Research Article

Valuing College Graduate Attributes and Skills: Employer Willingness to Pay as Elicited through Design Valuation

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Abstract

Design valuation (DV) is a new valuation method adapted from the Build-Your-Own (BYO) method used within the marketing literature. Within design valuation, subjects design their optimal good by selecting various attributes at select prices. Through a DV survey of college graduate employers, interval-censored willingness-to-pay (WTP) data are collected for 10 college graduate attributes. Both tangible and intangible attributes are evaluated. Average WTP estimates for the college graduate attributes are estimated relative to the type of college (agricultural, business, engineering, or other) from which the employer prefers to hire recent graduates. A high degree of character, ability to work well with others, and excellent communication skills are among the most highly valued attributes. In general, we find that intangible attributes such as these are valued higher than tangible attributes, which require relatively less subjectivity to determine. This finding points to the importance of the job interview, which is often the best tool employers have to evaluate whether candidates possess these intangible attributes. Analysis of the DV survey results will help academic advisors prepare students for the job market and students to better align their own goals with development of specific skills and attributes to increase their marketability and return on education investment on entering the job market.

1 Introduction

The total value of a good is often assumed to be the sum of the values of its components. Following this logic, we could similarly describe the value of a recent college graduate as a sum of the individual values of the attributes the graduate possesses. As employers seek to hire recent graduates, they may value some attributes more than others. Additionally, the values employers place on these attributes are likely heterogeneous and could differ significantly based on individual employer characteristics.

A significant amount of research has evaluated the relative importance of various college graduate attributes and skills in the context of employability. Suleman (2016) demonstrated that, although research points to the need for relational skills, namely interpersonal, communication, and teamwork abilities, there exists little consensus on which skills best foster employability. Using a web-based choice experiment, Noel and Qenani (2013) surveyed California-area agribusiness employers and found that skills such as creativity and critical thinking were becoming quite important in the labor market.

In addition to studies measuring the relative importance of graduate attributes, numerous studies have estimated the value of these attributes using various techniques (Barkley 1992; Barkley et al. 1999; Norwood and Henneberry 2006). Barkley (1992) and Barkley et al. (1999) regressed survey data of the salary of recent graduates on individual attributes to estimate the value of specific attributes. Norwood and Henneberry (2006) used a choice experiment to value recent graduate attributes by presenting respondents with job candidates who had differing attributes and salaries. The purpose of this study was to present a new method of stated preference elicitation called design valuation (DV) as well as to estimate the value employers place on various college graduate attributes. We add to this literature on graduate attribute values by further classifying these values by employer type. Our analysis uses four types of employers categorized based on preference for hiring graduates from an agricultural, business, engineering, or other college. We compare the value estimates for specific attributes across employer types.

2. Design Valuation

Numerous economic studies have developed, tested, and refined tools for measuring stated preferences through surveys (see Lusk and Hudson 2004 for an overview). The literature tends to use two methods: conjoint analysis and contingent valuation (CV). The goods evaluated with these survey instruments are defined as a collection of attributes. For example, a lake may be described by water clarity, frequency of algae blooms, and boat ramp access; and steaks may be described by their tenderness, marbling, and days of carcass aging. Harris and Briggeman (2019) used conjoint analysis to estimate willingness to accept changes in salary for preferred job attributes in the grain merchandising industry. Their analysis demonstrates how conjoint analysis can be particularly useful when parties to a transaction have incomplete information about one another.

In using these stated preference methods, the researcher designs various goods by assigning each good a unique collection of attributes. Subjects are then asked to make selections on the basis of preferences for the goods. Researchers then try to infer a consumer's preference for each attribute level based on his or her stated choices for selected versions of the product. For this reason, conjoint analysis is referred to as a decomposition approach; researchers must infer (decompose) preferences of individual attribute levels from choices made based on selected versions of the product as a whole. Subjects are involved in the research in a post-design stage, after the good has been designed. Post–design valuation is often touted because it mimics many real decisions, such as which brand of flour to purchase or whether to approve a referendum providing a public good.

However, consumers often face real decisions in the pre-design phase, decisions which can be mimicked using the DV process. Households purchasing a new home will often design it themselves by selecting the attributes they prefer; such as ceiling height, number of bathrooms, and number of stories. The chosen attributes are determined by both preferences and attribute prices.

Consider an alternative example, a computer upgrade. Assume a marketing researcher is interested in the values a consumer places on different computer components or upgrades (e.g., larger monitor, more powerful processor). A conjoint approach would present the consumer with upgrades above the baseline computer at varying prices. The upgrade is a collection of attributes with unique prices for each attribute collection. If the attribute list is long and the number of alternatives to peruse is large, the cognitive burden on the consumer could be significant. Imagine having to keep track of 5 upgrades, each described by a unique combination of 15 attributes.

An alternative to a decompositional conjoint analysis approach is a compositional approach. In a compositional approach, researchers directly ask individual participants about their preferences for each attribute (or level of attribute or both), and their preferences for a given product are then obtained by combining their preferences for the product's included attribute levels. One of the most well-known compositional approaches is the self-explicated approach. There are many variations of this method (see Green and Srinivasan 1990) but in general, participants are first asked to state their desire for various levels of a given attribute. Then, the participants are asked to allocate a constant sum (i.e., 100 points) across all attributes in which their allocations correspond to the importance of each attribute (Park et al. 2008). Within marketing, this approach is desirable because it is easy to implement and allows decision makers to evaluate a large set of attributes that may vary across many levels. However, this approach is not without its limitations, not the least of which is that it is not similar to a real-world situation and can be unfamiliar to respondents (Park et al. 2008). To help overcome some of the perceived weaknesses of the self-explicated approach, Park et al. (2008) introduced the upgrading method. They describe its steps as follows:

> *(1) A participant accesses the Web-based upgrading study through a Web browser (e.g., Internet Explorer); (2) the participant is endowed with a bare-bones configuration of the product; (3) the participant is shown all attributes that are available for upgrading (he or she can upgrade only once for each attribute) and is asked to select the attribute to upgrade next; (4) the participant is shown all levels in that attribute and is asked to state his or her willingness to pay (WTP) to upgrade from the current level to each of the desired levels for that attribute; (5) the computer randomly generates a cutoff price for each level and determines whether a level is upgradable (i.e., the stated WTP for this level is larger than or equal to the randomly drawn cutoff price for the same level); (6) the participant's product remains the same if no level is upgradable; otherwise, it will be upgraded to one of the upgradable levels (randomly chosen by the computer), but the participant pays only the randomly chosen cutoff price for the upgraded level; and (7) Steps 3-6 are repeated until the participant has upgraded all attributes of interest or until he or she decides not to upgrade any remaining attributes* (Park et al. 2008, 563).

