paid Asian applicants more and black applicants with natural hair more.

Profit tied into performance

It is possible that individuals would behave differently if they were making hiring decisions for a real firm or if they were more experienced at hiring. I tried to replicate lower cognitive strain and real consequences by running a simplified survey through Mechanical Turk to see if having wages tied to results affected the impact of hair on returns to education.

I surveyed 351 respondents through Mechanical Turk. To ensure response quality, I restricted participation to Mechanical Turk workers in the United States, with a HIT acceptance rate of over 98 percent and at least 1000 accepted HITs. Respondents in the Mechanical Turk survey were younger and had lower incomes than the respondents in the CINT survey. In addition there were more Asian and fewer black and Hispanic respondents in this survey.

Differences in the Mechanical Turk survey.

1. We told participants the number of puzzles the applicants completed in a 5 minute trial time instead of the number of seconds it took to complete an individual puzzle. This reduced the complexity of estimating the number of puzzles completed in the 20 minute period.
2. The applicants' relative performance was shown on a number line instead of in a normal distribution graph, so that it was easier to understand how the applicant performed relative to others.
3. Participants did not see an example of the puzzle that applicants completed.
4. Examples were included to better illustrate how firm profit was calculated.

5. The instructions were divided into several pages, so that it was easier to read.
6. A progress bar was added to reduce survey fatigue.
7. The Mechanical Turk workers may be more experienced in doing surveys of this type. After Mechanical Turk workers agreed to do the HIT, they were randomly assigned to a survey where they were or were not compensated based on the firm's profit. This allowed me to test for the difference in responses based on the new platform and simplified the effect of having wages tied to performance as a hiring manager.

Table 5: Demographics of Hiring Managers in Mechanical Turk Survey

Variable	Percent	Variable	Percent
Gender		Household Income	
Female	36.84	Over $200,000	0.88
Male	62.28	$150,000-$200,000	1.75
		$100,000-$149,999	7.60
Race		$75,000-$99,999	11.70
White	78.07	$50,000-$74,999	18.13
Black	6.14	$35,000-$49,999	15.79
Hispanic	5.56	$25,000-$34,999	13.45
Asian	13.45	$20,000-$24,999	9.36
		$10,000-$19,999	13.16
Employment Status		Less than $10,000	5.85
Full-time	61.40	Prefer to not say	2.34
Part-time	14.62		
Not in Labor Force /Unemployment	9.06	Age	
		21-24	13.45
Education		25-29	27.19
High School Graduate	16.96	30-34	20.76
Some College	13.31	35-39	12.87
Associate's Degree	13.16	40-44	6.73
Bachelor's Degree	40.64	45-49	6.14
Graduate Study	13.74	50-54	4.97
		55-59	4.39
		60-64	2.92
		65-69	0.58
		70-74	0.29

Table 6: Impact of hairstyle on wage offer

	no profit				profit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Natural	0.545	0.602	-0.192	-0.126	0.746	0.730	-0.122	-0.133
	(1.134)	(1.075)	(0.665)	(0.665)	(0.806)	(0.807)	(0.462)	(0.463)
TWA	1.029	0.975	-0.467	-0.540	0.403	0.397	-0.300	-0.305
	(1.092)	(1.097)	(0.681)	(0.683)	(0.807)	(0.808)	(0.466)	(0.467)
Straight	1.034	0.936	0.077	-0.044	0.999	0.988	0.074	0.052
	(1.038)	(1.043)	(0.646)	(0.648)	(0.810)	(0.813)	(0.467)	(0.478)
Race								
Asian	0.387		0.411		0.151		0.177	
	(0.560)		(0.329)		(0.422)		(0.229)	
Black	0.613		0.445		0.873		0.513	
	(0.858)		(0.520)		(0.672)		(0.375)	
Gender								
Female	0.024		0.034		-0.090		-0.171	
	(0.528)		(0.310)		(0.398)		(0.216)	
Photos								
(omitted: white female)								
Asian woman		0.612		0.606		-0.053		0.044
		(0.914)		(0.536)		(0.690)		(0.374)
White Male (1)		0.359		0.344		-0.213		-0.100
		(0.915)		(1.444)		(0.689)		(0.374)
White Male (2)		-0.085		-0.137		0.037		0.158
		(0.917)		(0.538)		(0.689)		(0.374)
Asian Man		0.332		0.349		0.141		0.179
		(0.917)		(0.053)		(0.690)		(0.374)
White female (2)		1.067		0.053		-0.253		-0.322
		(1.118)		(0.537)		(0.690)		(0.374)
Black Female (dark)		1.067		0.852		0.539		0.131
		(1.118)		(0.668)		(0.880)		(0.487)
Black Female (medium)		-0.090		-0.322		0.630		0.344
		(1.151)		(0.690)		(0.843)		(0.465)
Black Female (light)		0.942		0.802		1.005		0.590
		(1.111)		(0.664)		(0.864)		(0.478)
Puzzle's estimate	0.220****	0.219***	0.230***	0.228***	0.317***	0.316***	0.521***	0.520***
	(0.028)	(0.028)	(0.023)	(0.023)	(0.034)	(0.034)	(0.023)	(0.023)
Hiring Manager FE	NO	NO	YES	YES	NO	NO	YES	YES
Sample Size	1403	1403	1403	1403	1668	1668	1668	1668
Adjusted R^2	0.4493	0.4482	0.8100	0.8103	0.5402	0.5391	0.8649	0.8646

Standard errors are in parentheses; ***= 99 percent confidence, ** = 95 percent confidence, * = 90 percent confidence

I found that the photo information did not have a statistically significant effect on wage offers in the Mechanical Turk environment. However, the Mechanical Turk regressions had a higher adjusted R-squared than the comparable regressions in the CINT environment. This is because puzzle estimate had a larger impact on wage offers given by the Mechanical Turk workers, especially when they were compensated based on the profit of their firms. The increased reliance on the survey puzzle information may have been due to the fact that the simplified design made it easier to calculate the "optimal" wage. It might also be due to the Mechanical Turk sample. Individuals who have a high percentage of accepted HITs may have a more systematic approach to survey problem solving.

Conclusion

Edith Wharton wrote in “The Touchstone” that "Genius is of small use to a women who does not know how to do her hair.” This paper explored how true this statement was for African American women. I found that African American women may not be penalized for their hairstyle when working in a space where their hairstyle should be irrelevant. In the Mechanical Turk environment, neither race, gender or hairstyle impacted wage offers. However, when survey fatigue was increased along with the difficulty of determining optimal wages, there was evidence of a preference effect on wages.

Women were paid differentially based on their hairstyle and this difference was independent of the hiring manager’s estimate of the applicants’ ability. However, it seemed that natural and TWA hairstyles were paid more, which went against the general assumption that individuals with straight hair would be offered higher wages. The impact of hair was sensitive to the demographic characteristics of the hiring managers.

This does not mean that individuals with natural hairstyles will always be treated preferentially in the workforce. Individuals with natural hair may face more discrimination in jobs where there is direct interaction with customers and/or clients or where there is more subjectivity in hiring decisions. I also cannot say if there are differences in the way that individuals are treated in the workplace based on their hairstyle, which may impact their performance. It is also possible that the belief that hairstyles impact wages will cause African American women to behave differently as they change their hairstyle. Life experience tells women that hair matters, but perhaps not as much as we think.

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APPENDIX A: Comparative cost of hairstyles

Straight Hairstlyes

In order to have straight hair, black women must chemically straighten their hair with a perm, wear a weave or extension, or press their hair. The cost of straightening hair is generally larger than the cost of many natural hairstyles.

Perms/Relaxers The terms “perm” and “relaxer” are used interchangeably in the black community and usually refers to a process when the hair is chemically altered so that the hair follicles lies flat. Angela Onwuachi-Willig estimated that it can cost ”between $60 to $300 for each full permanent or $40-100 for each touch-up in between full relaxers with either a full relaxer or touch-ups occurring every four to eight weeks or sooner (Onwuachi-Willig, 2010).”

Weaves Weaves or extensions are a process where human or synthetic hair is attached to head by either sewing or gluing it to the existing hair. According to Toni Love, an Atlanta Beautician, ”Extensions can cost as low as $300 and go up to $10,000 based on the service.”(Madame Noire, 2011) This does not include the opportunity cost of weaves since it can take between 3-8 hours for a new weave to be installed. This also does not include the cost or time of maintenance in between installations.

Pressing Pressing hair is the least costly way to obtain straight hair but also takes the longest time commitment. When hair is pressed, a hot comb or flat iron is heated and passed through the hair. It can take between 2-3 hours for a professional hairstylist to straighten (shoulder length) natural hair. This hairstyle is more difficult to maintain then relaxers or weaves. Any moisture or humidity can cause the hair to slowly revert back to its natural state. Therefore hair must be repressed after washing.

0.0.1 Natural Hairstyles

Braids/Twists Braids are formed by twisting or plaiting hair either along the scalp (cornrows) or off the scalp (individual braids). Although the installation time can take as long, if not longer than weaves and perming the hair, the daily maintenance time is shorter. Braids can be left in the hair for 4-6 weeks depending on maintenance. The expense of braid installation will vary based on the length of the hair, the size of the braids and the whether synthetic or human hair is added to the braid for additional length and volume. Braids can cost as much, if not more, than perms and weaves.

Dreadlocks Dreadlocks are formed by matting several strands of hair together. Many women choose to form their locks by processing twisted or braided hair, so that they are uniformly sized. Lock installation can vary based on the length of hair and process used. However, once locks are formed, the maintenance process is relatively inexpensive. Individuals need to re-twist hair at the base as new hair grows to retain consistency of shape. Lc maintenance can be done at home. The lock installation process is permanent. Locks can only be removed by cutting off all of the individual’s hair.

Natural Natural or Afro-textured hair is the natural hair texture of many people of African decent. It is characterized by tightly coiled spring,"z"-shaped and/or "s"-shaped curl patterns in the hair. This hair texture is more fragile than other textures due to its curl pattern. Although individuals who wear their hair naturally may have lower cost of maintenance, it can take longer to wash, detangle and style natural hair due to the tight curl pattern.

TWA (Teeny Weenie Afro) The TWA(Teeny Weenie Afro) or close-cropped hair is a very short natural hairstyle. Hair is typically no more than 2 inches from the head, although the length of the actual hair can be significantly longer due to the tight curl pattern. This hairstyle is examined separately because many times people will cut off all of their hair (big chop) when transitioning from chemically treated to natural hair. Individuals also have to transition through this hairstyle if they choose to remove their dreadlocks. This hairstyle is the easier to maintain than longer natural hair and cheaper to maintain than straightened hair.

