

## ABSTRACT

PARKER, BRANDY NICOLE. Policy Capturing National Wage Data Using O\*NET and DOT Job Components as Predictors. (Under the direction of Dr. Adam Meade and Dr. Mark Wilson).

When evaluating job worth, organizations often use job analysis data in a process known as job evaluation. Some organizations and researchers use a policy capturing approach as it shows promise of being cost effective for organizations in addition to offering structure and transparency in the job evaluation process. Utilizing job components from an aggregated job analysis database, such as the Occupational Information Network (O\*NET) or the Dictionary of Occupational Titles (DOT), could help with reducing costs and creating more structure. The aim of this study was to examine the efficacy of two approaches to aggregation of job analysis data (the O\*NET and DOT) in their prediction of national wage data. The importance of job component weighting in policy capturing of national wage data was also explored. Findings suggest that statistical weighting of O\*NET job components provides the most utility in accounting for variance in national wages.

Policy Capturing National Wage Data Using O\*NET and DOT Job Components as  
Predictors

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## Policy Capturing National Wage Data Using O\*NET and DOT Job Components as Predictors

The job market is always changing. As organizations shift focus to different products and designs, they might be faced with creating new positions or engaging in substantial restructuring. With new positions and restructuring comes the struggle and cost of performing job analyses and setting wages. Using components or factors that make up a job, an organization can discern the aspects of each job that contribute to organizational value, a process known as job evaluation. Since the 1940s, the use of job evaluation has become widespread with various firms and consultants offering their services, each with their own approach to the process of setting wages (Arnault, Gordon, Joines, & Phillips, 2001). Some organizations and researchers use a policy capturing approach; a method by which existing wage structures are captured using regression analysis. This method shows some promise for organizations given its cost effectiveness, in addition to offering more structure and transparency to the job evaluation process. Policy capturing makes use of job analysis by aggregating the data into job components. What is not well understood is the relative efficacy of various levels of aggregated job analysis data.

Figure 1 illustrates the focus of this paper; how well can two alternative approaches to job analysis data aggregation predict national wage data, and how important is weighting to policy capturing of national wage data? To examine the relationships presented in Figure 1, details are first provided on the O\*NET and the DOT. Next discussed is job component validity, identifying what job components are and how they can be used in analyses.

Following this is a general definition for policy capturing and discussion of how it can be used in the present context. Studies that examined the use of weights within job evaluation are identified. Concluding this section is a more detailed explication of the research questions examined in this study.

This study investigated a policy capturing approach for predicting national wages using two sources of aggregated job components. In a traditional job evaluation, judgments are made as to which job components to use and how to weight those components. The selected components are then used to predict wages, typically using a policy capturing procedure. Once an equation has been developed organizations can use it to set wages for new jobs, knowing only the job component scores for the new positions. In this study, the Occupational Information Network (O\*NET) and the Dictionary of Occupational Titles (DOT) were used as the sources of job components, as the intention of both systems was to serve as large scale national databases to house job analysis information that represent the entire labor market. The DOT was designed to be as close to the level of work as it was actually performed (e.g., making distinctions between various occupations), but the job analysis information was aggregated in order to classify and make comparisons across jobs. This level of aggregation resulted in over 12,000 individual entries within the DOT and three job components per job title (Peterson et al., 1991; U.S. Department of Labor, 1991). In contrast, the O\*NET data were further aggregated at the job level, having far fewer individual entries: 1102 occupational titles (<http://www.onetcenter.org>). However, each occupational title has an expanded list of 41 job components<sup>1</sup>. Because the O\*NET was

designed to replace the DOT (Peterson et al., 1991; [www.oalj.dol.gov/libdot.htm](http://www.oalj.dol.gov/libdot.htm)), it contains current information and is designed to include emerging work and occupations that did not exist when the DOT was last updated (<http://onetcenter.org>).