When comparing the preference structures uncovered by the upgrading method and the self-explicated method, the researchers found the external validity of the upgrading method to be superior to that of the self-explicated method. They attributed much of the improvement to the added realism of the upgrading method. The authors noted that the upgrading method mirrors the real task that people engage in when they choose a product in the marketplace (Park et al. 2008).

Using the upgrading method, participants enter the maximum amount they would be willing to pay for each level of an attribute. However, in reality, consumers are not asked the price they would be willing to pay but rather are shown prices for the upgrades and must determine whether they are willing to pay them. Therefore, additional realism could be achieved if participants could evaluate the individual levels separately (decompositional approach) at stated prices. This is the idea behind what has become known as the build-your-own (BYO) method and is also the fundamental idea behind the DV method used in this study. BYO and DV methodology operates by defining a general good as a collection of attributes and assigning prices to those attributes. Respondents are then asked to design their optimal good based on those attribute prices (much like customers design their optimal personal computer). By varying the attribute prices across surveys, the value of each attribute can be inferred.

There are many variations of the BYO method (see Ben-Akiva and Gershenfeld 1998; Liechty et al. 2001; Dahan and Hauser 2002) but in general, the price of attribute levels does not vary within a survey. Even across surveys, the price variation typically used is similar to conjoint analysis in which the researcher predetermines price levels, and prices can only vary at those levels. The DV method used in this study builds on the ideas of the BYO method and is similarly constructed but allows prices of attribute levels both within and across surveys to update dynamically. The dynamics of the survey are described in more detail in the "Data" section.

In a sense, design valuation is similar to asking multiple CV questions. Returning to the computer example, the marketing researcher could ask the customer if she would purchase each individual upgrade at the stated price, which is analogous to one CV question per upgrade component. Each purchase would be in addition to the baseline computer at a base cost. But provided in a mail or phone survey, multiple CV questions might be too difficult for the customer to process. The customer might not be able to easily track the total price of her computer or her previously purchased upgrade and its price, and she might be unable to change her selections. Our proposed DV survey alleviates this problem with a built-in calculator that presents the individual with a relatively direct and concise question.

Design valuation has no obvious statistical advantages over post–design methods. If humans were perfectly rational, had well-defined preferences, did not suffer from survey fatigue, and had perfect memory, both design and post–design methods would elicit identical preferences. However, design valuation is preferred over traditional post–DV methods in this paper because it can extract much information from a simple question.

To achieve its purpose, our study called for creation of an internet-based DV survey of employers of college graduates that evaluate attributes resembling those in Norwood and Henneberry (2006), Boland and Akridge (2004), Berle (2007), and Litzenberg and Schneider (1987). In total, we evaluate 10 attributes. We divide the attributes into two groups of five—Attribute Set A and Attribute Set B—and evaluate each set separately using DV survey questions. Attribute Set A includes internship or work experience (as opposed to none), at least one high-quality academic award (as opposed to none), ability to speak and write in Spanish and other languages (as opposed to no such ability), at least one high leadership position in an academic organization (as opposed to none), and outstanding letters of recommendation (as opposed to mediocre letters). Attribute Set B includes high number-crunching ability (as opposed to low number-crunching ability), high degree of character (as opposed to difficult-to-perceive character), ability to work well with others (as opposed to uncertain ability to work well with others), excellent oral and written communication skills (as opposed to communication skills that need improvement), and excellent problem-solving abilities (as opposed to difficult-to-perceive problem-solving abilities).[1]

Norwood and Henneberry (2006) employed a choice-based conjoint survey or a post–design survey to estimate employer's willingness to pay for college graduate attributes. Therefore, their results can be compared with the results from our DV method. Our DV format provides interval-censored willingness-to-pay data (an interval known to contain the individual's true value) for attribute values. Using interval regression on the collected interval-censored data, we estimate the value that employers place on specific attributes.

3. Theory

Any good can be thought of as a collection of attributes and the goods' value a function of the individual attribute values (Rosen 1974). Let a hypothetical good be a set of attributes a_i where $i = 1, \dots, I$. An attribute a_i may be a dummy variable indicating the presence or absence of some trait (e.g., excellent communication skills), or it may be a continuous variable denoting the level of some attribute (e.g., grade point average). Only the binary variable case is considered here. Further, let the value of attribute a_i to an individual be denoted v_i, assumed independent of other attributes, and stated in money metric form. The value of good j is then measured by the function $\sum_{i=1}^{I} a_{i,j} v_i$, where a_{ij} refers to the presence or absence of attribute i in good j. If the price of the good j is P_j, the welfare surplus received from good j, defined U_j, is:

$$U_j = \sum_{i=1}^{I} a_{ij} v_i - P_j. \tag{1}$$

Assuming a consumer of good j is a welfare maximizer, the optimization problem the consumer faces is:

$$\max_{a_{ij}} U_j = \sum_{i=1}^{I} a_{ij} v_i - P_j. \tag{2}$$

Post–DV methods such as contingent valuation and conjoint analysis utilize questionnaires to determine whether U_1, the welfare surplus associated with selecting good one, is less than, equal to, or greater than U_2, the welfare surplus associated with selecting good two. Researchers observe only the sign of $U_1 - U_2$, and from this sign must infer the values of the v_i's. For example, suppose a respondent is asked to choose one of the following two goods: good 1 ($a_{11} = 1,\ a_{21} = 1, a_{31} = 1, a_{41} = 0, a_{51} = 0, P_1 = 1$) or good 2 ($a_{12} = 0,\ a_{22} = 0, a_{32} = 0, a_{42} = 0, a_{52} = 0, P_2 = 0$). This particular choice resembles a CV

[1] As an attribute, number-crunching ability is intended to help employers assess the quantitative/mathematical abilities of a potential job candidate.

question in which the respondent is asked if she would like a public good provided that it increases taxes by 1. If good 1 is chosen, all the researcher knows is that $v_1 + v_2 + v_3 \geq 1$.