APPENDIX B: Perception of hair signal by hair type

Figure 1: Professional

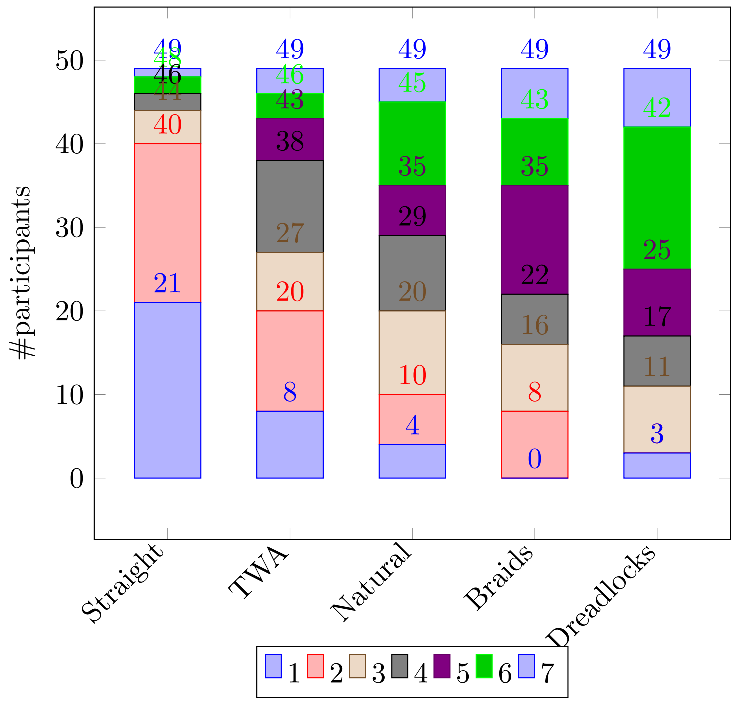


Figure 2: Down to Earth

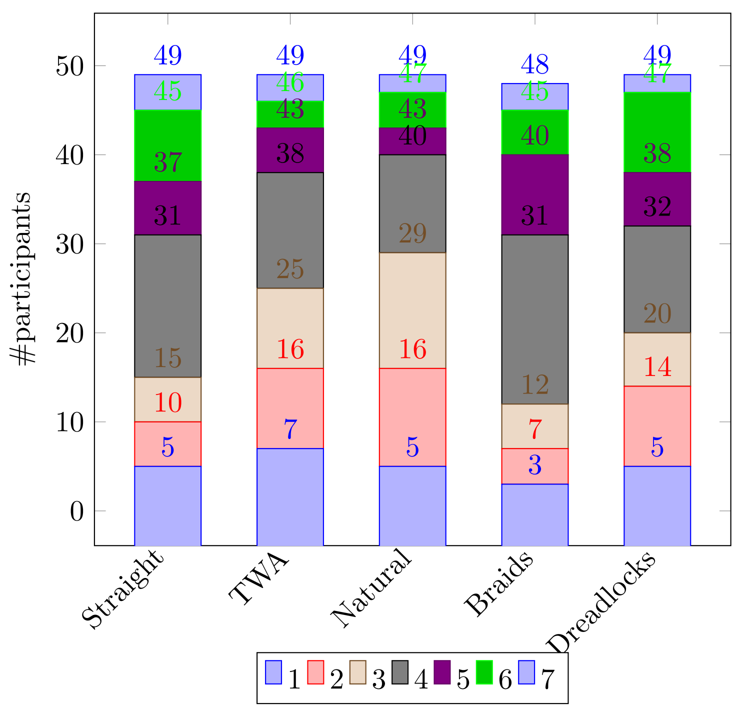


Figure 3: Assertive

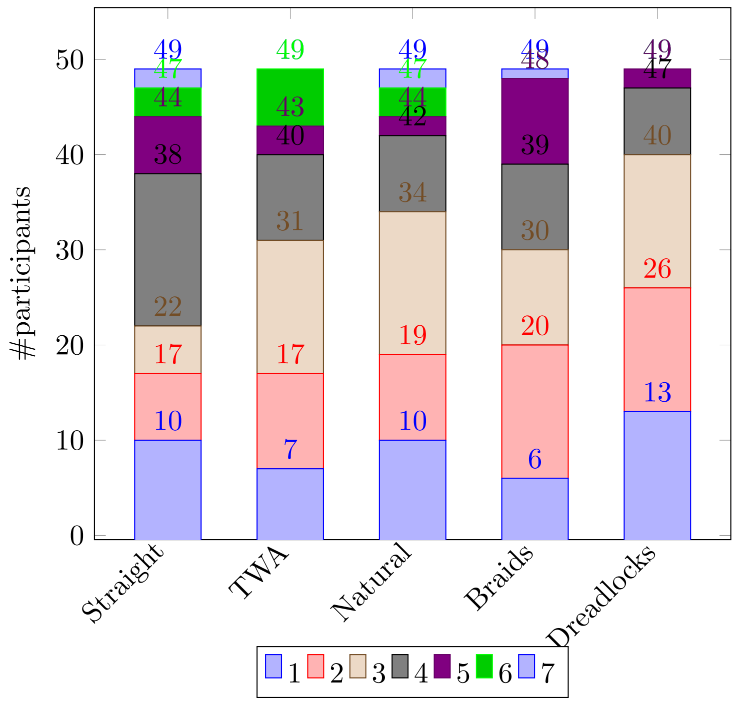


Figure 4: Radical

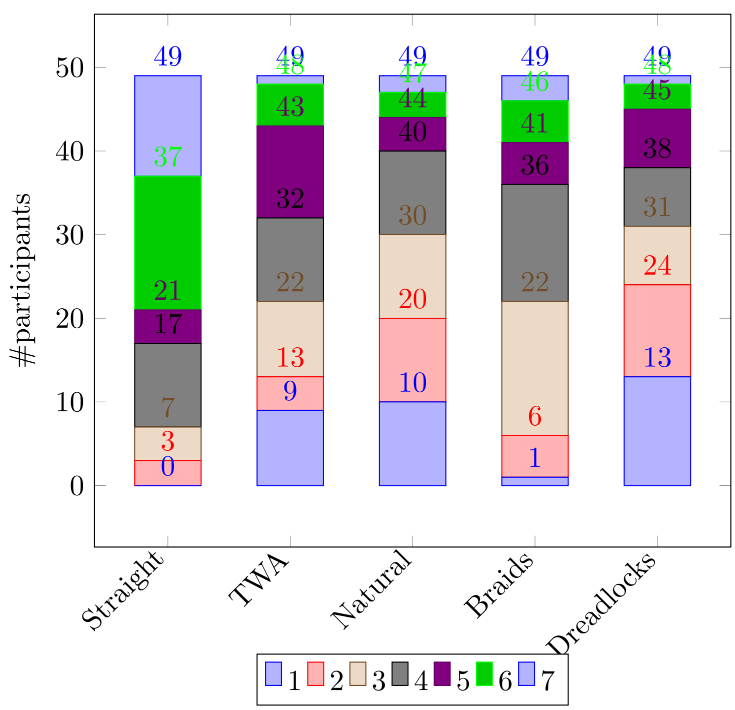


Figure 5: Organized

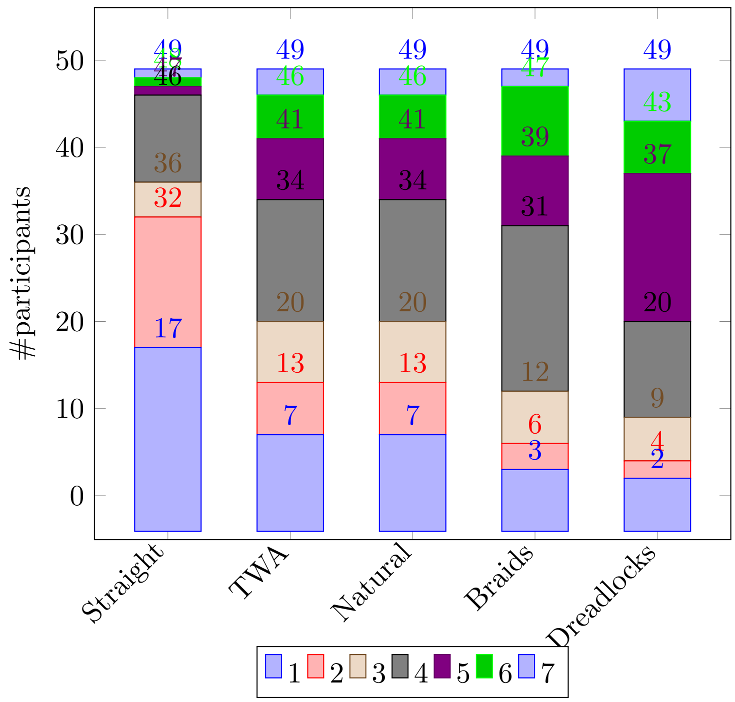


Figure 6: Unitelligent

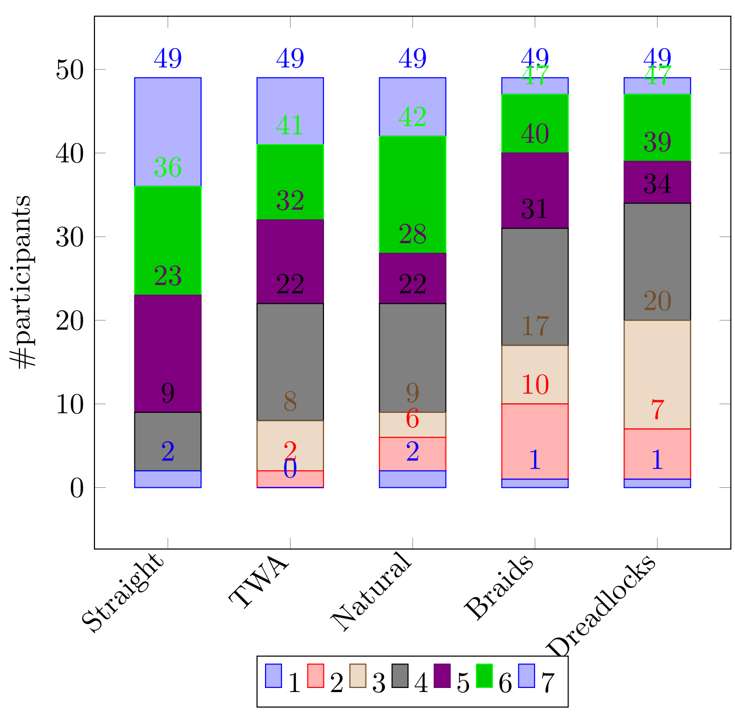


Figure 7: Likeable

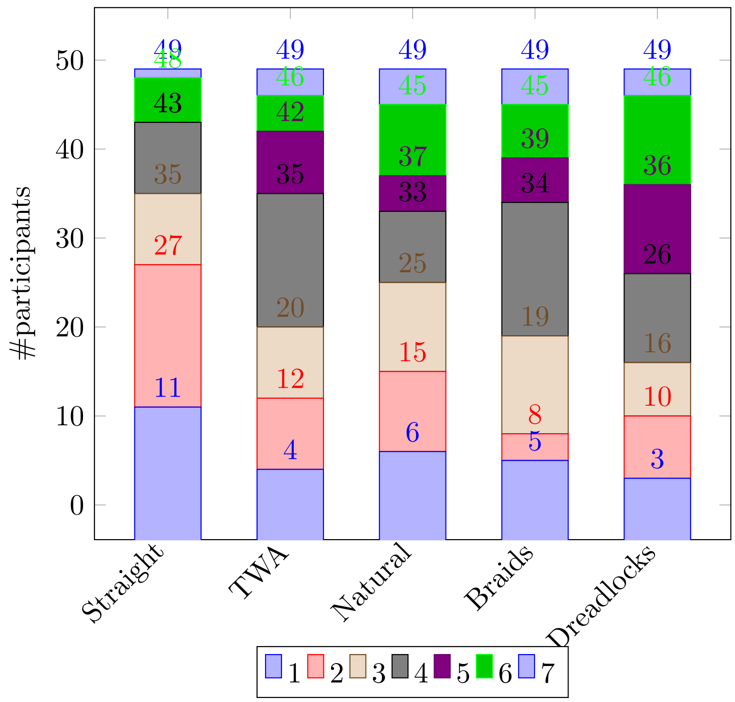


Figure 8: Quarrelsome

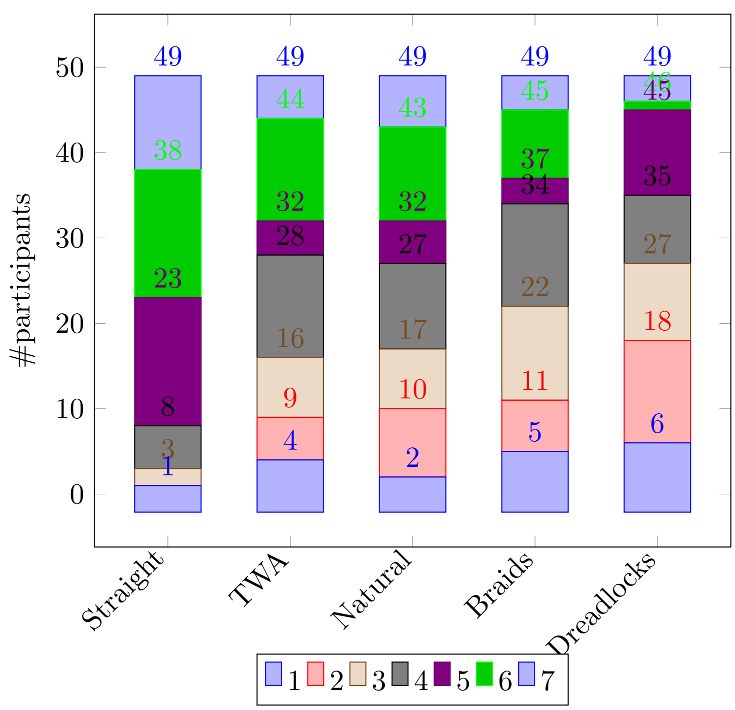


Figure 9: Trustworthy

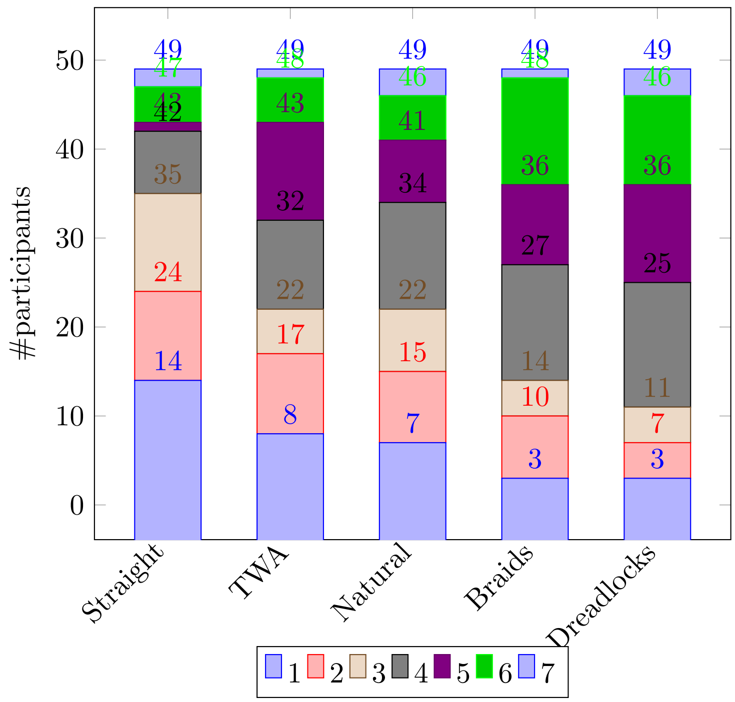


Figure 10: Extroverted

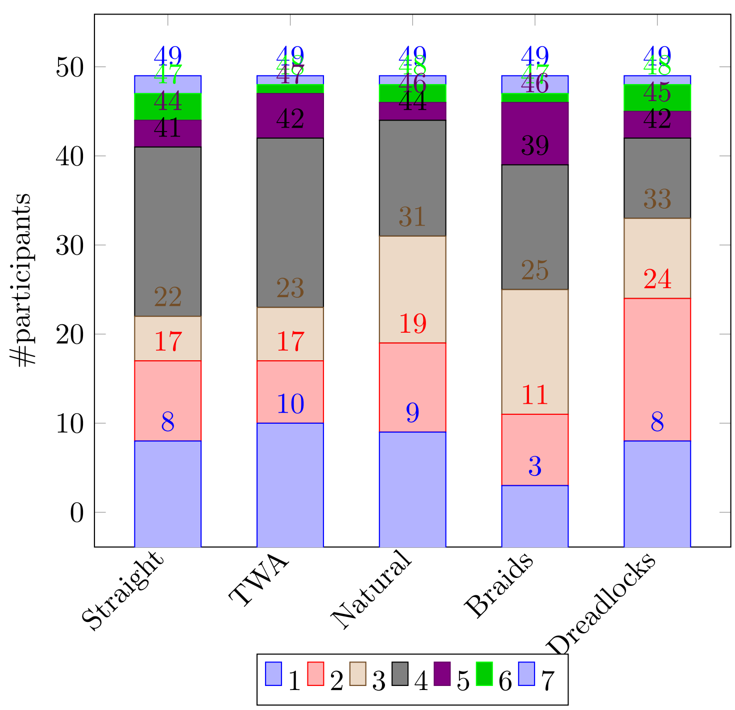
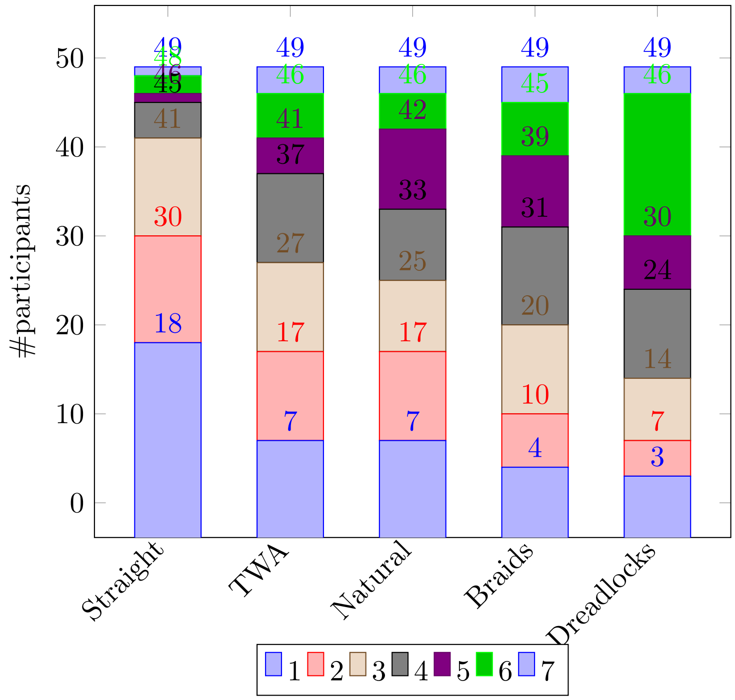


Figure 11: Competent

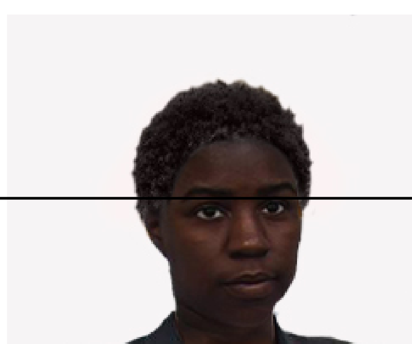


APPENDIX C: Photos of African American Women

Figure 12: Hairstyles

(a) Dreadlocks

(b) Natural



