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RESEARCH ARTICLE

Salaries in Forensic Anthropology and Academic Anthropology

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ABSTRACT: This project examined the salaries of forensic anthropologists in the United States. Additionally, the salaries of forensic anthropologists employed in academia were compared to those of other academic anthropologists. The goal of this project was to develop baseline data in terms of salaries for forensic anthropologists while also examining various factors that may affect forensic anthropology salaries. Salary information is important because salary transparency narrows wage disparities, reduces favoritism and discrimination, increases the bargaining power of employees, and potentially causes employers to focus more on salary differentiation in terms of productivity and seniority; essentially, wage transparency generates greater equity among employees (Estlund 2014).

In order to examine salaries in forensic anthropology, internet search engines were used to find open-access salary data for individuals currently listed as non-student members of the anthropology section of the American Academy of Forensic Sciences and/or the American Board of Forensic Anthropology. All variables were analyzed using random forest models.

Results found that in all models, there were no differences in salary between men and women. Further, no significant differences were found between anthropology subfields in academia. Importantly, years since terminal degree was the most important variable affecting salary in all models, with academic rank being the most important variable for individuals employed in the academic sector. Further, these results demonstrate inconsistencies in pay for forensic anthropologists, especially for those working in the applied sector.

KEYWORDS: forensic anthropology, wage transparency, salary, academia

Introduction

Salary transparency (also referred to as wage or pay transparency) is an individual's ability to access the compensations of other employees at a place of employment (Ramachandran 2011). Estlund (2010) argues that access to salary information is important because salary transparency narrows salary disparities, specifically for the most underpaid individuals (Gomez & Wald 2010:122–123). Moreover, salary transparency reduces favoritism, discrimination, and corruption (Azfar & Nelson 2007); increases the bargaining power of employees; and potentially allows employers to focus more on salary differentiation in terms of productivity and seniority. Ramachandran (2011) found evidence that women and racial minorities gravitate to workplaces with salary transparency, perhaps because there is better compensation in these workplaces for comparable jobs. Additionally, Rosenfeld and Denice (2015) argued that there are three main advantages to salary transparency: first, it can increase worker capability by legitimating potential demands for higher salary; second, it increases the likelihood that a worker or group of workers bargains for higher pay; and third, it raises the worker's or workers' probability of bargaining success. Essentially, salary transparency generates greater equity among employees. Estlund (2014:788) states that "accurate information about other people's salaries in one's own and other organizations is crucial to decisions about seeking a better opportunity elsewhere, asking for a raise, or simply staying on the job and accepting the status quo."

Salary secrecy, on the other hand, is the withholding of salary information regarding the compensation of employees (Janićijević 2016). Salary discrimination among employees is commonly highlighted as a negative impact of salary secrecy; however, there are potential positive impacts of keeping salary inaccessible as well. For example, salary data may be meaningless without also providing individual performance data (Gomez & Wald 2010:113). Additionally, attaching individual names to salaries can be considered an invasion of privacy, and salaries may be released blinded or as averages instead (Gomez & Wald 2010:115). Disclosure of public-sector salaries may demonstrate that public servants are underpaid in comparison to their private-sector counterparts, making public-sector careers less desirable and public-sector employees more difficult to retain (Gomez &Wald 2010:115). Further, the costs of lower-paid (i.e., below average) employees' dissatisfaction and increased likelihood to seek a new job may exceed beneficial costs of higher-paid employees' satisfaction and increased likelihood to stay (Card et al. 2012).

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Janićijević (2016) argued the following as advantages of salary secrecy: improved organizational control and less conflict, greater possibilities for differentiation between good and bad workers, ensuring employees' privacy, reduced turnover of employees, and better position of the employer during salary negotiations with the existing or potential employee. Similarly, Burroughs (1982) argued that a logical reason salary secrecy policies exist within companies is that some management may regard salary compensations as private information similar to birth date and medical history. An experimental study using data from college students in 1972 within an artificial work setting suggested it is possible that some employers are unable to make reward allocations based strictly on merit if a salary transparency policy exists (Burroughs 1982).

Of note, there has been a recent trend of restricting or eliminating access to state employee salaries due to privacy reasons (as noted on a number of academic web pages). For example, the salaries of all employees at Michigan State University were publicly available via an online database until 2014. Since 2014, access to this salary information has been restricted to only physical documents available at the Michigan State University library. The cause of this trend is unclear; however, during our searches, it was obvious that the restricting of access to salary information at public institutions was a relatively recent and growing phenomenon (Gomez &Wald 2010).

Using survey data, Cullen and Perez-Truglia (2018) found that employees were often (theoretically) willing to pay significant amounts of money in order to gain access to peer and managerial salary data, thus suggesting these salary data are highly desired. On a case-by-case basis, individuals seeking employment may independently compare salaries at various institutions for their own gain during the application, hiring, and/or bargaining processes; however, employers largely benefit from a lack of transparency in salaries through asymmetrical information and control of the market (Estlund 2014). Gardner et al. (2010) argue that possibly the only time an employee gains greater power than the employer in the employer-employee relationship is during a counteroffer negotiation, because during this time employees have the most access to salary information and leverage over their market value.