Now consider a DV question in which the individual is given the baseline good or good 1 $(a_1 = 0,\ a_2 = 0, a_3 = 0, a_4 = 0, a_5 = 0, P = 0)$ and is allowed to purchase any attribute a_i at a price of 0.4. Suppose attributes a_1 and a_2 are purchased, revealing to the researcher that $v_1 > 0.4$, $v_2 > 0.4$ and that v_3, v_4, and $v_5 < 0.4$. Clearly more information is obtained from the DV question, which does not imply that demand valuation is necessarily superior to post–design methods. The same information could be obtained through five CV questions, one comparing $(a_{11} = 1,\ a_{21} = 0, a_{31} = 0, a_{41} = 0, a_{51} = 0, P_1 = 0.4)$ to $(a_{12} = 0,\ a_{22} = 0, a_{32} = 0, a_{42} = 0, a_{52} = 0, P_2 = 0)$, another comparing $(a_{11} = 0,\ a_{21} = 1, a_{31} = 0, a_{41} = 0, a_{51} = 0, P_1 = 0.4)$ to $(a_{12} = 0,\ a_{22} = 0, a_{32} = 0, a_{42} = 0, a_{52} = 0, P_2 = 0)$, and so on. In fact, demand valuation can be thought of as a series of CV questions, one posed for each attribute and the respondent makes their decision for each attribute jointly in the same general question.

The statistical information gleaned from a DV question will then be equivalent to a number of CV questions. The advantage of design valuation is that it contains those CV questions in one compact question, easily answered in internet browsers. The DV format will also be familiar to consumers who, through manufacturers, design their own products, whether cars, computers, or homes. Subjects should be able to perform the DV task with little instruction, ensuring high response rates and greater information.

4. Data

In fall 2006, employers of Oklahoma State University graduates were asked to participate in an internet survey eliciting their preferences for new hires. The invitations were mailed to 4,401 employers, yielding 507 responses, for a response rate of 12 percent. This rate is similar to the response rate of employers surveyed by Norwood and Henneberry (2006). Unlike the Norwood and Henneberry study, we did not restrict the list of employers only to those who are known to hire agricultural graduates; the list included employers of all undergraduate degrees, yielding WTP estimates for those hiring graduates from agricultural and non-agricultural colleges, which may provide insightful information as comparisons are made.

Figure 1 illustrates one of this study's DV questions evaluating Attribute Set "B". Employers of college graduates are presented with a baseline graduate requiring a $25,000 salary and possessing low levels of five attributes. The employer is allowed to purchase any of the five attributes at different prices. The cognitive burden of this question is relatively low, especially considering it is the equivalent of five CV questions.

Internet surveys are the ideal platform for hosting DV questions because automatic calculators can be easily installed in the survey software. Within our survey, respondents could click on a "Recalculate Salary" button at any point while responding to a DV question to see an updated salary based on the attributes they had selected (see Figure 1).

CV questions often have a similar follow-up question, in which the price of the good purchased (or not purchased) in the first question rises (or falls) in the second question. This sequence is referred to as dynamic updating. The questions are dynamic in the sense that one question depends on the answer to a previous question. Following the previous example, because good 1 $(a_{11} = 1,\ a_{21} = 1, a_{31} = 1, a_{41} = 0, a_{51} = 0, P_1 = 1)$ is preferred to good 2 $(a_{12} = 0,\ a_{22} = 0, a_{32} = 0, a_{42} = 0, a_{52} = 0, P_2 = 0)$, the respondent can be asked to make the same choice wherein P_1 is increased to 2. Because the value of multiple attributes is of concern, researchers would rarely repeat the same combination of attributes as in this example. Additionally, attempting to dynamically update CV questions addressing each attribute in this context would result in a survey far too lengthy.