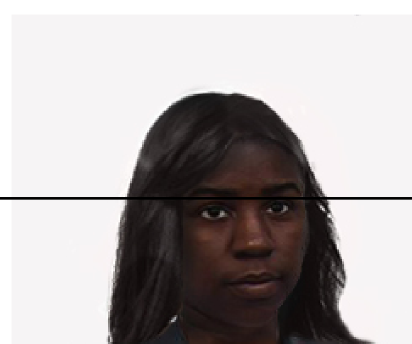
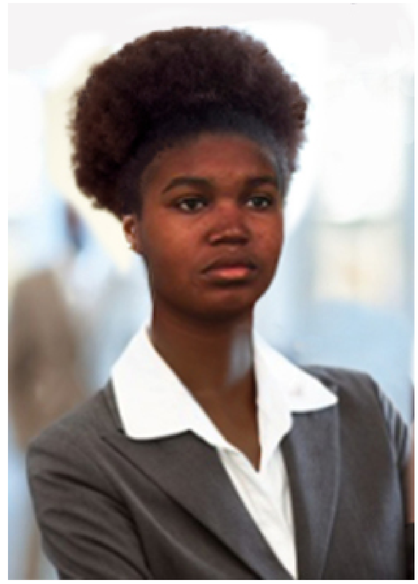


Figure 13: Hairstyles

(a) Braids



(b) Natural

(c) TWA

(d) Straight

Figure 14: Hairstyles

(a) Braids

(b) Natural

(c) TWA

(d) Straight

APPENDIX D: All other photos

All other photos

Figure 15: Applicants

Appendix E: Cint Survey Prompts

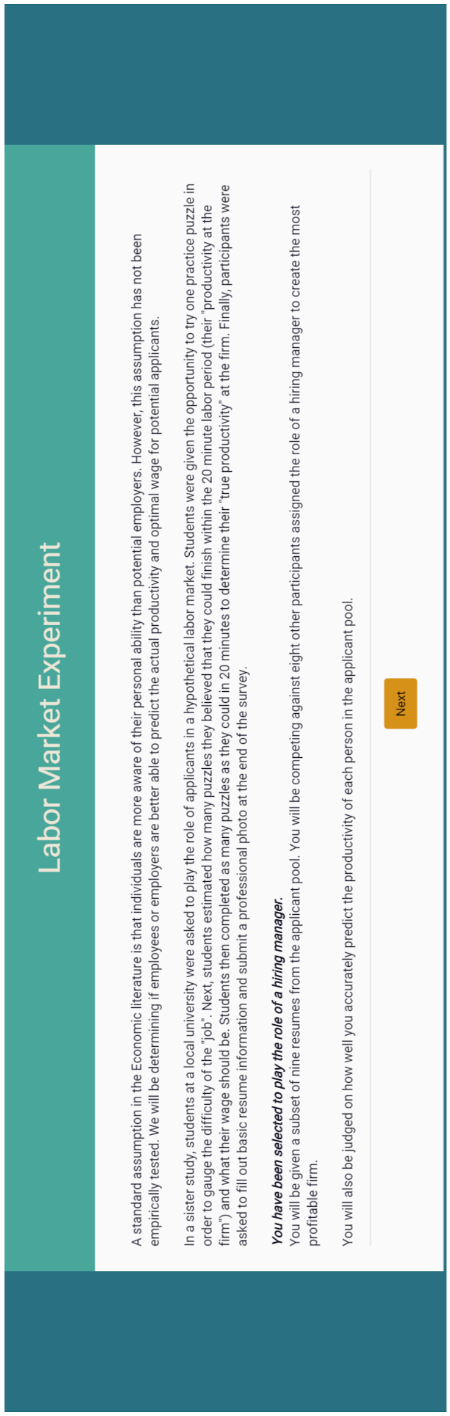


Figure 16: Cint survey: Page 1

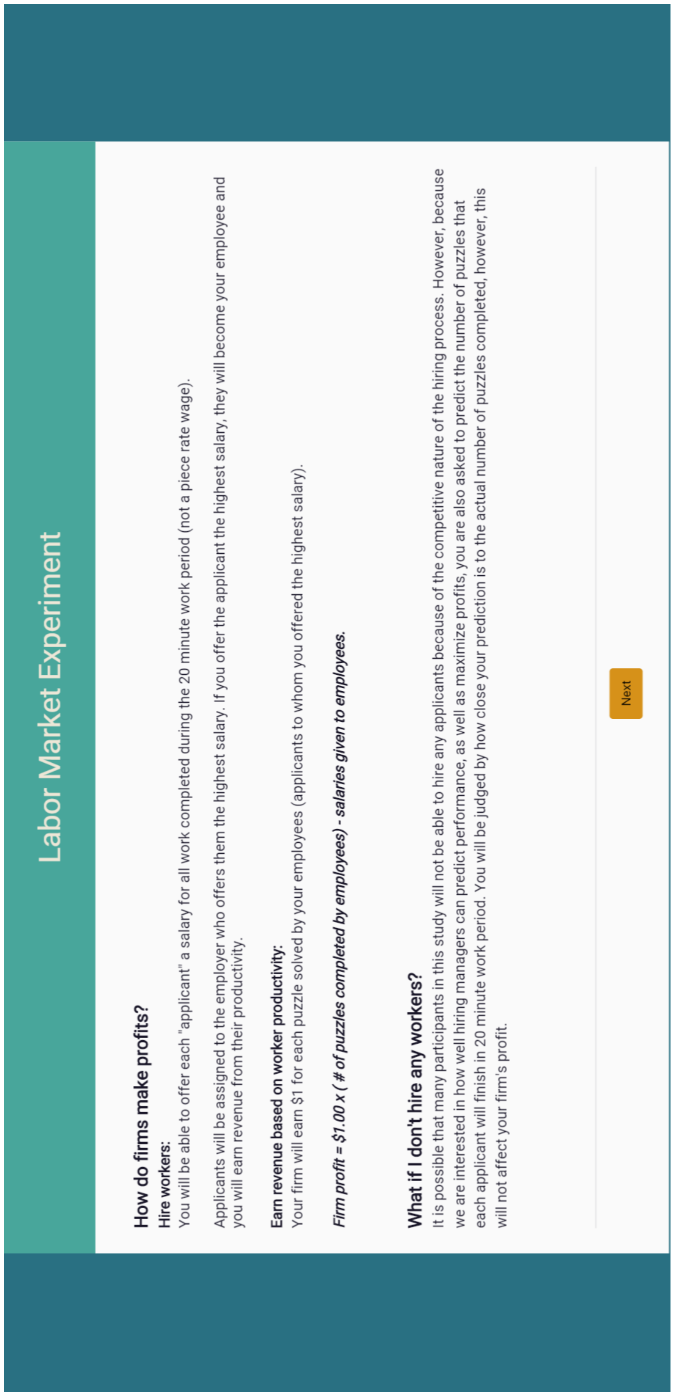
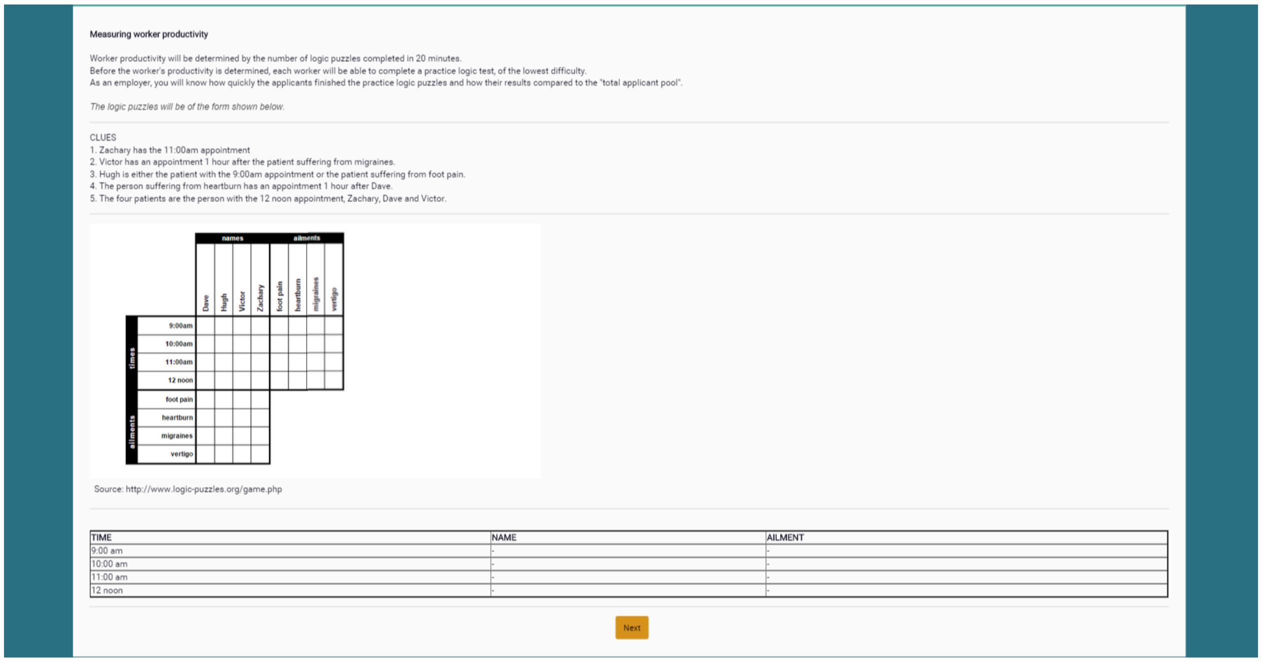


Figure 17: Cint survey: Page 2



Measuring worker productivity

Worker productivity will be determined by the number of logic puzzles completed in 20 minutes.
Before the worker's productivity is determined, each worker will be able to complete a practice logic test, of the lowest difficulty.
As an employer, you will know how quickly the applicants finished the practice logic puzzles and how their results compared to the "total applicant pool".