### **Occupational Information Network**

The O\*NET is a large-scale research database funded by the Department of Labor (DOL) and updated on a regular basis (<http://onetcenter.org>). It contains job analysis data aggregated into 1102 occupational units (OUs), 965 of which are linked to the Standard Occupational Classification (SOC) system (<http://www.bls.gov/soc>). The database is open to the public for a variety of uses (Peterson et al., 2001; see also <http://www.onetcenter.org>). Data are organized by six domains: worker requirements, worker characteristics, experience requirements, occupational requirements, occupational characteristics, and occupation-specific requirements. Each domain contains major taxonomies, in order to classify and distinguish between various occupations. The database also contains information linking DOT codes that are encompassed in a particular OU. Research utilizing data from the O\*NET is varied, including examination of health and worker characteristics (Alterman et al., 2008; Forstmeier & Maercker, 2008), occupational and worker requirements (Jeanneret & Strong, 2003; Lapolice, Carter, & Johnson, 2008), as well as wage and job characteristics and requirements (Maxwell, 2008; Rotundo & Sackett, 2004). While there have been studies examining O\*NET data using a job component validity (JCV) approach (Jeanneret & Strong, 2003; Lapolice et al., 2008), as well as research using O\*NET data and wages (Maxwell,

2008; Rotundo & Sackett, 2004), no one has specifically examined O\*NET job components as predictors of wages.

### **Dictionary of Occupational Titles**

The DOL has been collecting data on jobs in the American economy since the 1930s (Peterson et al., 2001). These job analysis data were compiled into the DOT (U.S. Department of Labor, 1991). The last revision to the DOT was the Fourth Edition, revised in 1991. Research utilizing the DOT includes “matching people to jobs, disability determination, vocational counseling, curriculum design, vocational rehabilitation, as base data for other taxonomies, personnel classification, research on the nature of occupations, and validation of selection procedures,” (Geyer, Hice, Hawk, Boese, & Brannon, 1989, p. 548). The job analysis data contained in the DOT are less aggregated than those in the O\*NET; the DOT contains descriptions on over 12,000 jobs, compared to 965 OUs for O\*NET. The more detail that comes from less aggregation at the job level of the DOT data may explain why some continue to use the DOT in research (e.g., Chi, Chang, Hsia, & Song, 2007; Poletaev & Robinson, 2008); too much aggregation can sometimes result in a loss of information. The DOT is still employed in legal cases (<http://www.oalj.dol.gov/libdot.htm>). While some research has used job components from the DOT to examine JCV (Steel & Kammeyer-Mueller, 2009) and abilities (Rotundo & Sackett, 2004), researchers have not specifically examined DOT job components as predictors of wage.

## **Job Component Validity**

The process of using job components for the purpose of prediction is most commonly recognized as JCV. Most researchers are familiar with using this approach for selection purposes, often considering it as either a form of, or synonymous with, synthetic validity. Lawshe (1952) introduced the idea of synthetic validity as a way to establish validity for a selection test through examining the requirements of the job. Balma (1959) expanded this definition: “The inferring of validity in a specific situation from a logical analysis of jobs into their elements, and a combination of those elemental validities into a whole” (p. 395). After the introduction of synthetic validity, researchers developed various approaches for conducting it, including the J-coefficient, Guion’s approach, and JCV (Scherbaum, 2005; see also Johnson, 2007).

McCormick (1959) first outlined JCV as a way to obtain indirect (synthetic) validity, in order to determine predictors for jobs. First, the “ingredients or attributes that are common to two jobs or types of jobs” are gleaned from a job analysis (p. 403). After a predictor is validated for one job, the information can be extended to jobs with the same “common denominator” (i.e., job component). Although initially proposed as an *approach* to synthetic validity, McCormick (1979) later stated that “synthetic validity has also been called (probably more appropriately) job component validity” (p. 51). In the basic sense, JCV is the method of using job components as a basis for comparison across jobs, in order to predict a criterion or outcome. Essentially, this is what is done in a policy capturing study for the

purpose of job evaluation. Researchers often use job components to predict wages. Job component validity, when applied to wages, is generally referred to as policy capturing.

### **Policy Capturing**

“Policy capturing encompasses any job evaluation process that attempts to link internal measures of job worth (i.e., content) with criterion wage rates,” (Davis & Sauser, 1991, p. 89). In the general sense, policy capturing is the use of judgments or factors to predict a given outcome or criterion; this relationship is analyzed using multiple regression. It is a commonly employed method for setting wages, typically involving researchers’ or subject matter experts’ judgments of the job analysis data and some form of data aggregation.

Using policy capturing in wage setting, job analyses are often evaluated and aggregated into job compensable factors (or job components) which are used to make comparisons across jobs by means of regression analysis. These job components can be differentially weighted in the regression, which can allow for distinction of those factors that contribute most to the differences in wages. In order to create the policy capturing (or job evaluation) model, benchmark jobs are used. Benchmark jobs are a sample of jobs considered stable by the organization. They are “selected to represent the normal hierarchy of responsibility and skill to which the prediction model will be applied” (Davis & Sauser, p. 100). These benchmarks and their known wages are used in the initial regression equation, capturing the wage setting values of the organization.