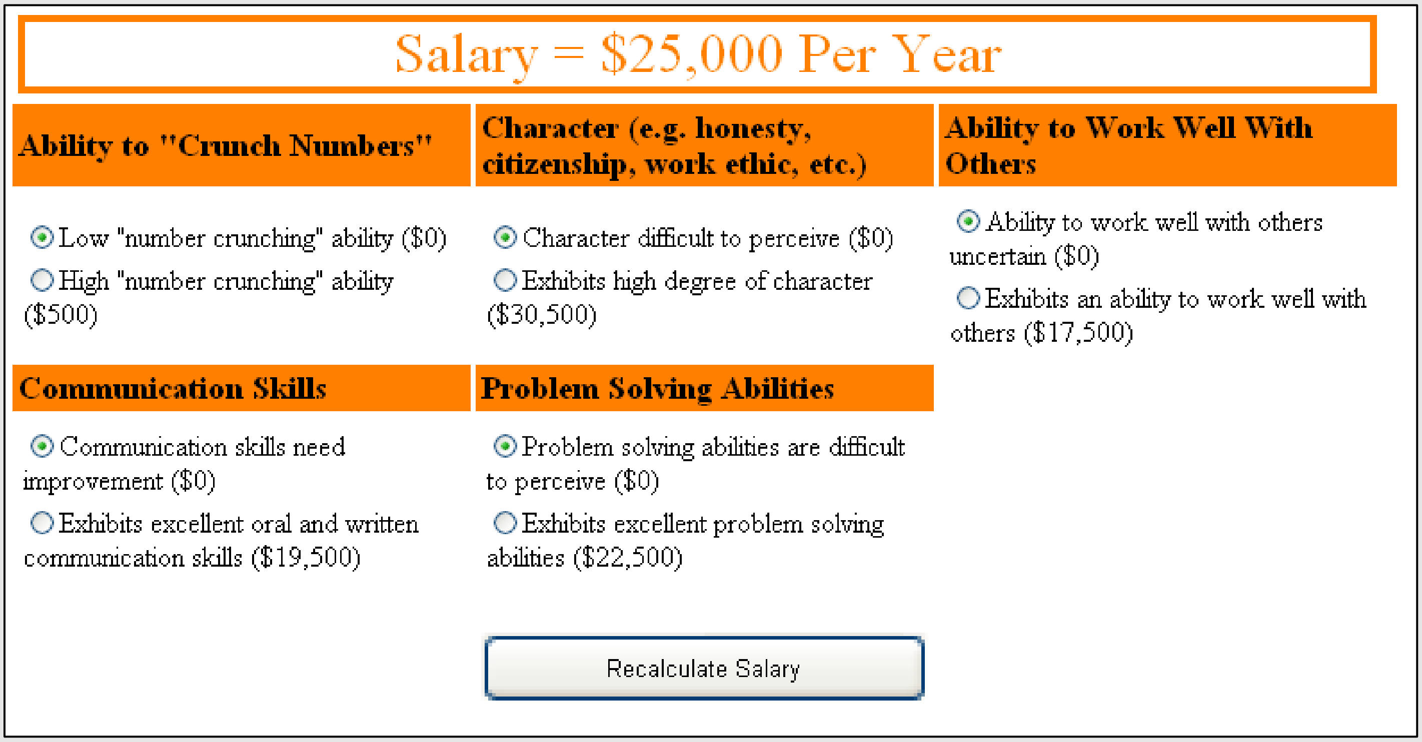

Figure 1. Design Valuation Question

Dynamic updating is straightforward in design valuation. Refer again to Figure 1. Suppose that the respondent chooses to purchase high number-crunching ability at $500 and ability to work well with others at $17,500, but none of the other attributes. A follow-up question would then increase the price of number-crunching ability and ability to work well with others while lowering the price of the remaining attributes. Such dynamic updating is employed in the survey, producing data on attribute values that are interval censored. For example, if the respondent purchased number-crunching skills for $500 in the first question but declined to purchase it in the second question when the cost rose to $5,000, the interval-censored observation would be ($500, $5,000). The true value of this attribute for the employer is known to reside within this interval. If the attribute is purchased at both prices, the interval would be $5,000, and an upper bound. If an attribute is purchased at neither price, assuming attribute values are non-negative, the interval would be zero, and the lowest price offered of $500.

The first page of the survey informed respondents that the purpose of the survey was to seek input on what kind of college graduate they prefer to hire, and it asked them to answer questions in a manner that best reflected their actual hiring practices. On the second page, a simple practice question was presented to help prepare respondents for the more complex DV questions later in the survey. Before the employer was asked to answer questions similar to the one in Figure 1, an information script was provided. This script on page 3 provided information on the DV questions and how to answer them. For example, respondents were told to assume that the graduate holds a degree from a four-year educational institution and possesses any unlisted attribute at an “average” level. If they would hire no college graduate at the $25,000 salary level, respondents were instructed to leave the questions unanswered. Because it is impossible to distinguish these respondents from respondents who simply did not wish to answer the questions, all nonresponses were excluded from the data analysis.

The fourth page of the survey contained the first DV question for Attribute Set A. Employers were first presented with a low-quality graduate earning a $25,000 salary with none of the attributes in Set A. They were then allowed to purchase each attribute at a particular price.

Some employers have direct control over the salary they offer. Others, such as government agencies, have a set salary they must pay, and they hire the most qualified applicant they can obtain at this salary. These employers will select the attributes they deem both most important and affordable, up to the preset salary they can offer. These employers resemble a consumer who can spend no more than $1,000 on a computer upgrade and who purchases valued and affordable upgrades until the $1,000 limit is exceeded by any additional upgrade.

After making their attribute selections, respondents were presented with a question (page 5) in which only the attribute prices differed. If an attribute was purchased in the previous question, its price was increased by a randomly selected percentage on the 1–100 percent interval. Otherwise, its price was decreased by the same random percentage. The purchase decision for any one attribute on the two DV questions provides an interval known to contain the employers' true WTP value.

The survey introduced a second dynamic element: On the basis of respondents' willingness to purchase a given attribute in prior surveys, the initial price of that attribute was increased or decreased for each successive respondent. For example, if more than 50 percent of respondents purchased internship experience, its initial price would increase on subsequent surveys. The initial price would increase across surveys until less than 50 percent purchased it, at which point the initial price would begin to decline. While the survey was administered, the initial price would drift up and down such that on average 50 percent purchased the attribute, increasing the statistical efficiency of the survey design. The degree to which attribute values increased or decreased varied across attributes. Attributes whose values were hypothesized to be lower increased or decreased in $200 increments; others rose or fell in increments of $500. Hypotheses of attribute values were based mainly on the Norwood and Henneberry (2006) study.

Pages 7 and 8 of the survey presented two similar DV questions designed to elicit the value for Attribute Set B, shown in Figure 1. The remaining questions concerned employer information, such as the type, size, and preference for employers' college degree. In addition, respondents were asked if they had influence over hiring decisions. If they did not, their responses were not included in the analysis. Excluding these respondents and those who purchased no attributes reduced the sample size from 507 to 453.

Summary statistics on the survey respondents are provided in Table 1. Most employers identified themselves as a government organization, a manufacturer, or other. Almost half are large employers with more than 500 full-time employees.

Respondents were presented with a list of degrees and were asked to select their one preferred degree: accounting; business; communications; finance; economics; management; marketing; agricultural engineering; agricultural communications; agricultural economics / agribusiness; agronomy; animal science; food science; horticulture; civil, electrical, mechanical or chemical engineering; industrial engineering; other. From these preferred degrees, we then grouped employers into four categories according to the type of college (agricultural, business, engineering, or other) from which they prefer to hire graduates.

5. Model

Responses to the DV questions were used to construct interval-censored willingness-to-pay (ICWTP) data for each attribute and employer. For example, employer *i's* value for a particular attribute j is given by the interval (L_{ji}, U_{ji}), where L_{ji} and U_{ji} are the attribute value's lower and upper bounds, respectively. Recall that each employer was given the opportunity to purchase each attribute at two prices. For employers that purchased an attribute at one price but not another, the values of L_{ji} and U_{ji} are taken directly from those two prices. For employers that declined the purchase at both prices, it is assumed that $L_{ji} = 0$ and U_{ji} equals the lowest of those two prices. Finally, for those who purchased the attribute at both prices, L_{ji} equals the larger of the two prices, and U_{ji} is set equal to the largest value of L_{ji} for other employers. Thus, we would expect that V_{ji}^*, the true value of attribute j in a recent college graduate when being hired by the ith

Table 1. Employer Demographics (Sample Size = 453)