Currently, data on salaries in forensic anthropology, or anthropology in general, within academia or in applied institutions are not widely available. Forensic anthropology, like all forensic sciences, is a discipline meant to serve the public through assistance provided to law enforcement, medical examiner's and coroner's (ME/C) offices, lawyers, and the courts (Passalacqua et al. 2019). As such, nearly all forensic anthropologists in the United States are employed as public servants, with individuals being employed by government-funded institutions at either the state or federal level (Houck & Siegel 2010; Passalacqua et al. 2019). In the United States, the salaries of government employees are typically considered to be public information; therefore, these salaries are often freely available in publicly accessible databases or via requests for information using such avenues as the Freedom of Information Act (FOIA). The goal of this project is to present current salary information (as of 2018) for forensic anthropologists in the United States, particularly given the arguments for salary transparency and the lack of currently available data on forensic anthropology salaries. These salary data are compared to the salaries of other anthropologists employed in academia. We also investigate various factors, such as gender, ABFA certification, classification of academic institution, and terminal degree obtained, that may be influencing salary rates of forensic anthropologists.

Materials and Methods

To examine the salaries in forensic anthropology, the authors first created a list of practicing forensic anthropologists in the United States. This list was generated in the summer of 2019 using the current membership directories of the American Board of Forensic Anthropology (ABFA) and the anthropology section of the American Academy of Forensic Sciences (AAFS). For the anthropology section of the AAFS, student members were not included on the list of practicing forensic anthropologists. Based on these directories, the list of practicing forensic anthropologists included 373 names. These individuals were investigated via internet search engines to confirm their current affiliations and employers. This information was then used to search various publicly available online databases of federal and state employee salaries (e.g., databases.usatodaynetwork.com /knoxnews/UTpay2018).

In addition to salary and affiliation data, information was collected on various demographic and employment parameters as determined via online individual biographies and common knowledge. These data included gender, terminal degree, graduation year (active years), graduate-degree institution, and certification by the ABFA. We also distinguished by type of position, whether applied or academic. For applied positions, distinctions were made between full-time and part-time lab work (lab time). For academic positions, Carnegie Classifications of academic institution as well as rank of employee (e.g., instructor, assistant professor, dean, etc.) were tabulated.

For forensic anthropologists in the United States, data were available for 114 individuals from the original list of 373 (no individuals in this study had salary information available for more than one affiliation). Of these, 74 were women and 40 were men who stemmed from academic ($n = 77$) and applied ($n = 37$) institutions (Fig. 1). For individuals employed