The model derived from the benchmark sample, as well as the weights (if they are to be used), can then be applied to other jobs in order to estimate wages. This compensation

model allows organizations to establish the appropriate wage for other jobs and positions that may have been restructured or newly created. This process is one of a number of techniques most often referred to as job evaluation. Researchers or compensation specialists use the job analyses from a large sample of jobs and determine how best to aggregate the data into job components/factors and the weights for those factors. The process could be called policy capturing using job components as predictors of wages.

The job components/factors that are derived from job analysis data can be determined via factor analysis or by expert judgment. The factors are often weighted either rationally or statistically. Rational weights are just that: weights based upon rational judgment. Statistical weights are commonly derived from regression analyses, taking the beta weights from a benchmark sample and applying them across other jobs. (For more information on conducting policy capturing see Aiman-Smith, Scullen, & Barr, 2002; Karren & Barringer, 2002.)

### **Weights**

Research examining weight effects is not new, though it has only recently been examined within the job evaluation literature (Davis & Sauser, 1991). In their investigation of weighting methods as it applies to policy capturing, Davis and Sauser (1991; 1993) reviewed previous literature on weights and compared different factor weighting methods used within job evaluation. In their initial paper, Davis and Sauser (1991) identified three broad categories of weighting: rational, equal, and statistical. A panel of subject matter experts usually decides the rational weights a priori. According to Davis and Sauser (1991),

“equal nominal weights are derived in different ways”; they identify equal weights more specifically as natural weights and unit (simplified) weights (pp. 92-93). When referring to equal unit weights, researchers typically use a weight of 1.0 for all factors, essentially summing across predictors (e.g., Van Sliedregt, Voskuijl, & Thierry, 2001). Although Davis and Sauser (1991) refer to this method as “natural weighting” (a type of equal weighting), for the purposes of this study I refer to this method as equal unit weights. As previously stated, statistical weights are derived via regression using a benchmark sample.

In their examination of different weighting methods with both homogenous and heterogeneous job evaluation instruments, Davis and Sauser (1991; 1993) found high agreement between the various methods when correlations between job components were high. Using the more homogenous job evaluation instrument (which had higher correlations between job components), they found no statistical difference between weighting methods. The job components with lower correlations among them resulted in significantly lower predictions when using non-statistical weights (i.e., rational weights). It is assumed that the job analysis data from the DOT and O\*NET are broad, yet encompassing, due to their aggregated nature. One would expect strong correlations among job components, but they are meant to be different enough so that information about jobs is adequately captured. Although some studies using data from O\*NET or DOT assigned weights citing previous literature (e.g., Chi et al., 2007; Poletaev & Robinson, 2008; Van Sliedregt et al., 2001), no one has directly examined differences in weighting DOT or O\*NET job components for the purposes of predicting national wages.

The purpose of this study was to use a policy capturing approach to examine the relationship between job components at two different levels of aggregation and their efficacy in predicting wages (see Figure 1). More specifically, how much of the variance in national median wages is accounted for by job components from the DOT and from the O\*NET? Additionally, this study examined the effects of weighting methods on the relationship between job components and wages. Specifically, do statistical or equal unit weights moderate the relationship between job components (from the DOT and O\*NET) and wages?

## **Method**

### **Samples**

The samples used in this study came from the O\*NET and the DOT. I selected all OUs from the O\*NET that met a wage cutoff described below. Each OU was linked to a corresponding list of job titles from the DOT. The National Crosswalk Service Center (NCSC) website provided a crosswalk between OUs and DOT job titles ([www.xwalkcenter.org](http://www.xwalkcenter.org)). The number of DOT titles linked to one OU ranged from 1 to over 100. To create matched samples, I selected a prototypical DOT job title from the list associated with each OU. This prototypical title was selected primarily based on the wording of job title from the DOT as it compared to wording of the OU title from the O\*NET.

To ensure consistency, a second evaluator checked 20% of the job titles. For half of these titles, the coder verified whether the prototypical title I selected made logical sense by comparing the OU to the selected prototypical job title. To check reliability, the coder made his/her own selection of prototypical job titles with the remaining half of the titles. These were compared to my selections.