Organization Type	Percent	Preferred Degree	Percent Preferred Degree	Number of Full-Time Employees	Percent
Government organization	15	Accounting	6	< 10	4
Manufacturer	20	Business Communications	4	10–49	16
Financial service provider	9	Finance	4	50–59	13
Consultant	10	Economics	0	100–500	22
Food processor	2	Management	8	> 500	45
Retailer	4	Marketing	6		
Wholesaler	3	Ag Engineering	2		
Farm or livestock producer	2	Ag Communications	1		
Farm input supplier	3	Ag Economics / Ag Business	8		
Other	32	Agronomy	3		
		Animal Science	4		
		Food Science	1		
		Horticulture	1		
		Civil, Electrical, Mechanical, or Chemical Engineering	22		
		Industrial Engineering	3		
		Other	24		

Notes: Numbers may not sum to one due to rounding.

employer, resides within the constructed interval $[L_{ji}, U_{ji}]$ but is unobservable or latent. To estimate this latent value for each attribute, we could simply use the midpoint of each interval. However, as noted by Stewart (1983), this method would generally result in inconsistent estimates. Stewart (1983) outlined approaches to yield maximum likelihood estimates under the assumption of normality. STATA's "intreg" command facilitates the estimation of the maximum likelihood function for interval regression estimation. The interval regression estimates the probability that a latent variable exceeds one threshold but is less than another threshold; it estimates the probability of the latent variable within a certain interval (Cawley 2008; Corso et al. 2013). The interval regression model fit by intreg is a generalization of a tobit model because it extends censoring beyond fixed left-censored data or fixed right-censored data to allow for interval-censored data (StataCorp, 2019). Although V_{ji}^{*} was not directly observed for respondent i, it is known to lie in the interval $[L_{ji}, U_{ji}]$, and the corresponding likelihood contribution is:

$$\Pr\left(L_{ji} \leq V_{ji}^{*} \leq U_{ji}\right) = \Pr\left(L_{ji} \leq X_{ji}\beta + \varepsilon_{ji} \leq U_{ji}\right). \tag{3}$$

When an upper bound is unknown (right-censored data) the likelihood contribution is:

$$\Pr\left(L_{ji} \leq X_{ji}\beta + \varepsilon_{ji}\right). \tag{4}$$

When a lower bound is unknown (left-censored data), we set a lower bound of zero, and the likelihood contribution is:

$$\Pr\left(0 \le X_{ji}\beta + \varepsilon_{ji} \le U_{ji}\right). \quad (5)$$

Thus, the data generating process for this study is:

$$V_{ji}^{*} = \beta_{0j} + \beta_{1j}Buscollege_i + \beta_{2j}Engcollege_i + \beta_{3j}Othercollege_i + \varepsilon_{ji} \quad (6)$$

where V_{ji}^{*}, is the true (latent) average value of attribute j in a recent college graduate when being hired by the ith employer; $Buscollege_i$ is a dummy variable equal to 1 when the ith employer most often prefers to hire graduates from a business college and equal to 0 otherwise; $Engcollege_i$ is a dummy variable equal to 1 when the ith employer most often prefers to hire graduates from an engineering college and equal to 0 otherwise; $Othercollege_i$ is a dummy variable equal to 1 when the ith employer most often prefers to hire graduates from a college other than an agriculture, business, or engineering college and equal to 0 otherwise; and $\varepsilon_{ji} \sim N(0, \sigma_{ji}^2)$. To avoid the dummy variable trap, no variable is included when the ith employer most often prefers to hire graduates from an agricultural college. Thus, the constant β_0 can be interpreted as the value for attribute j when the ith employer most often prefers to hire graduates from an agricultural college. The estimates for $\beta_{2j}, \beta_{3j,}$ and β_{4j} can be interpreted as the value premiums or discounts associated with attribute j when the ith employer most often prefers to hire graduates from a business college, engineering college, or other type of college respectively.[2]

6. Results

The mean value of each college graduate attribute was estimated using MLE as outlined in equation (6). Each attribute's value estimates and their estimated standard errors for employers that most often prefer to hire graduates from agricultural colleges are summarized in Table 2. The table also contains the attribute value premiums or discounts estimated for employers that typically prefer to hire from non-agricultural colleges.

Consider the types of attributes valued. Attribute Set A (internship experience, at least one high-quality award, foreign language, held leadership position, and recommendation) includes attributes that are tangible in the sense that they are easily verifiable and measurable. Attribute Set B (number-crunching ability, high degree of character, works well with others, excellent communication, and problem-solving ability) includes attributes that are intangible in the sense that they are unmeasurable and require the employer's subjective judgment to evaluate. On average, the intangible attributes have a much higher value to employers than the tangible attributes. The larger mean values as well as greater variability within the intangible attributes is not unexpected. Velasco (2012) demonstrated that intangible attributes (soft skills) are the most desired attributes in the hiring process. Additionally, we expect that employers will have varying interpretations of intangible attributes and hence those attributes will be subject to greater heterogeneity than more tangible attributes, which require much less subjectivity. As shown by Briggeman et al. (2007), the assessment of these intangible attributes is most critically accomplished through a personal interview by the potential employer.

According to our survey analysis, possession of an academic award is the attribute with the lowest value ($381). Ability to work well with others is the attribute with the highest value ($17,920), followed closely by high degree of character and excellent communication ($17,366 and $17,464, respectively).

Statistical differences between estimates for employers that prefer to hire from agricultural colleges and for employers that prefer to hire from business, engineering, and other colleges have been noted in Table 2. For many of the attributes, there are no statistical differences (at 0.05 significance level). This finding indicates that we have insufficient evidence to suggest that the value estimated for employers that

[2] Equation 6 assumes independence among attributes. We could modify equation 6 to relax the independence assumption and allow for correlation among attributes to be estimated, as shown in the appendix.