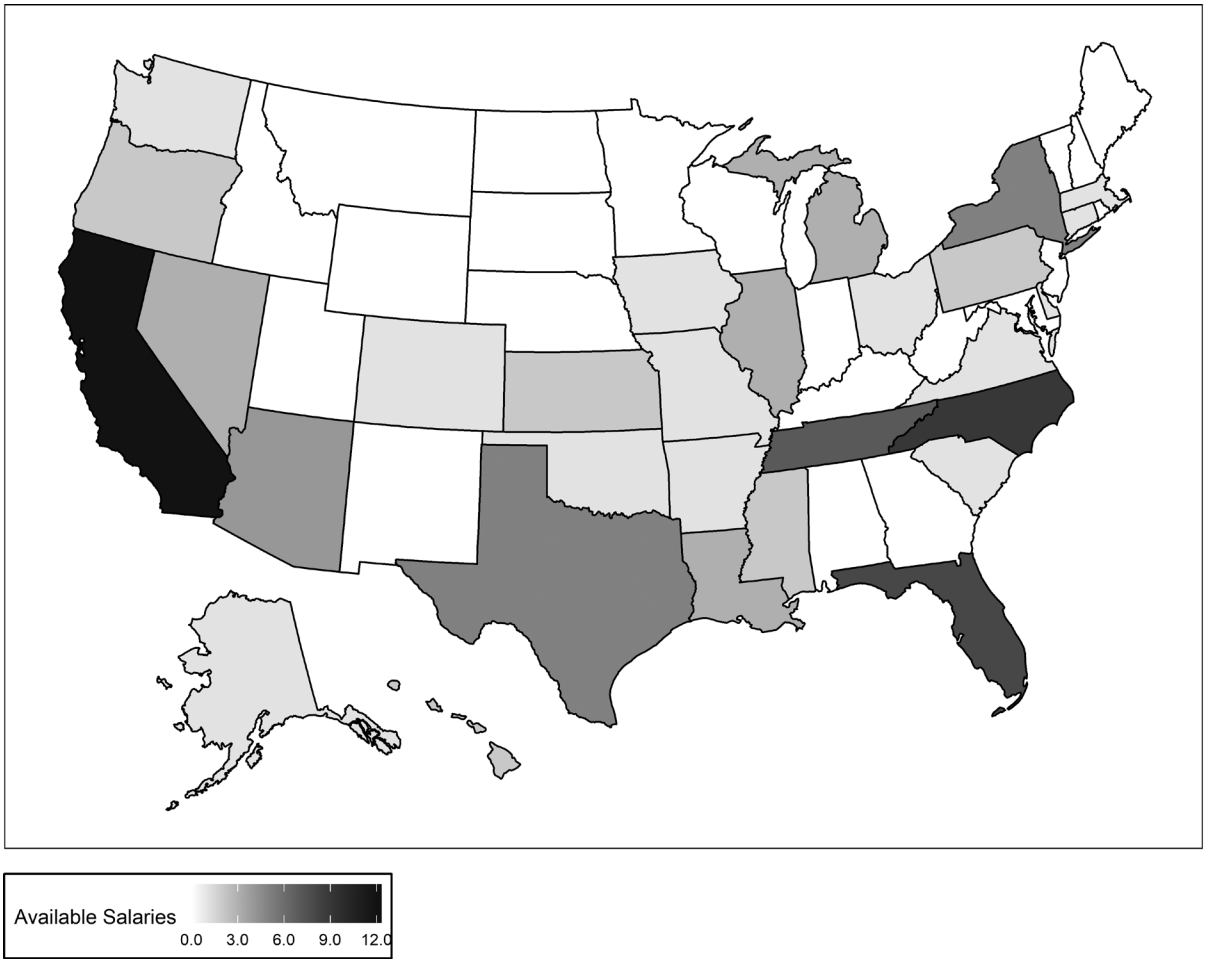

FIG. 1—*Distribution of salary information of academic and applied forensic anthropologists used for analysis.*

at academic institutions, most had traditional ranks ($n = 25$ assistant professors, $n = 15$ associate professors, and $n = 20$ full professors) and several had term positions ($n = 14$, lecturers, visiting assistant professors, adjunct instructors, postdoctoral scholars, and instructors). A number also had additional administrative duties ($n = 13$), such as program director, department head, facility director, and so forth, while a few had additional university distinctions (such as Distinguished Professor) ($n = 3$).

We wanted to compare the salaries of academic forensic anthropologists to those of other academic anthropologists. Therefore, data were also collected on other (non-forensic) anthropologists ($n = 601$) employed at the same academic institutions that employed forensic anthropologists ($n = 77$; $N = 678$ total academic anthropologists). Information regarding gender, Carnegie Classification of institution, rank, administrative duties, subfield, and salary were collected for each individual in this data set. Figure 2 provides a geographic distribution of all academic anthropologists included in this study.

To control for salary variability throughout the United States, a salary index (SI) was created. The SI was calculated by dividing annual salary by the average cost of living (COL) for each state based on data collated and presented by the Missouri Department of Economic Development (Missouri Economic Research and Information Center 2019). This value was then divided by the term length of the position (e.g., 9 months, 10 months, 12 months) (eq. 1). For example, an individual making $90,000 in California (COL = 138.7) employed in a nine-month position would have a salary index of 72.10, whereas an individual earning $68,000 in North Carolina (COL = 94) in a ten-month position would have a salary index of 72.34.