Both the O\*NET and the DOT samples were split for subsequent cross-validation of the regression equations created from the statistical weights, thus resulting in four samples: one initial sample and one cross-validation sample from both the O\*NET and the DOT. In splitting the data, I used two thirds for the derivation samples and one third for the cross-validation samples. The total sample size was 744, resulting in sample sizes of 496 and 248 for derivation and cross-validation, respectively. These split samples had approximately equal distribution of wages because they were stratified based on the wage data. To do this, I segmented the wage data at the 20th, 40th, 60th, and 80th percentile and randomly selected one third of the job titles from each quintile for the holdout sample.

### **Measures**

**DOT job components.** The job components from the DOT consisted of the Worker Functions ratings. These ratings are the fourth, fifth, and sixth digits of the DOT job code and are identified as *data*, *people*, and *things*, respectively. The aggregation of information into the data, people, and things categories is based on Fine's Functional Job Analysis approach (for more information see Fine, Harvey, & Cronshaw, 2004). These three job components are consensus ratings based on several job analysts' ratings of each job contained in the DOT. The data ratings range from 0 to 6, people ratings range from 0 to 8, and things ratings range from 0 to 7. For each code, a lower rating indicates a more complex component (see U.S. Department of Labor, 1991). These data were reverse coded to maintain consistency with other variables. The DOT data were downloaded from the NCSC (2000b).

**O\*NET job components.** Peterson et al. (2001) suggested that Generalized Work Activities (GWAs) could serve as compensable factors in job evaluation efforts. Therefore, job components from the O\*NET consisted of the 41 GWAs. These fall under the occupational requirements domain, as outlined by the O\*NET Content Model (Peterson et al., 2001). For the majority of the OUs, each GWA is rated by job incumbents on a 5-point Likert-type scale of importance ranging from 1 (*not important*) to 5 (*extremely important*), which is averaged and converted to a 100-point scale. All 41 GWAs were included initially. These data were downloaded from the NCSC website (2000a). Because of the substantial difference in the number of potential job components contained within the O\*NET system relative to the DOT system, stepwise regression was employed as an O\*NET job component descriptor data reduction technique (see Appendix). This also helped reduce multicollinearity within the GWAs. The top three O\*NET job components (GWAs) were retained: “Analyzing data or information” (analyzing), “thinking creatively” (creative), and “provide consultation and advice to others” (advice).

**Wages.** Wage data were from the 2008 Occupational Employment Statistics survey. These data were downloaded from the Bureau of Labor Statistics (BLS) website (U.S. Bureau of Labor Statistics, 1995a). National median wages were used for each occupation. The BLS collects data on jobs as classified by the SOC code. Wage data were collected on 965 OUs. There was a non-linear relationship between job components and national wages when the highest paying jobs were included in the same analysis with lower- and middle-

income jobs. To control for this, only wages that fell within two standard deviations of the mean of the medians were included in the analysis.

**Weights.** For the analyses, I used both statistical and equal unit weights. Statistical weights were included because they are the most commonly employed weighting method. I chose to include equal unit weights for contrast, because they imply that each job component contributes equally to wage determination. Additionally, Davis and Sauser (1991) stated that equal unit weights “deserve more consideration for use in job evaluation” (p. 92). The statistical weights came from conducting a multiple regression with both the DOT and O\*NET derivation samples; the standardized beta weights associated with each job component were applied in the cross-validation sample. For the equal unit weights, I summed the values of job components, creating a job component composite. Wages were regressed on the job component composite. Following Davis and Sauser (1991; 1993), differences between the statistical and equal unit weight  $R^2$  values were tested using a formula developed for dependent samples (Howell, 2007; Steiger, 1980). This test is distributed as  $t$ , with  $N - 3$  degrees of freedom.

## Results

### Prediction

To address the question of variance accounted for in national median wages, I first regressed the wages onto the DOT job components using the derivation sample. The data, people, and things job components accounted for 39% of the variance in national median wages (Table 1). The data job component had the strongest relationship with wages. The

things job component had a negative, non-significant relationship with wages ( $p = .068$ ).

Next, I regressed wages onto the O\*NET job components using the derivation sample. The analyzing, creative, and advice job components accounted for 58% of the variance in national median wages (Table 1). All three job components were significant predictors of wages; the analyzing job component had the strongest relationship with wages.