Table 2. Value for Recent College Graduate Attributes with Respect to the Type of College from Which the Employer Prefers to Hire

Attribute	Value If Employers Prefer to Hire from Agricultural Colleges	Change in Value If Employers Prefer to Hire from		
		Business Colleges	Engineering Colleges	Other Colleges
Internship experience	$15,681 (1,741)	$2,233 (2,158)	$5,383* (2,251)	-$689 (2,241)
At least one high-quality award	$381 (66)	-$100 (82)	$49 (86)	$77 (87)
Foreign language	$1,376 (212)	-$191 (260)	-$279 (268)	-$379 (272)
Held leadership position	$2,890 (288)	-$467 (356)	-$376 (371)	-$1,161* (369)
Recommendation	$2,392 (294)	-$406 (360)	$40 (379)	-$36 (381)
Number-crunching ability	$2,473 (302)	-$491 (369)	-$262 (390)	-$1,118* (383)
High degree of character	$17,366 (2,319)	$4,542 (2,874)	$6,917* (2,991)	$6,372* (3,022)
Works well with others	$17,920 (1,854)	-$1,767 (2,295)	$1,986 (2,405)	-$161 (2,417)
Excellent communication	$17,464 (2,329)	$4,033 (2,878)	$8,745* (3,026)	$4,513 (3,021)
Problem-solving ability	$14,638 (2,274)	$6,527* (2,817)	$11,733* (2,953)	$8,551* (2,970)

Notes: Numbers reported in parenthesis are standard errors.
* indicates estimates that are significantly different at the 0.05 level from value if employers prefer to hire from agricultural colleges

prefer to hire from agricultural colleges (the omitted category) would be different than the value estimated for employers that prefer to hire from the other types of colleges.

With regard to the tangible attributes, the only statistical differences we see are for internship experience and held leadership position. On the basis of our estimates, we expect employers that prefer to hire from engineering colleges to place a higher value ($5,383 premium) on internship experience than employers that prefer to hire from agricultural colleges. Accordingly, the total expected value for internship experience would be $21,064 for employers that prefer to hire from engineering colleges. This value indicates relevant past experience would be expected to garner a larger premium within engineering careers. In the case of the leadership position attribute, however, we would expect a discount of $1,161 for employers that prefer to hire from other (nonagricultural) colleges compared with employers that prefer to hire from agricultural colleges.

With regard to the intangible attributes, we see a greater variability in attribute value among types of employers. Significant differences are found within all but one attribute: works well with others. The attribute with the greatest value heterogeneity is problem-solving ability. For employers that prefer to hire graduates of agricultural colleges, the estimated value of this attribute is \$14,638—significantly less than the estimated value for the other three employer types.

The average value of foreign language skills is \$1,376, but this value is not the best rate-of-return estimate for students acquiring this skill. The average value refers to the value of that attribute for both employers that do and employers that do not need employees fluent in Spanish and other languages. We assume that graduates with foreign language skills will be more likely to interview at jobs stressing multiple language skills, and we assume those jobs would be with employers that place comparatively high value on these skills. For students considering learning Spanish, a rate-of-return higher than the average would be expected. The same argument can be made for number-crunching ability. Many jobs do not require employees to possess significant quantitative skills, thus the relatively low average value of \$2,473 for number-crunching ability. But graduates with this ability will likely interview with employers that place a greater-than-average value on this skill, and thus they could expect to receive a return higher than the average value.

To get a better idea of the distribution for attributes values, we use the Turnbull estimator, which is best described as a nonparametric maximum likelihood estimator (Turnbull 1974). Suppose that observation i contains a lower bound L_i and an upper bound U_i known to contain the true value willingness to pay WTP_i. The Turnbull estimator requires ordering of the L_i and U_i values (stacked in the same column) in ascending order and then identification of those intervals $(L_i\ , U_j)$ (where j can equal i but does not have to) for which no other lower or upper bound are captured. These so-called equivalence classes are the only intervals over which the likelihood can assign probability mass (Day 2007).

Suppose these equivalence classes are denoted $C_0 < C_1 < C_2 <, \ldots, < C_E$. The Turnbull estimator estimates the cumulative distribution for WTP_i—specifically, the cumulative distribution at each C_i, denoted $F(C_i)$—by maximizing the log-likelihood function:

$$LLF = \sum_{i=1}^{I} \ln\left[\sum_{e=1}^{E} d_{ie} \left(F(C_e) - F(C_{e-1})\right)\right], \tag{7}$$

where $d_{ie} = 1$ indicates the WTP interval $(L_i\ , U_i)$ spans the equivalence class $(C_{e-1}\ , C_e)$. The optimization routine must be constrained so that $0 < F(C_0) < F(C_1) <, \ldots, < F(C_E) < 1$.

After estimation of the CDF for both language skills and number-crunching ability, we see that, as expected, the value of these attributes for the majority of employers is much lower than the mean.[3] However, for a minority of employers, the value of these attributes is much greater than the average. For language skills, the estimated CDF indicates that for nearly 49 percent of employers the value of language skills would be less than \$255. For approximately 15 percent of employers, the value of these skills would be between \$3,096 and \$5,852, and for just less than 10 percent of employers, the value would be more than \$8,000. This same pattern appears within the estimated CDF for the number-crunching ability attribute. For approximately 50 percent of employers, the value of number-crunching ability would be less than \$540, but for 25 percent of employers, the value would be more than \$6,435 and for 13 percent of employers, more than \$10,920. Thus, we would expect graduates with these attributes for which the dispersion of employer values is quite large to seek out employers that highly desire what they have to offer. These graduates could likely realize returns much greater than the average value estimates would otherwise indicate.

Because the study conducted by Norwood and Henneberry (2006) employed a choice-based conjoint survey or a post–design survey to estimate employer's willingness-to-pay for college graduate attributes, its results can be compared to the results from our DV method. The values for internship experience, character, and communication skills are consistent with those values calculated by Norwood and Henneberry (2006) using a traditional choice experiment and conventional estimation techniques.

[3] Figures A1 and A2 in the appendix show the estimated CDFs for language skill and number-crunching ability, respectively.

Using the parameter estimates in Table 4 of Norwood and Henneberry (2006, 490), and the conventional value (WTP) calculation, their value estimates for internship experience, character, and communication skills are $22,000, $39,430, and $35,602, respectively. These estimated values are either equal to or greater than the values reported in Table 2. Moreover, Norwood and Henneberry report average values for at least one academic award and one leadership position of $663 and $2,406, both of which are similar to those reported in Table 2.

7. Future Research and Limitations

Design valuation is a unique survey method that allows respondents to participate in the pre-design survey process. Respondents are given a general good described by various attributes and are allowed to change the attribute levels at prescribed prices. In this way they design the good. Design valuation is equivalent to a number of CV questions; the two are statistically equivalent, but they are implemented differently. Thus, the preference of one design valuation or multiple CV questions depends on the practicality and the cognitive burden posed on the respondent.

Future research should measure the cognitive burden of each approach and respondent preferences for the two methods. Similar research could be expanded to compare design valuation to conjoint analysis. Essentially, we suggest that researchers measure preferences for stated preference instruments. If two methods elicit the same degree of information but one is answered more easily by respondents, that instrument should receive some preference.