The logic puzzles will be of the form shown below.

CLUES
1. Zachary has the 11:00am appointment
2. Victor has an appointment 1 hour after the patient suffering from migraines.
3. Hugh is either the patient with the 9:00am appointment or the patient suffering from foot pain.
4. The person suffering from heartburn has an appointment 1 hour after Dave.
5. The four patients are the person with the 12 noon appointment, Zachary, Dave and Victor.

Source: http://www.logic-puzzles.org/game.php

TIME	NAME	AILMENT
9:00 am	-	-
10:00 am	-	-
11:00 am	-	-
12 noon	-	-

Next

Figure 18: Cint survey: Page 3

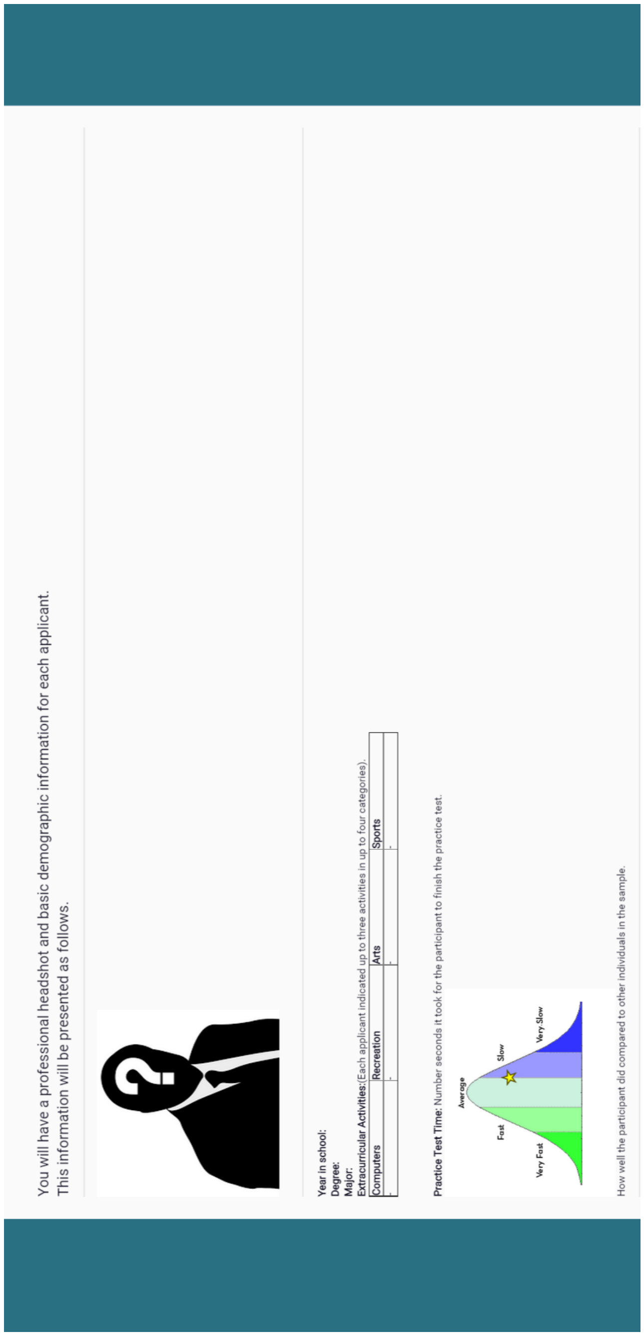


Figure 19: Cint survey: Page 4

Appendix F: CINT Survey Resume Information (Applications)

Appendix G: Mechanical Turk Survey Prompts

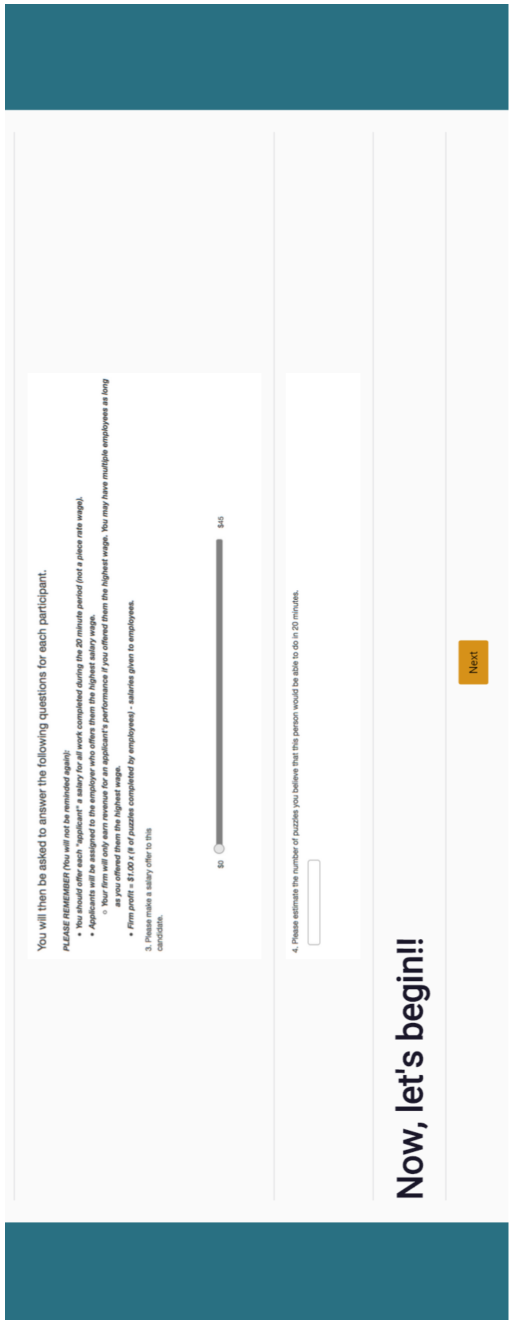


Figure 20: Cint survey: Page 4 (continued)