### **Weighting**

I used the cross-validation samples to determine whether weighting method moderated the relationship between job components and wages. The standardized beta weights obtained in the derivation sample regressions were applied as the statistical weights in the cross-validation samples. The DOT job components, using statistical weights, accounted for 36% of the variance in wages (Table 2). For the equal unit weights, I summed across the three DOT job components and regressed wages onto the job component composite score. Equal unit weighting accounted for 24% of the variance in wages (Table 2). The difference between the  $R^2$  values obtained using the statistical weights (.359) and the equal unit weights (.242) was significant, demonstrating that weighting method does moderate the relationship between national median wages and DOT job components ( $t = 2.69, p < .01$ ).

The O\*NET job components, using the statistical weights obtained from the derivation sample, accounted for 49% of the variance in wages (Table 2). As with the DOT sample, I summed across the three O\*NET job components, and regressed wages onto the job component composite score. Equal unit weighting accounted for 44% of the variance in

national median wages (Table 2). Though there appeared to be little difference between the  $R^2$  values of the statistical and equal unit weights, this difference was statistically significant ( $t = 2.55, p < .05$ ).

### **Discussion**

Results from this study indicated job components from the DOT and O\*NET (derivation samples) accounted for 39% and 58% of the variance in national median wages, respectively. As noted in Davis and Sauser (1993), many job evaluation studies “have consistently found  $R^2$  values for policy-capturing models in the range of .78 to .90” (p. 94). The large discrepancy between the findings from this study and previous job evaluation studies might be due to the nature of the data used. Many of those studies conducted a job analysis and formed job components based only on a select number of jobs, typically all within the same organization. These job components would be less aggregated than either the DOT or the O\*NET. Also, the samples from these studies were typically small (i.e., less than 300). The sample used by Chi and colleagues (2007) consisted of over 1000 jobs from several different organizations and they were only able to predict 23.7% of monthly pay rate.

Additionally, the wage data used in other job evaluation studies were either current salaries of the jobs included in the study, or were based on benchmarks (e.g., average pay at regional companies of similar size), which would likely result in a stronger relationship between the job components and wages. As noted by Chi and colleagues (2007), “wage rates can be influenced by many other factors such as industry, regional cost of living, union status, full- and part-time employment, [etc.]” (p. 1203). The influences of these factors are

likely lost in national wage data. Rotundo and Sackett (2004) found occupational groups accounted for a substantial portion of the variance in wages; they were only able to account for 9% to 28% of wage variance above that explained by occupation, using skills/abilities as predictors.

Weighting method was demonstrated to moderate the relationship between job components and wages in both the DOT and the O\*NET cross-validation samples (Table 2). These findings are consistent with those from Davis and Sauser (1991), in that the statistical weights accounted for a larger portion of the variance in wages. An interesting finding from this study is the differences in the moderator effects for the DOT and the O\*NET job components. The change in  $R^2$  for the DOT sample was noticeably larger than for the O\*NET sample (though both were statistically significant). Research suggests that equal unit weights can be used when there is a low to moderate correlation between predictors and criterion (Raju, Bilgic, Edwards, & Fleer, 1997). The three O\*NET predictors were all highly correlated with wages; only two of the DOT predictors were highly correlated. The low, non-significant relationship between the things predictor and wages might have contributed to the larger change in  $R^2$  from statistical to equal unit weights. Furthermore, Davis and Sauser (1993) found little difference between weighting methods when the predictors had high multicollinearity. It is likely that this was the case for the O\*NET sample because a stepwise regression was used to capture only the top three job components. For more heterogeneous predictors (like the DOT), equal unit weights produce significantly lower  $R^2$  values (Davis & Sauser, 1993).

One might have expected a smaller difference between the O\*NET  $R^2$ s and the DOT  $R^2$ s, due to the O\*NET being based on the DOT and both samples being aggregated job analysis data. There are two potential reasons for the large disparity. First, the O\*NET data were linked to the national median wages by SOC code, thus it is not too surprising that there was a stronger relationship between the O\*NET job components and wages. Second, the DOT data have not been updated since 1991; some industries and jobs likely have changed (or have been recently created) which would not be reflected in the DOT job components. If possible, future research could utilize wage data that are not linked to the O\*NET or include data that are linked to the DOT, for comparison.