Future studies should also measure the extent to which design valuation is subject to anchoring. It is well known that in double-bounded CV questions, individual values depend on the initial prices posed (Chien et al. 2005; Kato and Hidano 2007). Such biases would then be expected in design valuation as well. Yet, even single-bounded contingent valuation is subject to anchoring (Green et al. 1998), so conjoint analysis may be as well. More information on the presence of anchoring under these three alternative formats is desirable.

The attribute value estimates beg a number of questions. Attributes like ability to work well with others is valued highly, but what exactly does this mean? Does it imply ability to engage in stimulating conversations, general manners, or emotional intelligence as often studied by psychologists and others (Khalili 2012)? Similarly, although problem-solving abilities are highly valued, what type of problems are employers thinking of when they complete the DV questionnaire? Finally, when employers indicate they value “high character,” what percent of college graduates do they perceive have such high character? If academic advising is to make full use of the values estimated in this paper, these questions would should be further addressed.

The attributes evaluated in this paper varied at only two levels, perhaps oversimplifying respondents’ comparison task. Representation of many of these attributes, especially the intangible attributes in Attribute List B, as all or nothing qualities may make the task for employer respondents difficult. When making hiring decisions, they would be accustomed to evaluating these attributes over a continuum of possibilities. Further research should evaluate these attributes at additional levels.

For many hiring decisions, the choice employers face might be finding the best-fitting candidate at a predetermined salary. Or perhaps employers have some flexibility in the range of salaries they can offer but must remain within the range regardless of the candidate’s qualifications. It is unknown within our pool of respondents how many of them would face such a decision. This limitation of our research is reflected in our DV method, which assumes that employer respondents have flexibility in the salaries they can offer. Although this limitation may reduce the applicability of specific value estimates, the results still provide clear evidence of the importance of the attributes relative to one another and relative to employer type.

Because the survey that collected the data for this study was conducted in 2006, it is reasonable to expect that some employer preferences may have changed. The extended amount of time between data collection and the publishing of these results is also a noted limitation of this study.

8. Conclusions

Despite these limitations, the study provides useful information for advisors and students alike, particularly regarding the importance (magnitude of value estimates) of attributes to employers that prefer to hire from specific types of colleges. Employers that prefer to hire graduates of agricultural colleges put the highest value on ability to work well with others, excellent communication skills, and a high degree of character. As compared with employers that prefer to hire graduates of other types of colleges, they put the least value on problem-solving ability. This finding does not necessarily indicate that graduates with this attribute would be better suited for majors outside of agriculture, but rather it demonstrates that employers that prefer to hire from agricultural colleges place less importance on this attribute than employers that prefer to hire from other colleges. Employers that prefer to hire from agricultural colleges. Place the highest value on number-crunching ability. This finding demonstrates the relative importance of this attribute for students who intend to seek employment from such employers. This information, along with this study's other estimated values for recent college graduate attributes, allow students to better align their own goals with development of specific skills and attributes to increase their marketability and return on education investment on entering the job market. This information also benefits college advisors. Comparing attribute value estimates by employer classification type demonstrates heterogeneity among the employer types. As students graduate and seek employment, they must market themselves according to their talents, skills, experience, and abilities. Students are not always successful at initially finding a job. Knowing that firms are heterogeneous in their valuation of attributes supports advisors' advice to students that finding a job may require finding the employer that best values the student's specific skills and attributes. Additionally, intangible attributes are found to consistently be among the highest valued attributes among all employer types. As past research has shown, these types of attributes are best evaluated through a job interview (Briggeman et al. 2007), and our findings provide support for the importance of interviewing well in order to highlight possession of these intangible attributes.

Appendix

In conjoint or stated choice experiments, the independence-among-attributes assumption can be relaxed. Similarly, within design valuation we could easily modify equation 6 to allow for correlation between attributes to be estimated. The data could be "stacked" to estimate an equation as:

$$\boldsymbol{V_{ji}^{*}} = \sum_{j=1}^{J} \boldsymbol{X_{ij}}\left(\boldsymbol{\beta_{0j}} + \boldsymbol{\beta_{1j}Buscollege_i} + \boldsymbol{\beta_{2j}Engcollege_i} + \boldsymbol{\beta_{3j}Othercollege_i} + \boldsymbol{\varepsilon_{ji}}\right) \quad (8)$$

where $\boldsymbol{X_{ij}}$ equals 1 if the observation concerns attribute $\boldsymbol{j}$ and 0 otherwise and all other variables are as previously defined in equation 6. This equation would give the same estimates as those in Table 2. The equation could then be modified such that the parameters $\boldsymbol{\beta_{0j}}$ are random and correlated, allowing us to estimate the correlation between attributes 1 and 2 by the correlation between $\boldsymbol{\beta_{01}}$ and $\boldsymbol{\beta_{02}}$. Interaction terms could be added to the equation to allow the value of $\boldsymbol{\beta_{0j}}$ to rise or fall when the respondent happens to purchase one of the other attributes. For example, $\boldsymbol{\beta_{01}}$ could be specified as $\boldsymbol{\beta_{01}} = \widetilde{\boldsymbol{\beta_{01}}} + \widetilde{\boldsymbol{\alpha_{01}}}\boldsymbol{Z_{i2}}$, where $\boldsymbol{Z_{i2}}$ equals 1 if the individual purchased attribute 2 in the question and 0 otherwise. Because we were concentrating mostly on the mean values for the attributes, and values across different employer types, we did not include such techniques in the current study. Future research using DV techniques may benefit from further exploration of the method demonstrated above.