Figure 21: Cint: Application 1

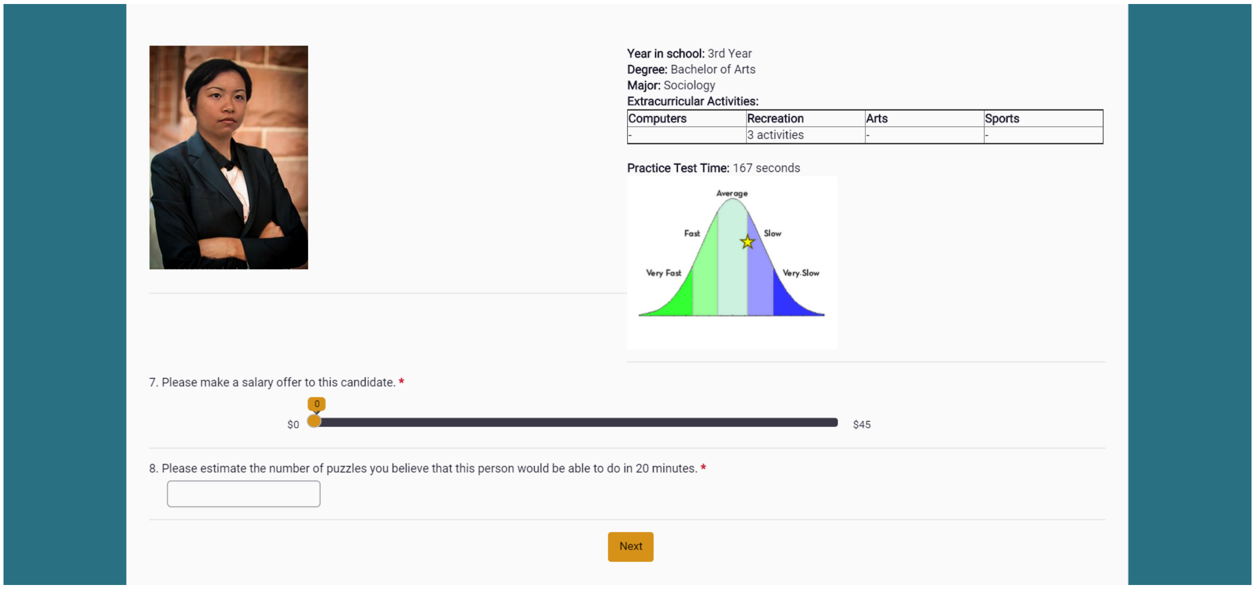


Figure 22: Cint: Application 2

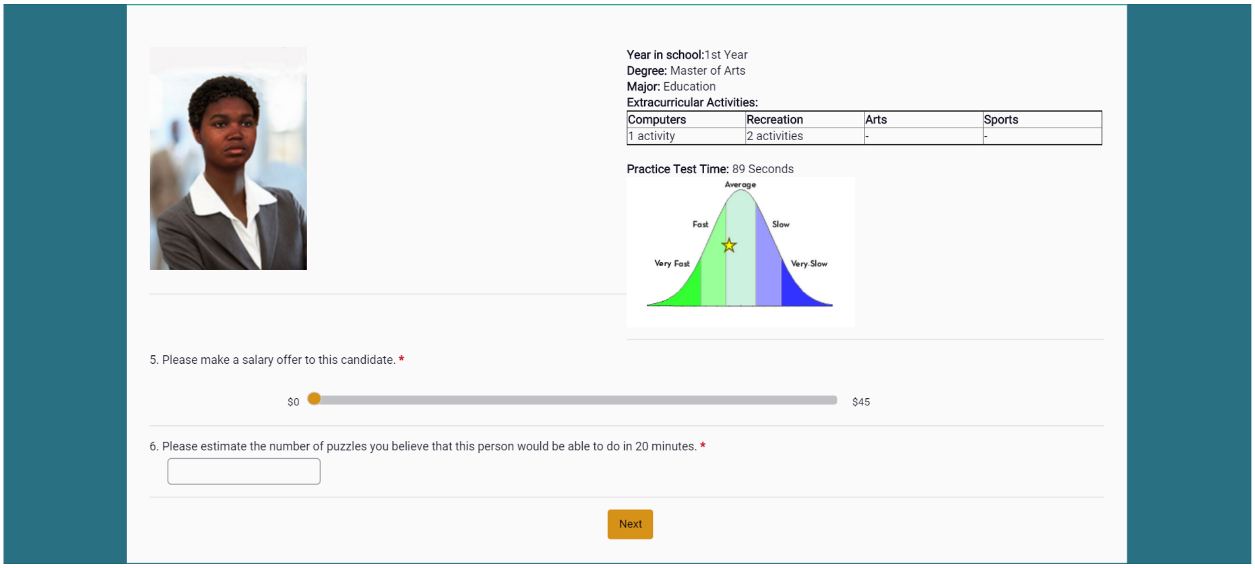


Figure 23: Cint: Application 3

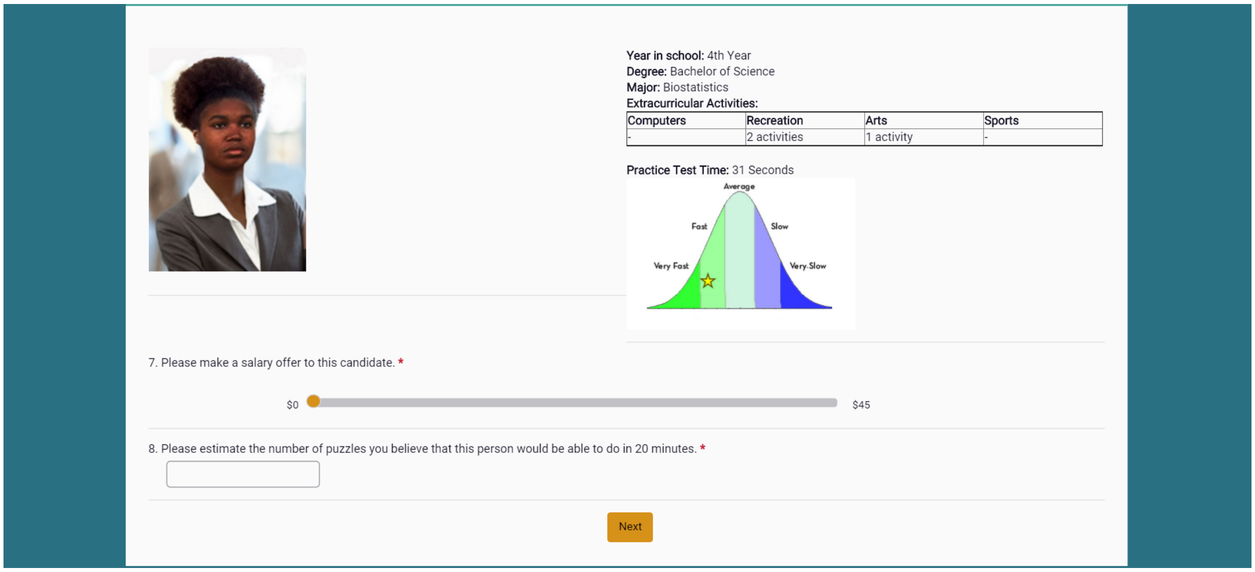


Figure 24: Cint: Application 4

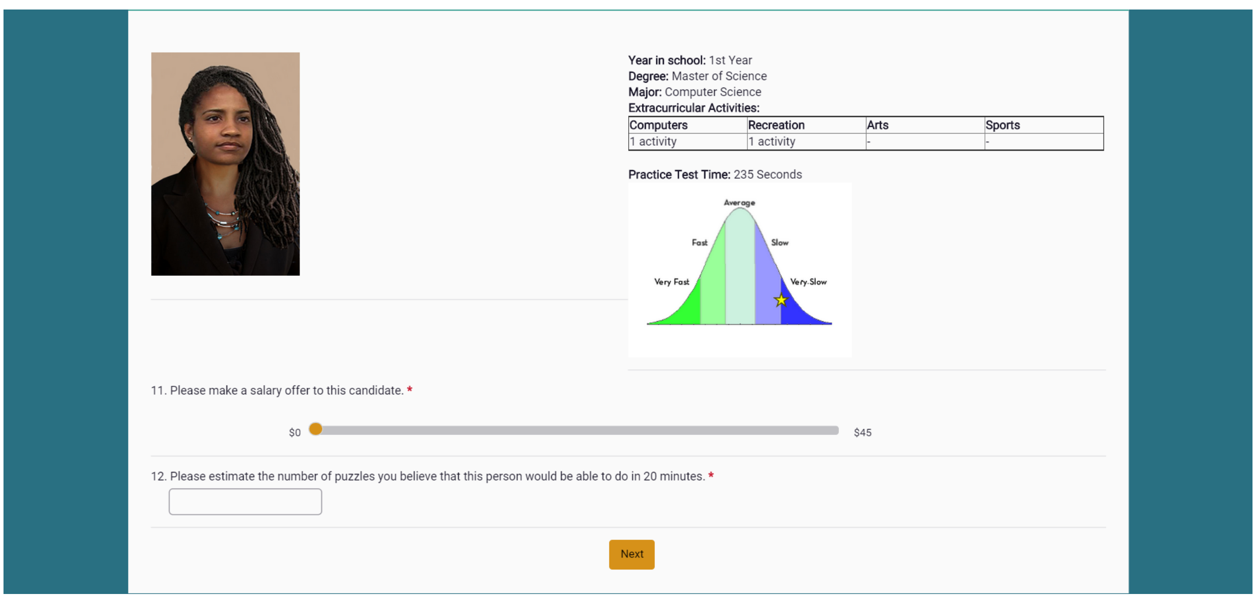


Figure 25: Cint: Application 5

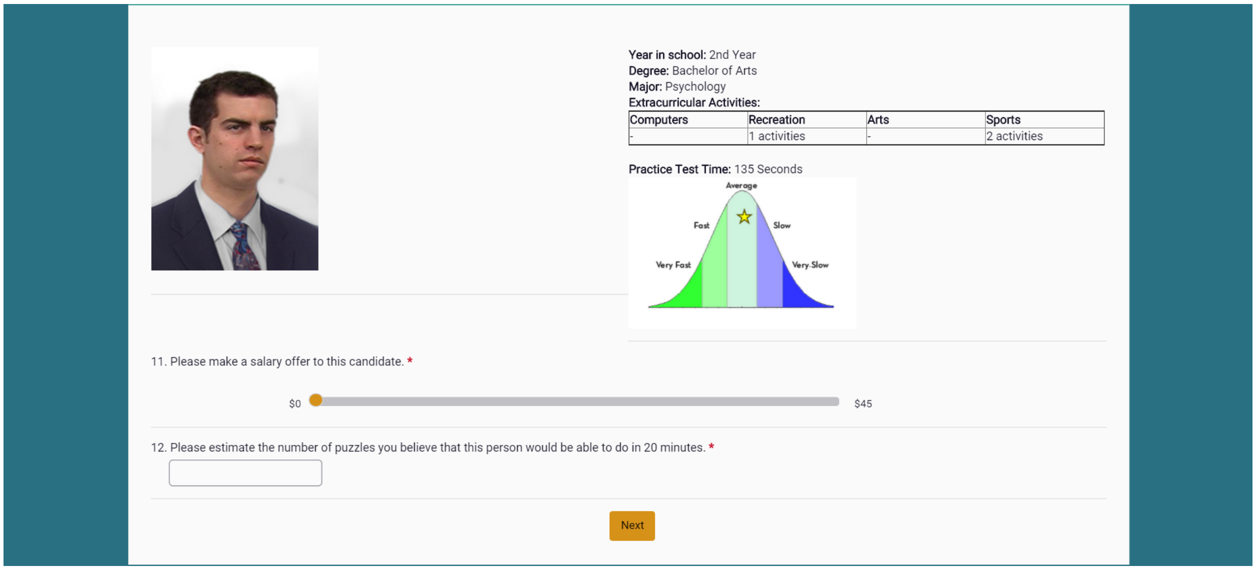


Figure 26: Cint: Application 6

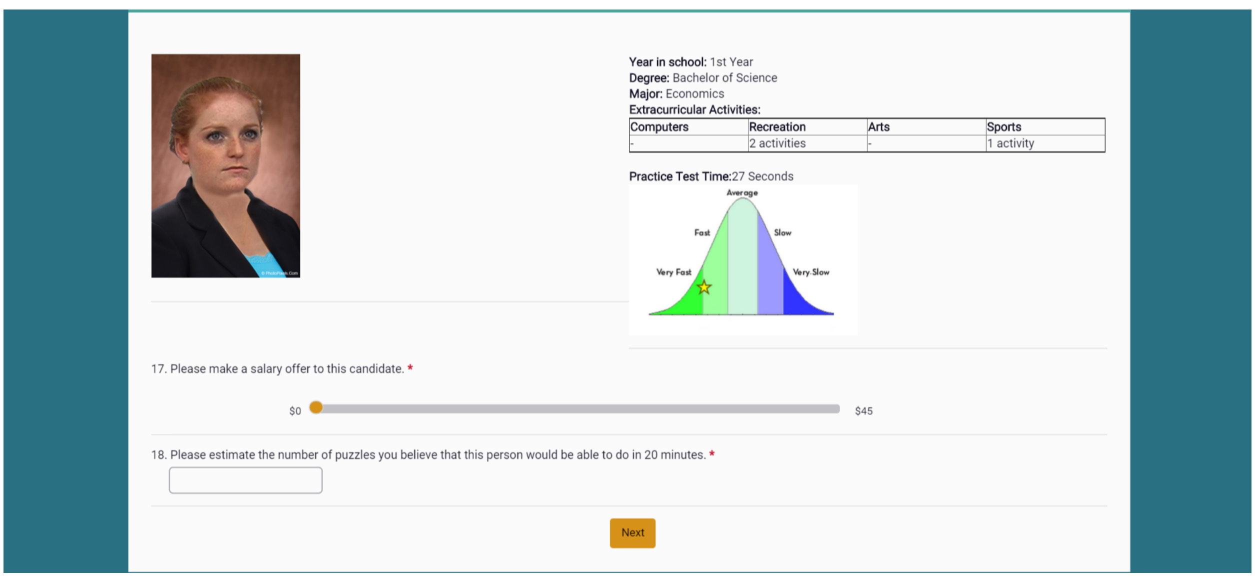


Figure 27: Cint: Application 7

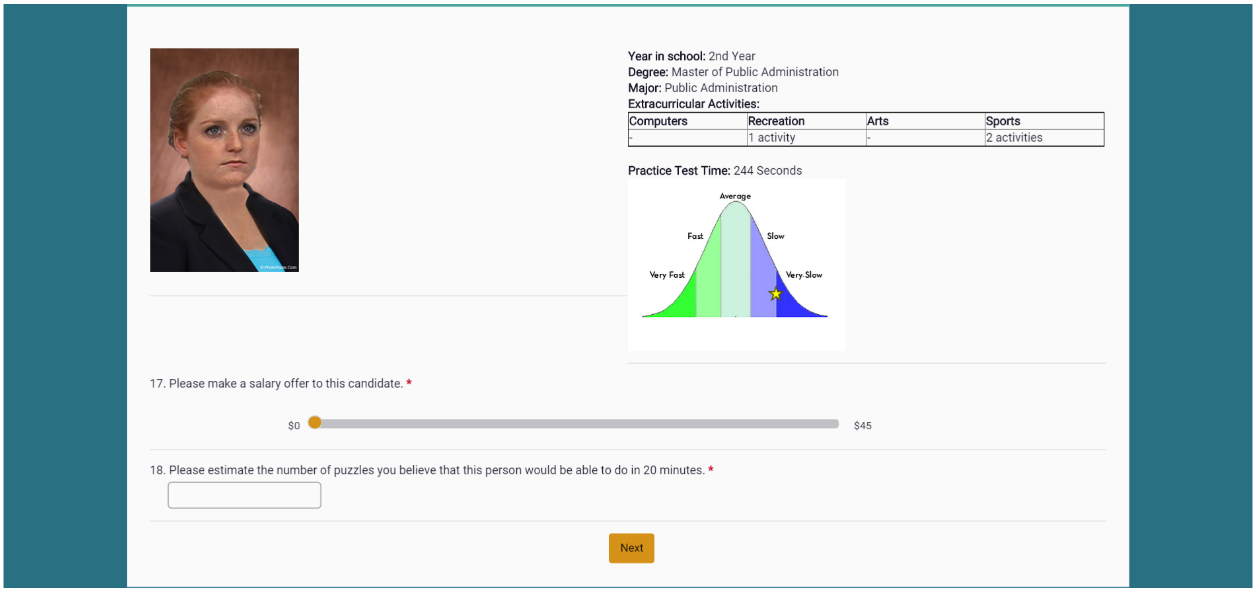


Figure 28: Cint: Application 8

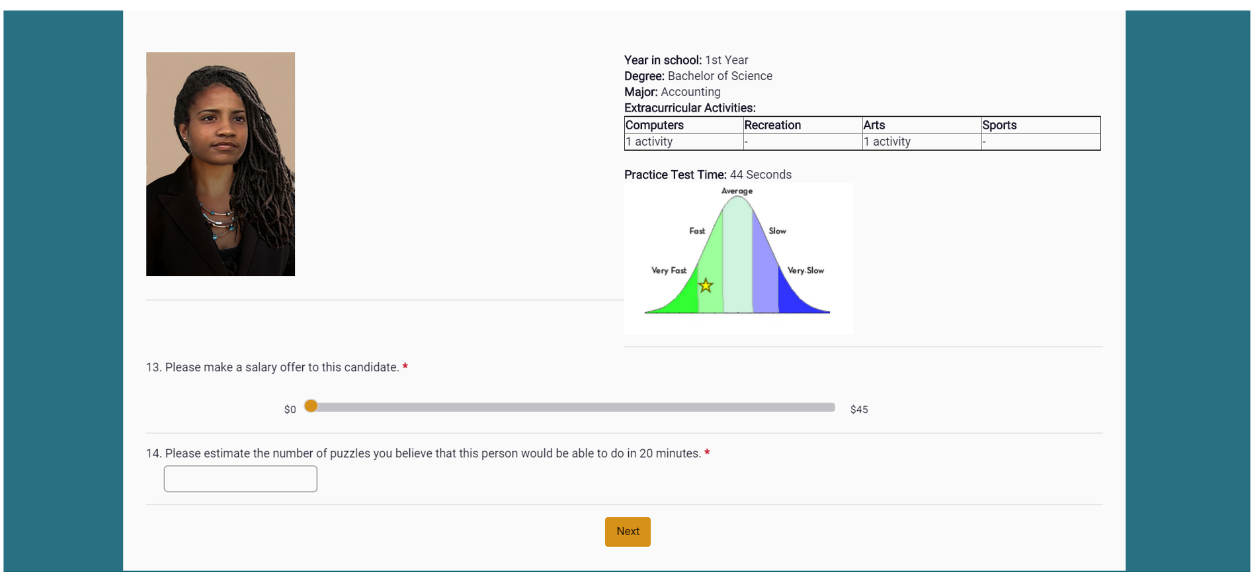


Figure 29: Cint: Application 9

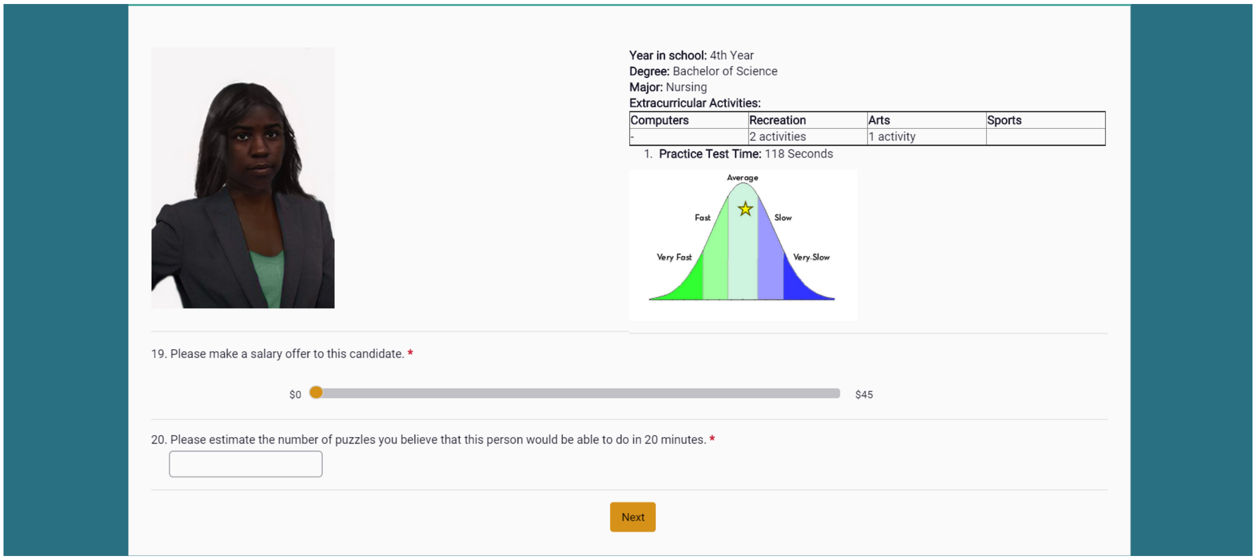


Figure 30: Cint: Application 10 (Branch page)