The DOT things job component was found to have a negative, non-significant relationship with national median wages (Table 1). The negative beta weight may have been due to the categories of the things job component; they are typically associated with blue-collar (i.e., lower-wage) jobs (e.g., driving/operating). The negative relationship with the criterion is particularly a problem when using equal unit weights (see Davis & Sauser, 1991). This could also explain why the weighting method had a stronger moderating effect in the DOT sample than in the O\*NET sample. A possible explanation for the non-significant relationship between the things job component and wages is the somewhat nominal nature of the things scale (Table 3). Though indicated otherwise, the categories do not appear to have clearly increasing levels of complexity; that is to say, someone performing at a higher level may not necessarily be capable of also performing the “lower level” categories.

### **Limitations and Future Research**

One clear limitation of the current study is the bias in the criterion. The O\*NET OUs were linked to the national median wages by SOC code, with the DOT job titles reduced to match the O\*NET. Furthermore, the DOT was last updated in 1991. The scope and structure of many jobs have changed over the past 20 years, likely resulting in a change in job components. These factors possibly contributed to the weaker relationship between the DOT job components and wages. Future research should use DOT level wage data to test whether there is, in fact, bias in favor of the O\*NET.

The negative, non-significant relationship between the things job component and wages was also a limitation. Rotundo and Sackett (2004) correlated the DOT job components with wages and found a positive correlation between the things job component and wages. However, they used “annual average median weekly wage for 1979 converted to an hourly wage based on a 35-hour work week” (p. 139). The specificity of the wage data and its closer link to the DOT might explain the difference between their study and this study. This could be an argument against the things job component being nominal. The relationship found in this study may be an artifact of the wage data used. Researchers may still want to consider recoding or reclassifying the things job component to see how this might change the relationship with wages.

Another limitation was the small number of predictors. The DOT had only three worker functions ratings (data, people, and things). O\*NET GWAs were determined to be most similar to the DOT job components and thus, were reduced in number to match. Many job evaluation studies use anywhere from 4 to 10 or more job components as predictors (e.g.,

Davis & Sauser, 1993; Robinson, Wahlstrom, & Mecham, 1974; Rotundo & Sackett, 2004). Some studies also included other factors in addition to the job components, such as education or tenure. Future research should explore the addition of other sources of job components from the O\*NET and DOT, like skills or aptitudes, respectively.

Researchers might also consider reexamining a policy capturing or job evaluation study, substituting in either DOT or O\*NET job components and comparing the results to those originally obtained in the study. This would help in understanding whether the level of aggregation in the DOT and O\*NET is too high. Similarly, it would be interesting to know if the job components from those policy capturing and job evaluation studies would account for the same amount of variance in national wages as they did for specific wage data used in the studies.

## **Conclusion**

This paper explored the use of two national job analysis databases, the DOT and the O\*NET, in a job evaluation study using a policy capturing approach to predict national wage data. Although the job components explained less than 60% of the variance in wages, there is some argument for using information from these job analysis databases in wage setting. Smaller companies that cannot afford the services of job evaluation firms could apply the information from such databases to set or adjust wages as needed. However, caution must be used as reliance on only job components from these sources may not be enough. Furthermore, a study conducted by Arnault and colleagues (2001) demonstrated inconsistencies in job evaluations conducted by firms, an argument for a standardized

approach to job evaluation. Using a source like the DOT or O\*NET would help to provide consistency in job evaluations and comparisons across jobs.

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### Footnotes

1. Peterson et al. (2001) identified 42 GWAs; however, there are only 41 GWAs published on the O\*NET website ([www.onetcenter.org](http://www.onetcenter.org)). The GWA “implementing ideas, programs, systems, or products” was either removed or subsumed into another GWA.

Table 1  
*Statistical Weights for O\*NET and DOT Predictors*

Predictors	<i>B</i>	<i>SE B</i>	<i>B</i>
DOT			
Data	4886.102	386.665	.518**
People	1322.547	366.791	.159**
Things	-473.370	258.630	-.071
O*NET			
Analyzing	12768.263	955.029	.539**
Creative	3790.217	874.185	.153**
Advice	4889.936	1164.830	.175**

*Note.* Derivation sample  $n = 496$ . DOT  $R^2 = .385$ ; O\*NET  $R^2 = .581$ .  
 $*p < .05$ .  $**p < .01$ .