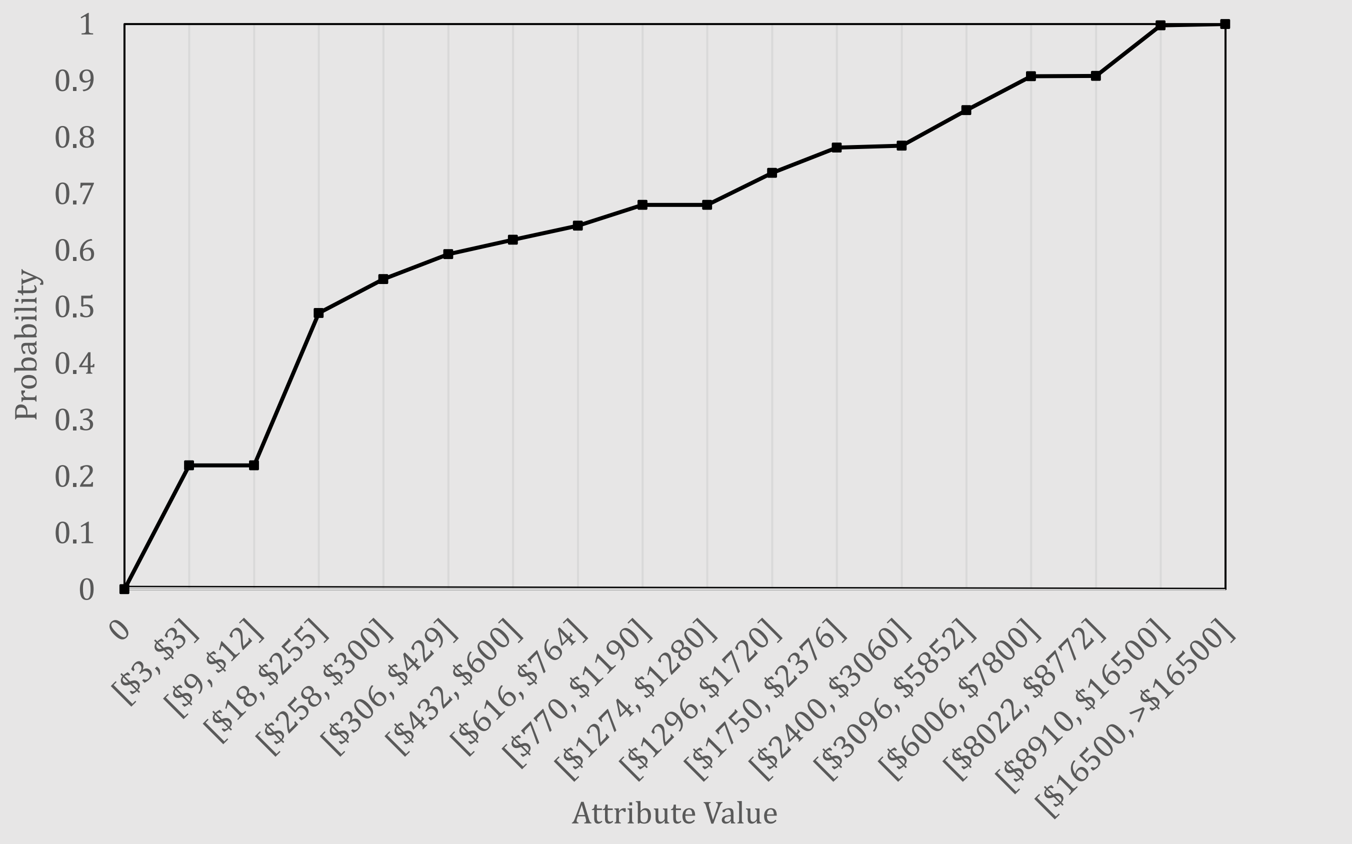

Figure A1. CDF Mean Value of Language Skills

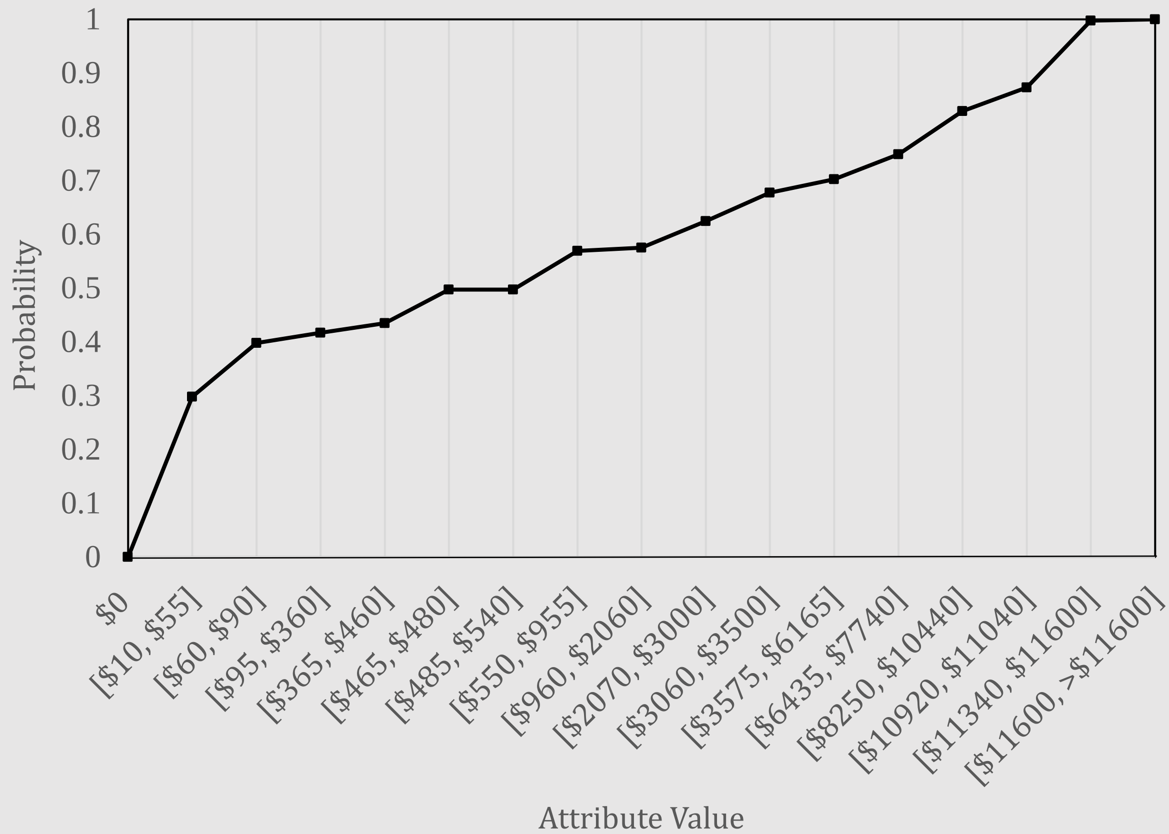

Figure A2. CDF Mean Value of Number-Crunching Ability

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