Figure 31: Cint: Application 11 (Branch page)

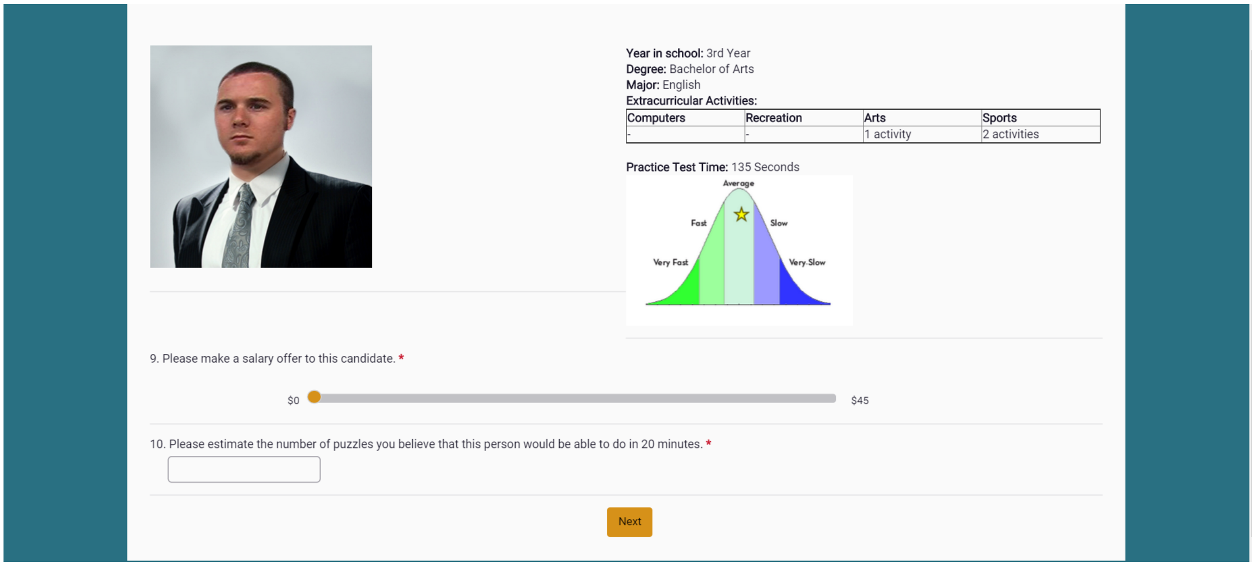
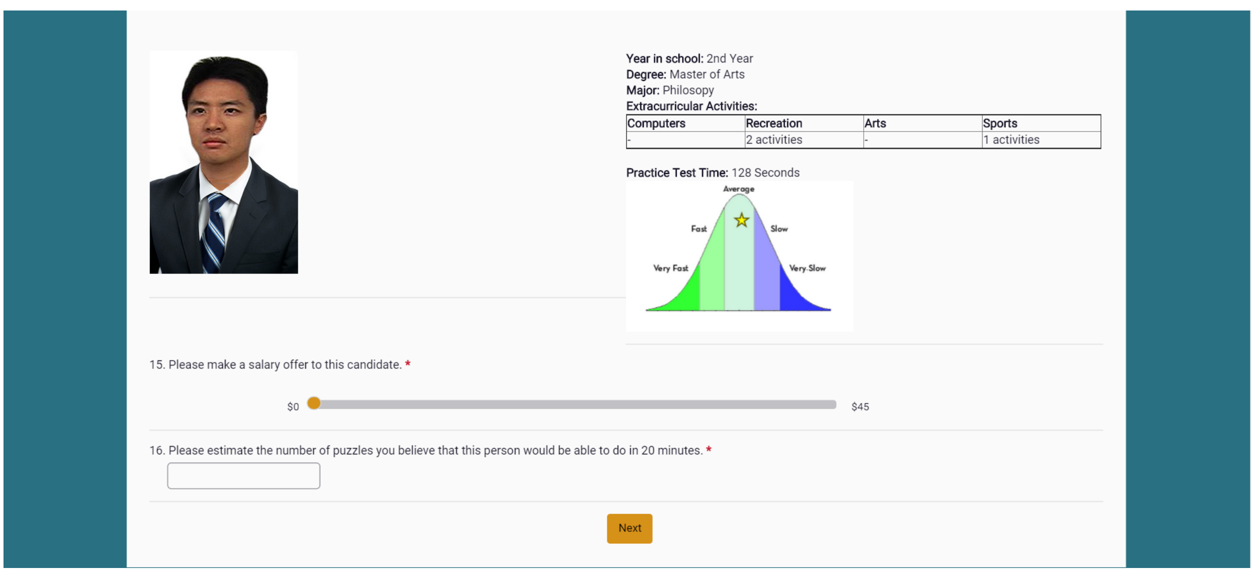


Figure 32: Cint: Application 12 (Branch page)



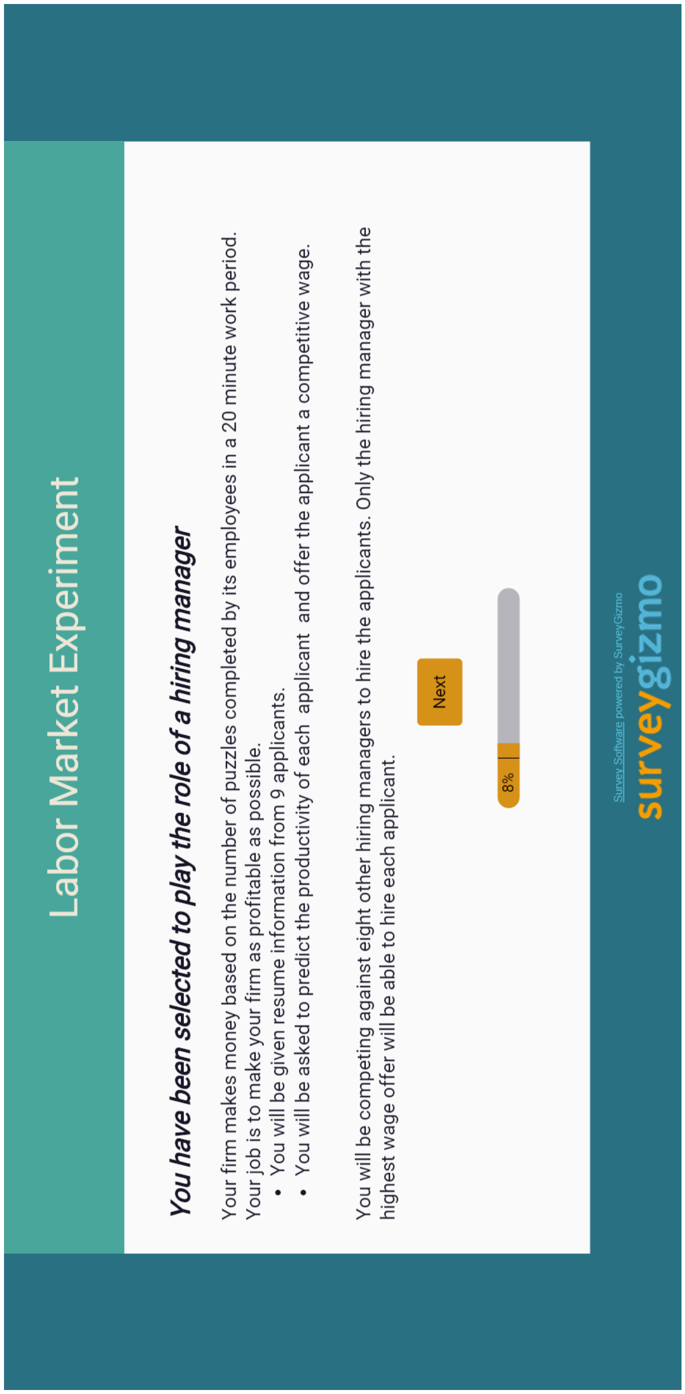


Figure 33: Mechanical Turk survey: Page 1

Appendix H: Mechanical Turk Resume Information(Applications)

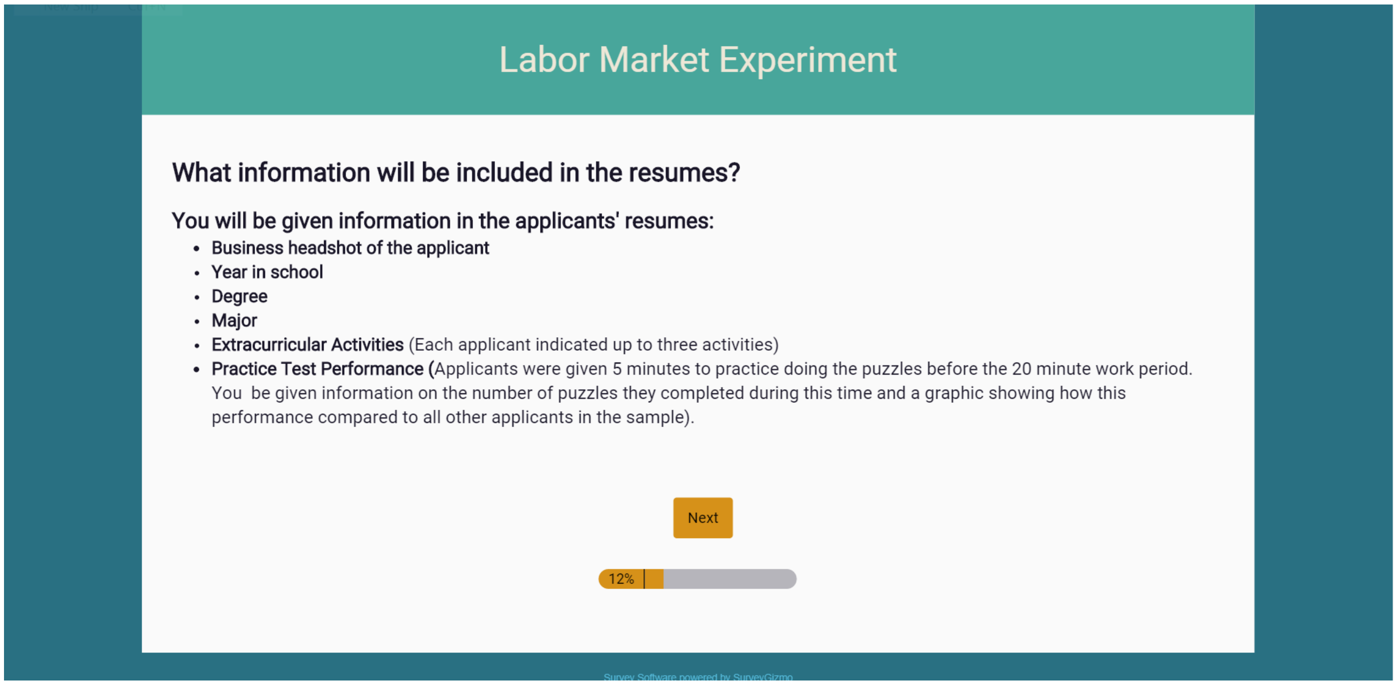
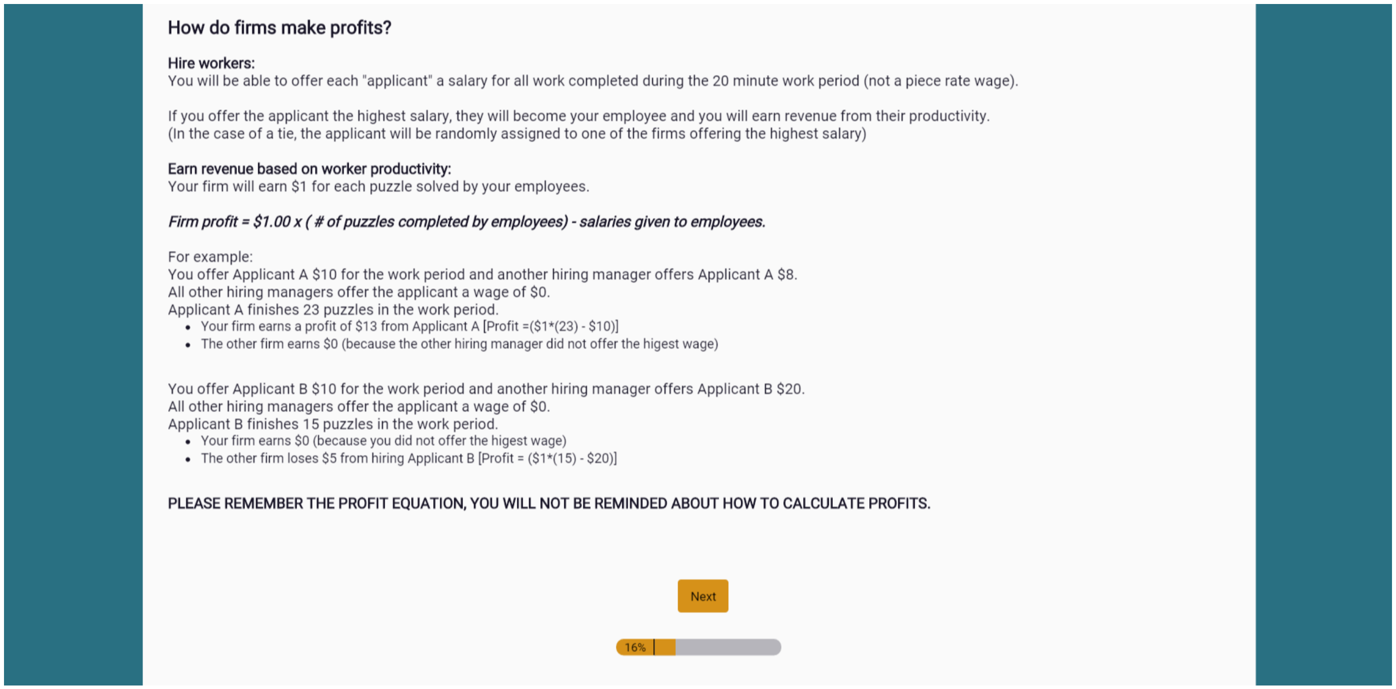