$$\frac{Salary/COL}{Term\ length} = S$$

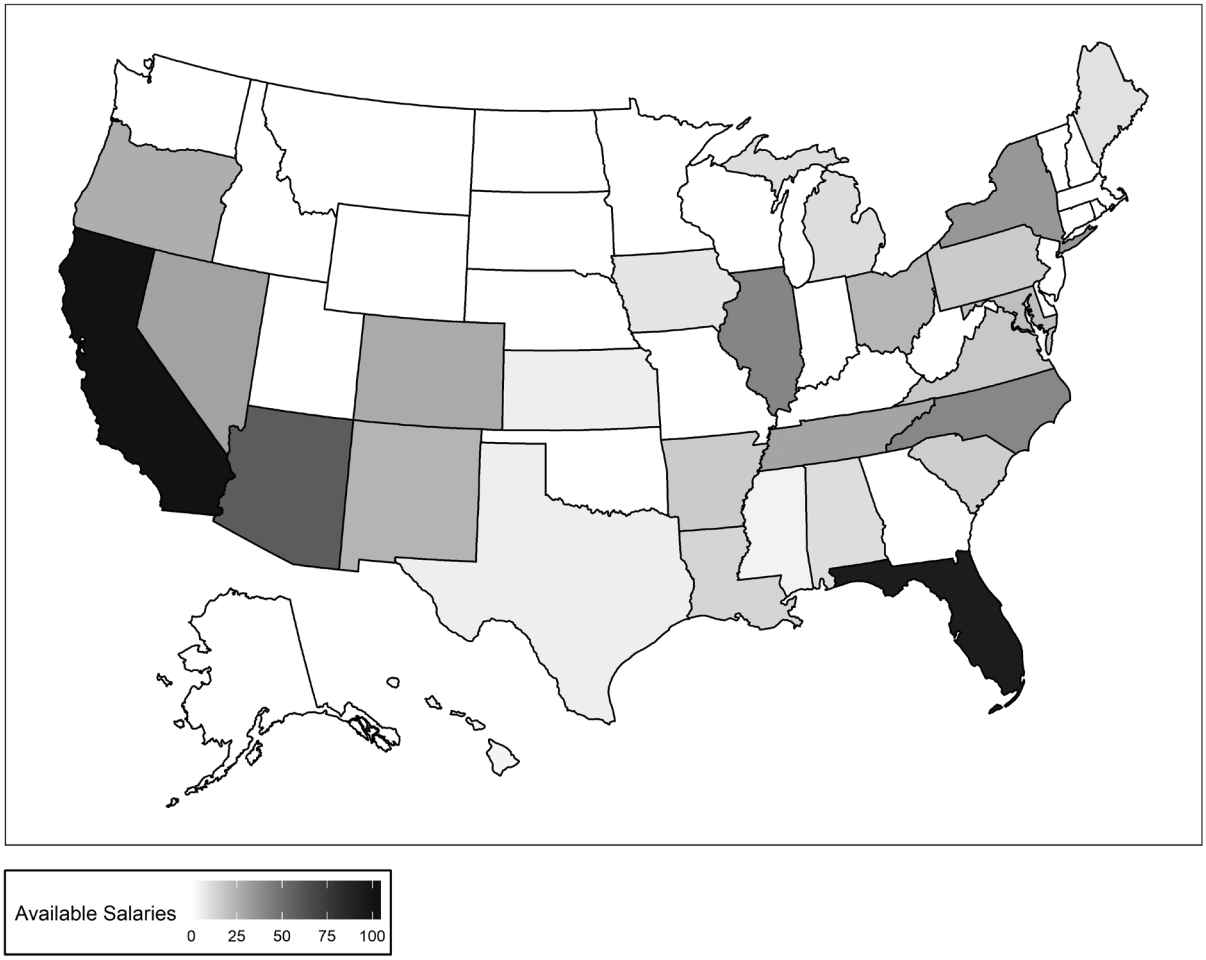

FIG. 2—*Distribution of salary information for academic anthropologists from all subfields used for analysis.*

The SI was then investigated using various statistical analyses in the R computing environment (R Core Team 2019) using the graphical interface RStudio (R Studio Team 2018). First, SI was collapsed into categories using an unsupervised (non-labeled) *k*-means clustering algorithm using the *classInt* package (Bivand 2019). *K*-means clustering finds *k* number of cluster centers to group given data by minimizing the within-cluster sum of squares, thus creating the smallest clusters. One to 15 clusters were created using SI values from the academic anthropologist data set only (omitting applied forensic anthropologists), as this data set was the largest and most robust. The total within-cluster sum of square value was calculated for each number of clusters, and the optimal number of clusters was visually selected using the elbow method (Marutho et al. 2018). The resulting SI categories were used in subsequent analyses.

To investigate individual variable influence on SI category, we used two tests of association. Cramer's V test was used to evaluate the relationship between each categorical explanatory variable and SI category and to provide strength of correlation (>0.5 considered "strong") between variables using contingency tables. Kruskal-Wallis rank sum tests were used to evaluate the relationship between continuous explanatory variables and SI category, by testing for significant differences between mean continuous values and categorical variables. Separating the explanatory variables to compare with the response variable (i.e., SI category) in this manner assumes independence between each variable. Because of the multifactorial nature of individual salaries, it cannot be assumed that all explanatory variables used in this study are independent.

To account for potential correlation of variables, we employed random forest models (RFMs) and the Gini index. RFMs use the basic model of a decision tree but create *n* number of trees and take the majority vote from all trees to assign a classification. The Gini index is a measure of variation found in the data (Raileanu & Stoffel 2004) and is used by the model to make decisions on which

variable is used at each node (new branch) of the decision tree. The greater the mean decrease in the Gini index, the more important a variable is to the model, as the amount of variance decreases with the removal of that explanatory variable.

The use of RFMs for this study instead of single decision trees is to improve generalizability and produce more realistic results (Breiman 2001). For this study, each RFM was built on the outcomes of 500 trees instead of 1, thus increasing the model's flexibility when encountering new data. The *randomForest* package (Liaw & Wiener 2002) was used to generate each RFM. A built-in measure of model performance is provided by the package by reporting the out-of-bag (OOB) error rate (Liaw & Wiener 2002). RFMs were built for the pooled forensic anthropologist data set, a subset of only academic forensic anthropologists, a subset of only applied forensic anthropologists, and the all-academic anthropology data set. Each RFM output included a confusion matrix, classification error for each SI category, and OOB error rate. Confusion matrices show the number of individuals classified into each SI category, with true category represented by rows and estimated category represented by columns. The mean decrease in the Gini index value was also extracted from each model to evaluate explanatory variable importance. Because of a small sample size for the forensic anthropologist data set ($n = 114$), RFMs were trained on all available data. The larger size of the all-academic anthropology data set ($n = 678$) allowed for an 80-20 separation of training and testing samples using the *caret* package (Kuhn 2020).