Table 2  
*Regression of Wages on Job Components Using Two Weighting Methods*

Weighting Method	<i>R</i>	<i>R</i> <sup>2</sup>	<i>df</i>	<i>F</i>	<i>SE</i>
DOT					
Statistical	.599	.359	1-247	137.946**	12441.112
Equal Unit	.492	.242	1-247	78.521**	13532.333
O*NET					
Statistical	.698	.488	1-247	234.272**	11123.732
Equal Unit	.665	.442	1-247	194.915**	11609.591

*Note.* Holdout sample  $n = 248$ .

\* $p < .05$ . \*\* $p < .01$ .

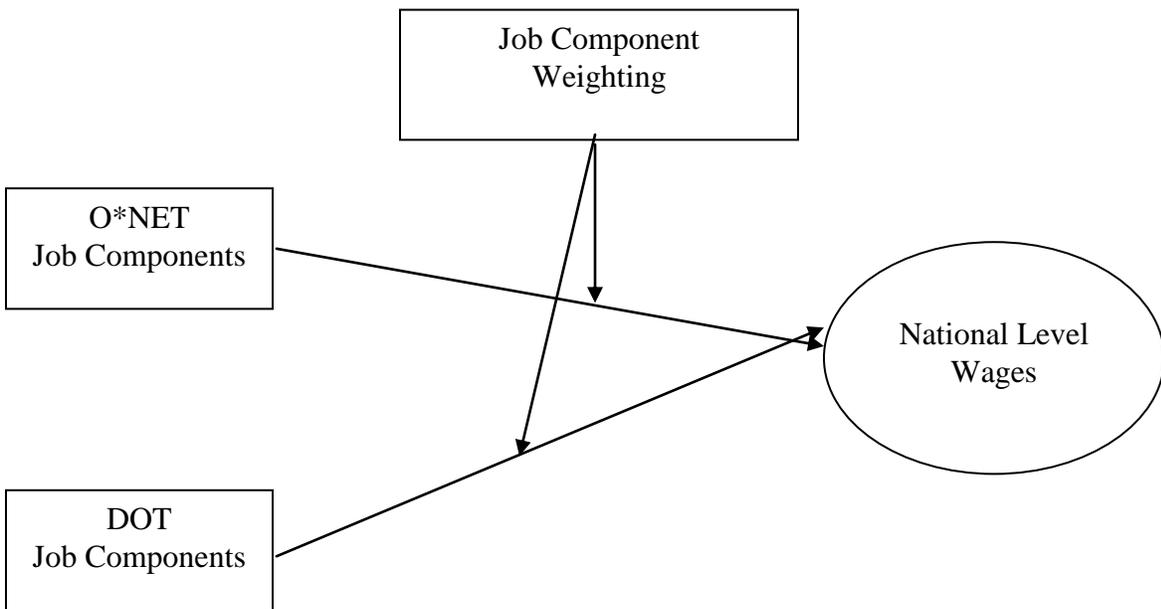
Table 3  
*Categories from the DOT's Things Job Component*

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Things
Setting up
Precision working
Operating-controlling
Driving-operating
Manipulating
Tending
Feeding-offbearing
Handling

---

*Note.* Ordered from most to least complex.



*Figure 1.* Conceptual model of important variables in policy capturing of national wage data.

APPENDIX

Appendix A  
Stepwise regression of O\*NET job components

Model	$R$	$R^2$
1	.731 <sup>a</sup>	.535
2	.752 <sup>b</sup>	.566
3	.762 <sup>c</sup>	.581
4	.771 <sup>d</sup>	.594
5	.781 <sup>e</sup>	.610
6	.788 <sup>f</sup>	.620
7	.790 <sup>g</sup>	.624
8	.793 <sup>h</sup>	.629
9	.796 <sup>i</sup>	.633
10	.797 <sup>j</sup>	.636

*Note.* The job components analyzing, creative, and advice are V9, V11, and V38, respectively.

a. Predictors: (Constant), V9

b. Predictors: (Constant), V9, V11

c. Predictors: (Constant), V9, V11, V38

d. Predictors: (Constant), V9, V11, V38, V32

e. Predictors: (Constant), V9, V11, V38, V32, V17

f. Predictors: (Constant), V9, V11, V38, V32, V17, V10

g. Predictors: (Constant), V9, V11, V38, V32, V17, V10, V19

h. Predictors: (Constant), V9, V11, V38, V32, V17, V10, V19, V31

i. Predictors: (Constant), V9, V11, V38, V32, V17, V10, V19, V31, V36

j. Predictors: (Constant), V9, V11, V38, V32, V17, V10, V19, V31, V36, V22