Figure 34: Mechanical Turk survey: Page 2



How do firms make profits?

Hire workers:
You will be able to offer each "applicant" a salary for all work completed during the 20 minute work period (not a piece rate wage).

If you offer the applicant the highest salary, they will become your employee and you will earn revenue from their productivity.
(In the case of a tie, the applicant will be randomly assigned to one of the firms offering the highest salary)

Earn revenue based on worker productivity:
Your firm will earn $1 for each puzzle solved by your employees.

Firm profit = $1.00 x (# of puzzles completed by employees) - salaries given to employees.

For example:
You offer Applicant A $10 for the work period and another hiring manager offers Applicant A $8.
All other hiring managers offer the applicant a wage of $0.
Applicant A finishes 23 puzzles in the work period.

- Your firm earns a profit of $13 from Applicant A [Profit =($1*(23) - $10)]
- The other firm earns $0 (because the other hiring manager did not offer the higest wage)

You offer Applicant B $10 for the work period and another hiring manager offers Applicant B $20.
All other hiring managers offer the applicant a wage of $0.
Applicant B finishes 15 puzzles in the work period.

- Your firm earns $0 (because you did not offer the higest wage)
- The other firm loses $5 from hiring Applicant B [Profit = ($1*(15) - $20)]

PLEASE REMEMBER THE PROFIT EQUATION, YOU WILL NOT BE REMINDED ABOUT HOW TO CALCULATE PROFITS.

Figure 35: Mechanical Turk survey: Page 3

Figure 36: Mechanical Turk survey: Page 4 (Compensated survey only)

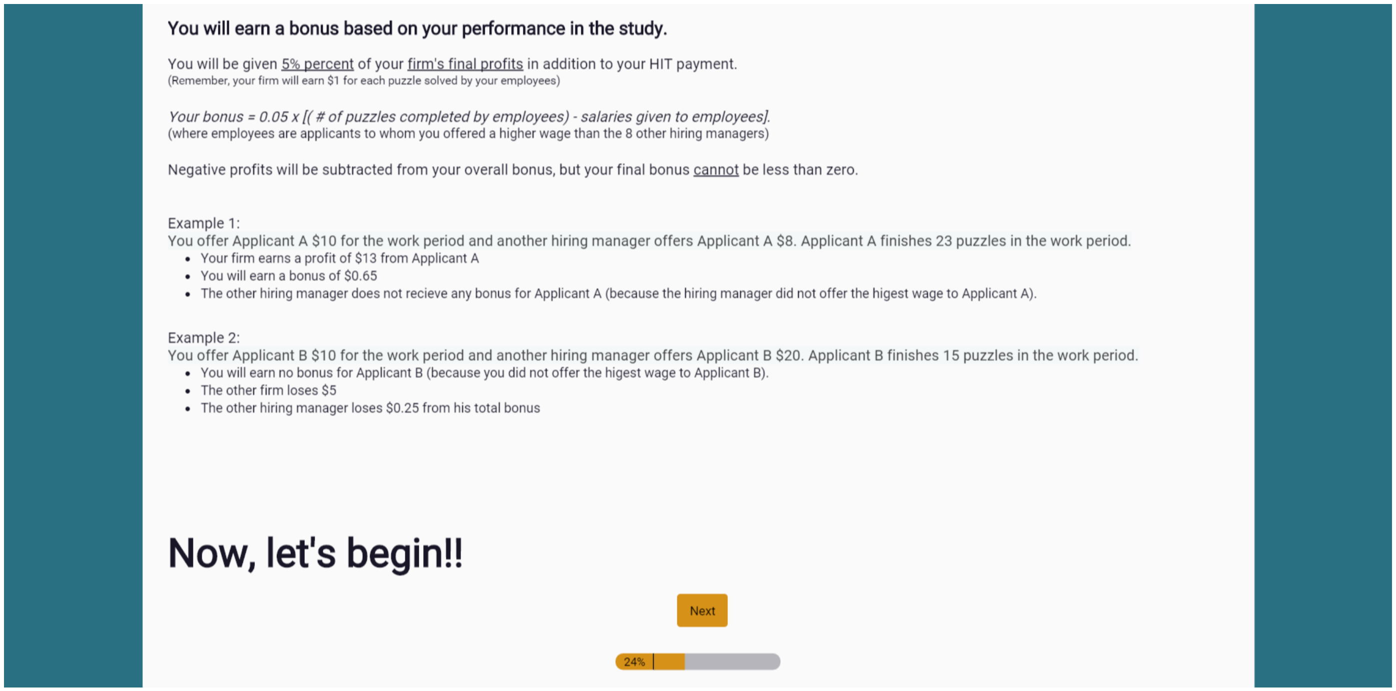


Figure 37: Mechanical Turk survey: Page 5 (Compensated survey only)