Results

Salary Index

Among forensic anthropologists, the highest SIs were found at two-year associate's colleges and among full professors or those with special rank and/or administrative duties. Overall, academic forensic anthropologists had a higher SI than those in the applied sector (Table 1). These same trends are seen in the data for all academic anthropologists, with higher-ranked professors earning more as well as individuals at two-year colleges (Table 2). The overall SI for forensic anthropologists (mean = 80.97; see Table 1) is lower than that of all academic anthropologists (mean = 94.64; see Table 2). However, the standard deviation for the academic anthropologists is quite high ($\sigma = 43.40$; see Table 2), indicating a large amount of variation within the data. Additionally, there were relatively few individuals employed at two-year associate's colleges, which likely biases those data.

Salary Categorization

Using *k*-means clustering and the elbow method, four SI category clusters were selected for further analyses (Table 3). The distribution of forensic anthropologists in each SI category by type (academic vs. applied) is represented in Figure 3. Results of the Cramer's V tests indicate that gender has the lowest association with SI category (Cramer's V = 0.1109) and that rank (for academic forensic anthropologists only) has

TABLE 1—*Salary index data for all forensic anthropologists.*

			Salary Index		
Variable	Subcategories	*N*	Median	Mean	SD
		114	76.34	80.97	29.89
Sex	Women	74	73.01	81.29	32.18
	Men	40	82.54	80.38	25.49
ABFA certification	No	71	72.60	76.26	27.90
	Yes	43	79.63	88.74	31.74
Terminal degree	MA	14	53.24	59.26	23.68
	PhD	100	78.07	84.01	29.50
Type of forensic anthropologist	Academic	77	79.81	88.20	30.87
	Applied	37	61.84	65.93	21.16
Classification of institution (academic FAs only)	Associate's colleges	2	110.74	110.77	26.57
	Baccalaureate colleges	3	45.39	71.31	45.33
	Master's colleges and universities	20	71.77	74.40	20.45
	Doctoral universities	52	89.05	93.61	32.08
Rank (academic FAs only)	Term	14	63.00	61.74	14.69
	Assistant professor	25	72.31	73.63	16.46
	Associate professor	15	90.33	91.38	18.02
	Full professor	20	115.06	112.96	30.44
	Special rank	3	165.52	152.11	24.67
Additional administrative duties (academic FAs only)	No	101	74.50	76.73	25.79
	Yes	13	110.06	113.92	39.26
Lab time (applied FAs only)	Part-time	19	59.81	64.11	23.51
	Full-time	18	66.66	67.84	18.87

TABLE 2—*Salary index data for all academic anthropologists.*

Variable	Subcategories	*N*	Salary Index Median	Mean	SD
		678	90.61	94.64	43.40
Sex	Female	347	84.13	88.55	40.84
	Male	332	95.29	100.87	45.14
Classification of institution (academic FAs only)	Special-focus four-year	20	76.58	77.74	33.13
	Associate's colleges	3	91.99	103.71	22.42
	Baccalaureate colleges	14	37.88	43.96	29.34
	Master's colleges and universities	127	73.05	77.90	40.58
	Doctoral universities	515	93.24	100.66	42.78
Rank	Term	80	52.17	49.13	21.52
	Assistant professor	145	75.47	74.20	17.99
	Associate professor	196	91.37	91.13	24.02
	Full professor	238	110.26	115.22	37.45
	Special rank	20	184.04	211.99	87.17
Additional administrative duties (academic FAs only)	No	509	86.73	89.03	37.11
	Yes	170	99.36	111.15	55.23
Subfield	Archaeology	181	90.98	97.77	50.07
	Biological	150	91.09	92.93	47.91
	Cultural	254	91.98	95.65	38.34
	Forensic	78	81.80	87.99	30.92
	Linguistic	16	74.24	88.75	46.23

TABLE 3—*Summary of the SI categories.*

SI Category	SI Range	Count
One	14.58–69.26	170
Two	69.27–90.58	170
Three	90.59–110.81	169
Four	110.82–451.12	169

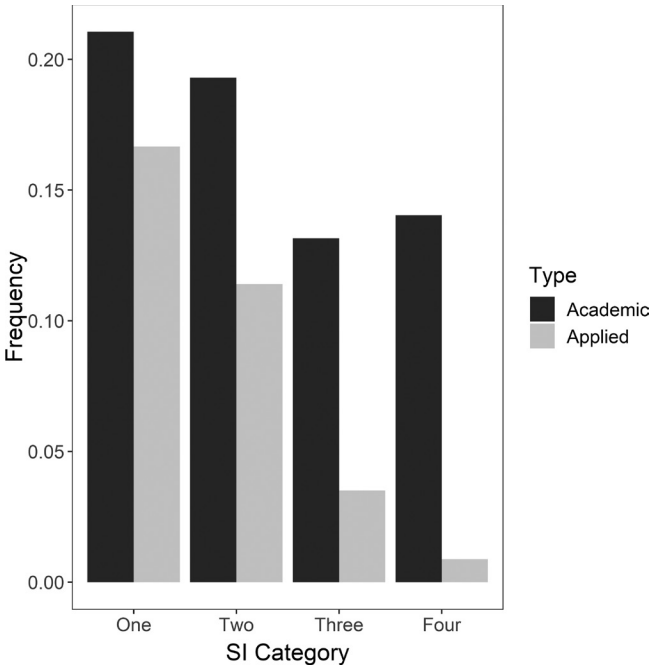

FIG. 3—*Frequency of individuals in each SI category by type of forensic anthropologist.*

the highest association with SI category (Cramer's V = 0.5463; see Table 4). The Kruskal-Wallis rank sum test indicates that there were no statistically significant differences ($p = 0.1368$) between SI category and mean number of active years (Table 4). The OOB errors from each RFM (pooled, academic, and applied) are 55.26%, 58.44%, and 37.84%, respectively. Confusion matrices for each RFM are presented in Tables 5–7.

Academic Anthropology

The distribution of anthropologists by subfield in each SI category by type is represented in Figure 5. Results of the Cramer's V tests showed that subfield had the lowest association with SI category (Cramer's V = 0.0953) and rank had the highest association with SI category (Cramer's V = 0.5463; see Table 8). The OOB error for the RFM is 45.93%. The confusion matrix for the RFM used on the test sample are presented in Table 9.

In terms of variable importance, Figure 6 summarizes the mean decrease in the Gini index for each variable in each model. For all three models, active years was the most important variable, even though the Kruskal-Wallis rank sum test indicated no significant differences between SI category and active years. For applied forensic anthropology, active years is substantially more important than any other explanatory variable. Rank, presenting as the second-most-important variable in the academic sector, alludes to the non-uniform way in which academic forensic anthropologists reach different ranks, with some individuals being promoted more quickly and others remaining longer or indefinitely in a single rank.

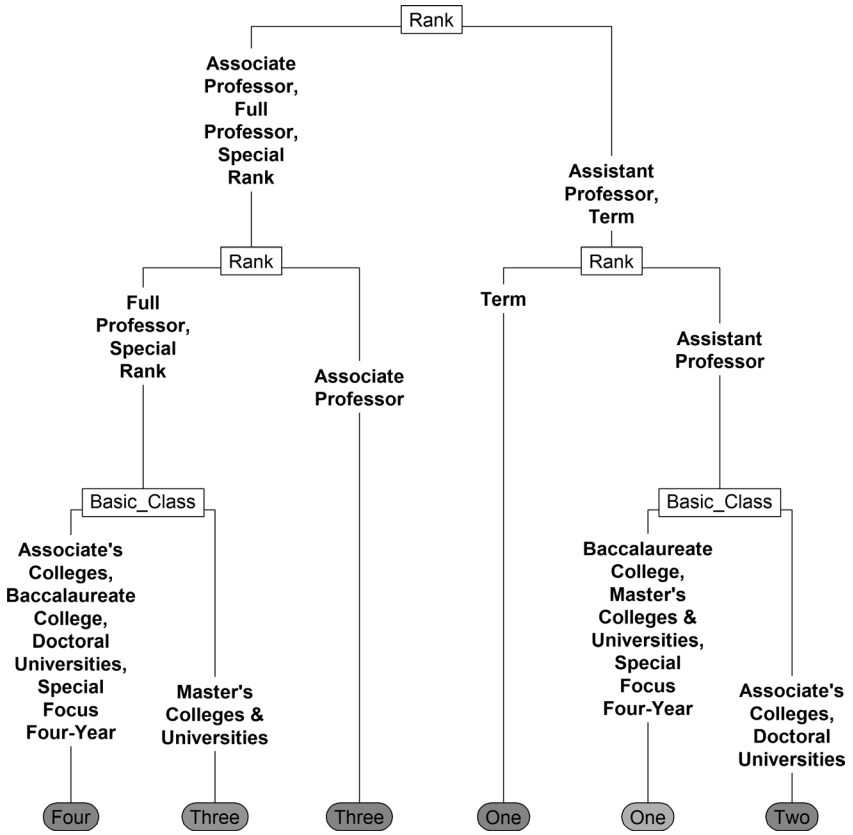

FIG. 4—*Sample decision tree produced using the all-academics data set. Rectangles represent the variable used for each split, words in bold are the categories associated with each branch, and ovals represent the resulting classified SI category.*

TABLE 4—*Summary of tests of association between SI categories and predictor variables for forensic anthropologists.*