Figure 38: Mechanical Turk: Application 1

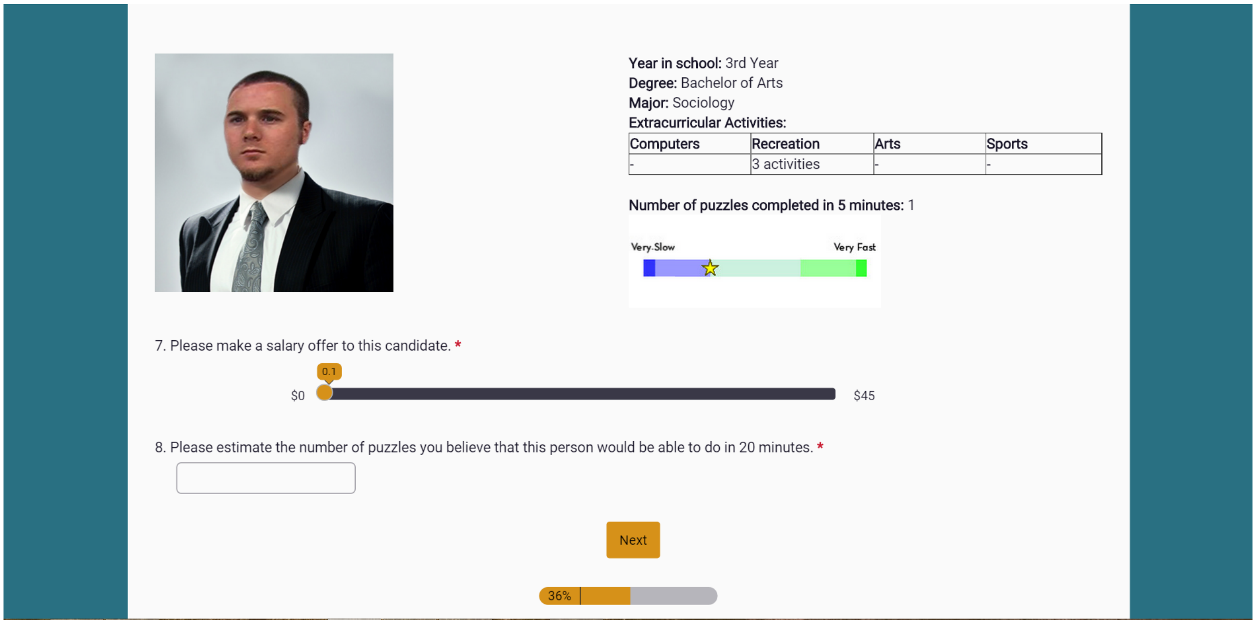


Figure 39: Mechanical Turk: Application 2

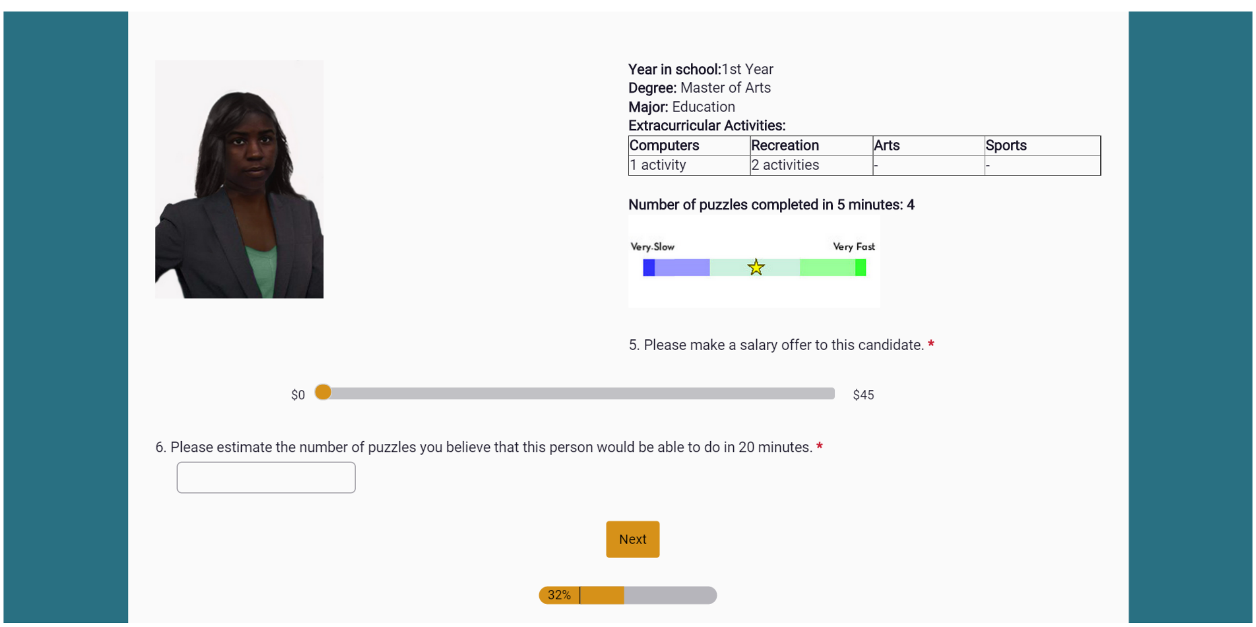


Figure 40: Mechanic Turk: Application 3

Figure 41: Mechanical Turk: Application 4

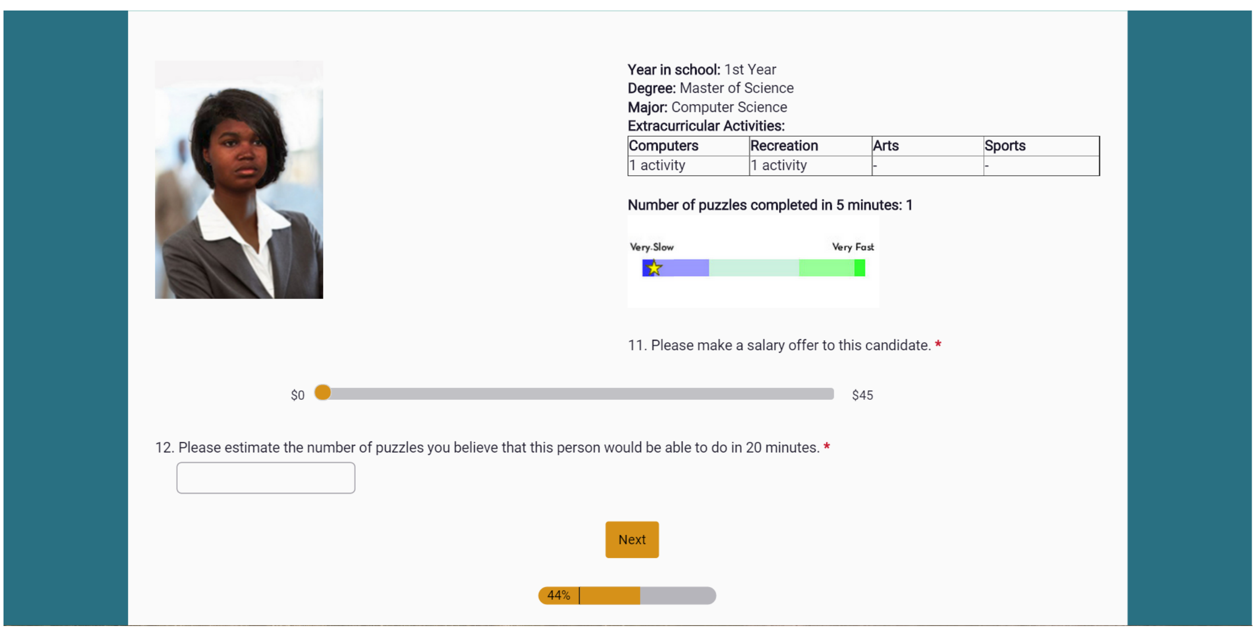


Figure 42: Mechanical Turk: Application 5

Figure 43: Mechanical Turk: Application 6

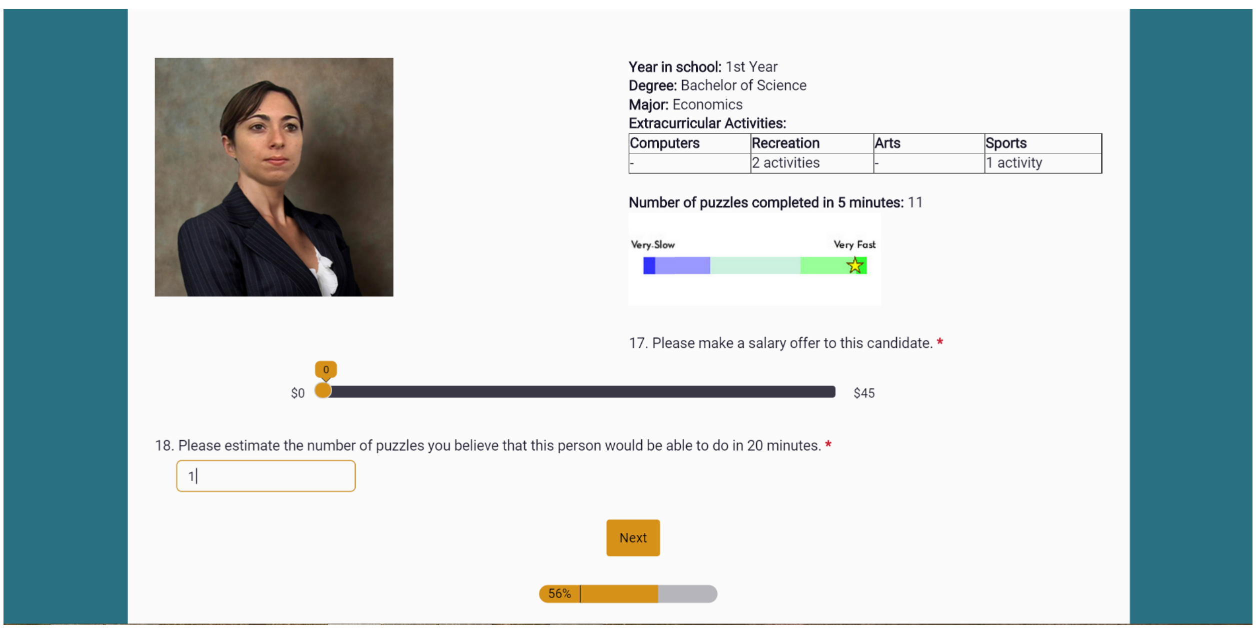


Figure 44: Mechanical Turk: Application 7

Figure 45: Mechanical Turk: Application 8

Figure 46: Mechanical Turk: Application 9

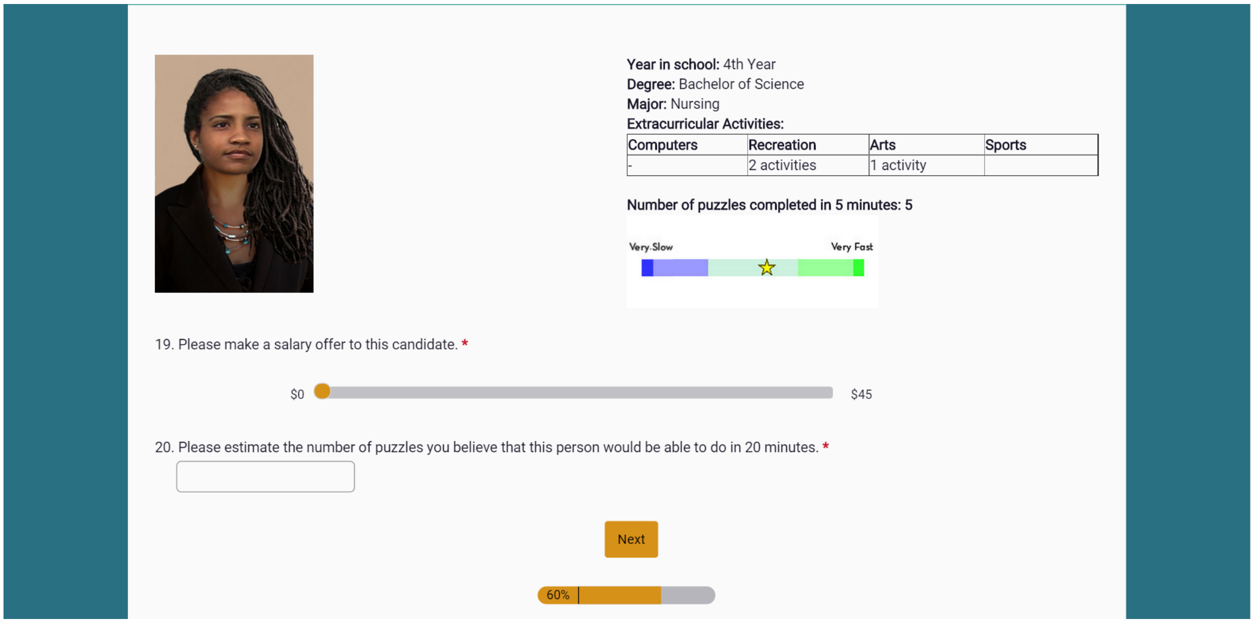


Figure 47: Mechanical Turk: Application 10 (Branch page)

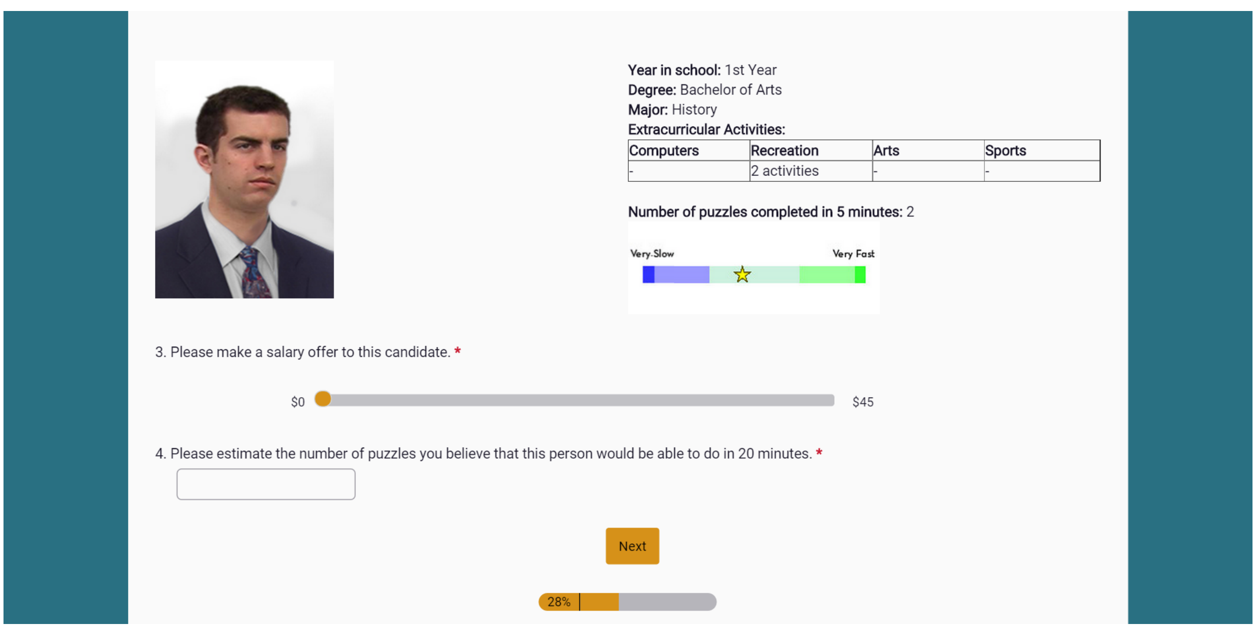
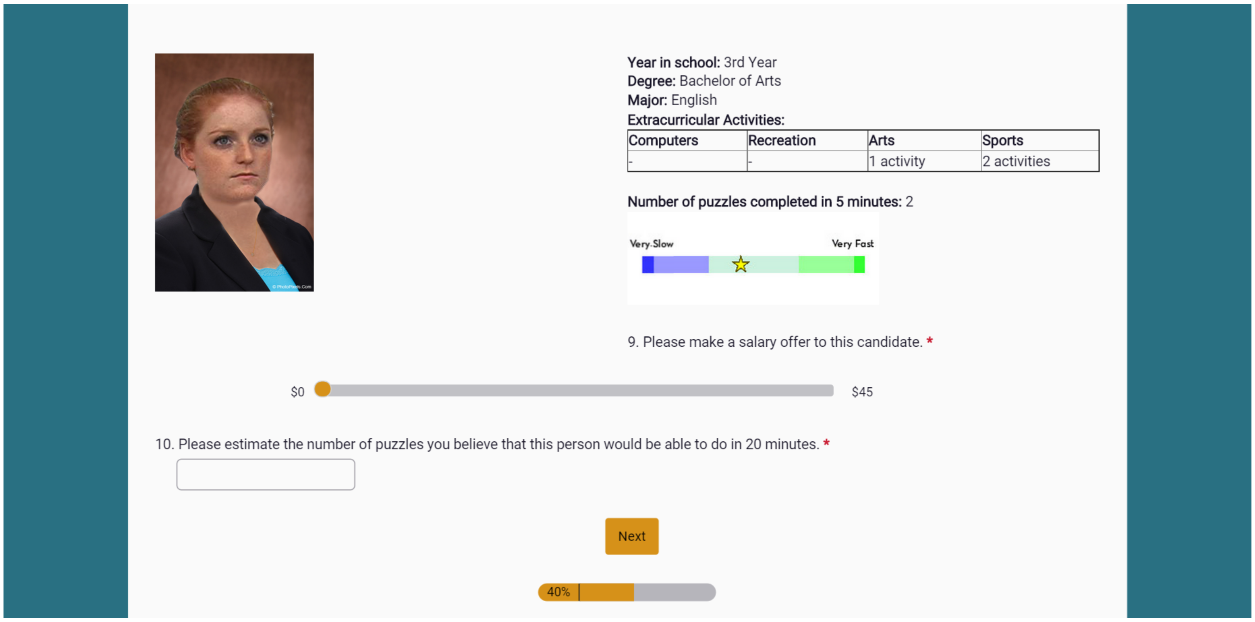


Figure 48: Mechanical Turk: Application 11 (Branch page)



Year in school: 3rd Year
Degree: Bachelor of Arts
Major: English
Extracurricular Activities:

Computers	Recreation	Arts	Sports
-	-	1 activity	2 activities

Number of puzzles completed in 5 minutes: 2

9. Please make a salary offer to this candidate. *

$0 $45

10. Please estimate the number of puzzles you believe that this person would be able to do in 20 minutes. *

Next

40%

Figure 49: Mechanical Turk: Application 12 (Branch page)

Year in school: 2nd Year
Degree: Master of Arts
Major: Philosopy
Extracurricular Activities:

Computers	Recreation	Arts	Sports
-	2 activities	-	1 activities

Number of puzzles completed in 5 minutes: 3

15. Please make a salary offer to this candidate. *

$0 $45

16. Please estimate the number of puzzles you believe that this person would be able to do in 20 minutes. *

Next

52%