Variable	Method	Statistic
Sex	Cramer's V	0.1109
ABFA certification	Cramer's V	0.1303
Terminal degree	Cramer's V	0.2067
Type of forensic anthropologist	Cramer's V	0.2827
Classification of institution (academic FAs only)	Cramer's V	0.2379
Rank (academic FAs only)	Cramer's V	0.5463
Additional administrative duties (academic FAs only)	Cramer's V	0.3728
Lab time (applied FAs only)	Cramer's V	0.1713
Active years	Kruskal-Wallis rank sum	50.88 (p-value = 0.1386)

TABLE 5—*Confusion matrix for the all-academic forensic anthropology RFM.*

SI Category	One	Two	Three	Four	Classification Error
One	24	14	4	1	0.44
Two	16	15	3	1	0.57
Three	7	8	0	4	1.00
Four	1	3	1	12	0.29

TABLE 6—*Confusion matrix for the academic forensic anthropology RFM.*

SI Category	One	Two	Three	Four	Classification Error
One	11	8	4	1	0.54
Two	7	9	5	1	0.59
Three	3	8	1	3	0.93
Four	0	3	2	11	0.31

TABLE 7—*Confusion matrix for the applied forensic anthropology RFM.*

SI Category	One	Two	Three	Four	Classification Error
One	15	3	1	0	0.21
Two	4	8	1	0	0.39
Three	3	1	0	0	1.00
Four	0	1	0	0	1.00

In the analysis of all academic anthropologists, the four-means clustering of SI into SI categories resulted in an almost even distribution of individuals within each category (see Table 3). From the Cramer's V tests, we see a strong correlation between SI category and classification (Cramer's V = 0.4655) and rank (Cramer's V = 0.5463). The lowest correlation was found between SI category and subfield

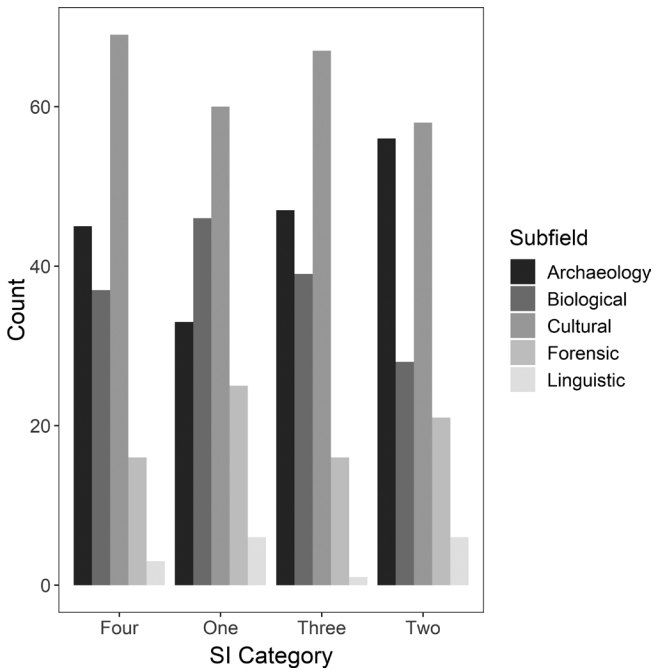

FIG. 5—*Bar plot showing the number of individuals in each SI category by anthropology subfield.*

(Cramer's V = 0.0953). Figure 7 illustrates the findings from the Cramer's V tests, although there is an observable majority of outliers in archaeology.

The RFM trained using the all-academic anthropology training data was applied to the test data and resulted in a 54.07% classification accuracy (see Table 5). Revisiting the confusion matrix and classification errors indicates clear delineations for the extreme SI categories (One and Four) and less differentiation between SI categories Two and Three.

Figure 8 summarizes the mean decrease in the Gini index for each variable for the all-academic anthropology RFM. Evaluating variable importance, rank is visibly the most important variable. Contrary to the Cramer's V results, which showed a low association between subfield and SI category (from Table 8: Cramer's V = 0.0953), subfield is the second-most-important variable in the RFM, potentially due to the disproportionate number of cultural anthropologists in the sample and of cultural anthropologists and archaeologists who occupy the higher ranks (Fig. 9).

TABLE 8—*Summary of tests of association between SI categories and predictor variables for academic anthropologists.*

Variable	Method	Statistic
Sex	Cramer's V	0.1739
Classification of institution	Cramer's V	0.4655
Rank	Cramer's V	0.5463
Additional administrative duties	Cramer's V	0.2053
Subfield	Cramer's V	0.0953

TABLE 9—*Confusion matrix for the RFM of all academic anthropologists.*

SI Category	One	Two	Three	Four	Classification Error
One	20	8	4	0	0.38
Two	7	15	5	1	0.46
Three	6	10	15	10	0.63
Four	1	0	10	23	0.32

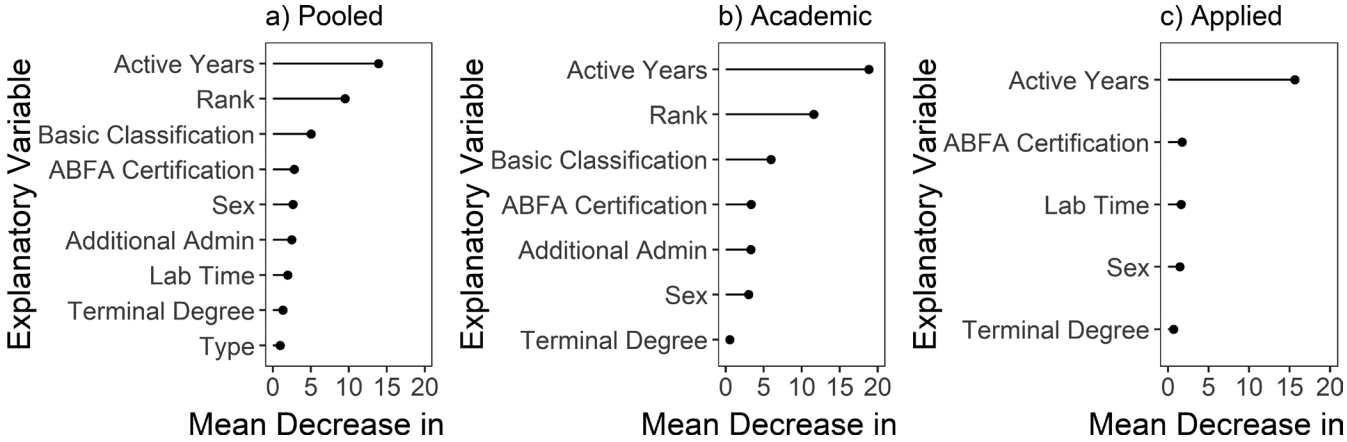

FIG. 6—*Variable importance plots for the (a) pooled forensic anthropologists, (b) academic forensic anthropologists, and (c) applied forensic anthropologists.*

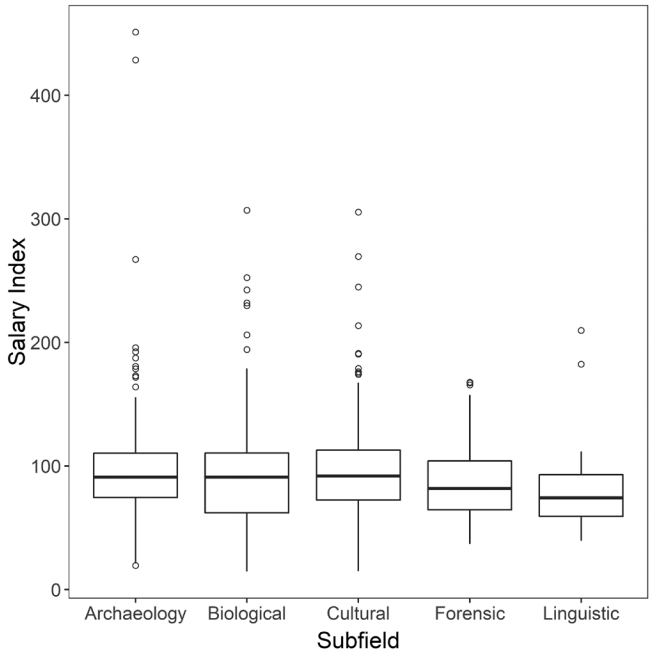

FIG. 7—*Box plot of the spread of SI separated by anthropological subfield.*

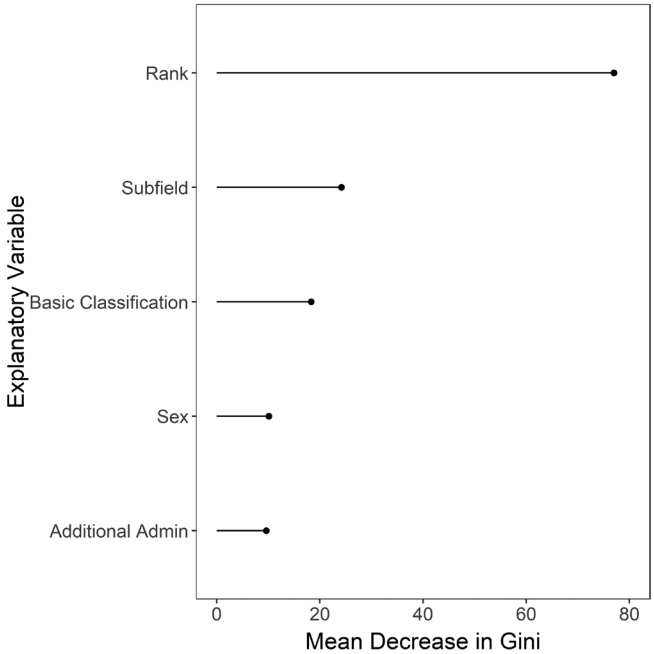

FIG. 8—*Variable importance the all-academic anthropology data set.*

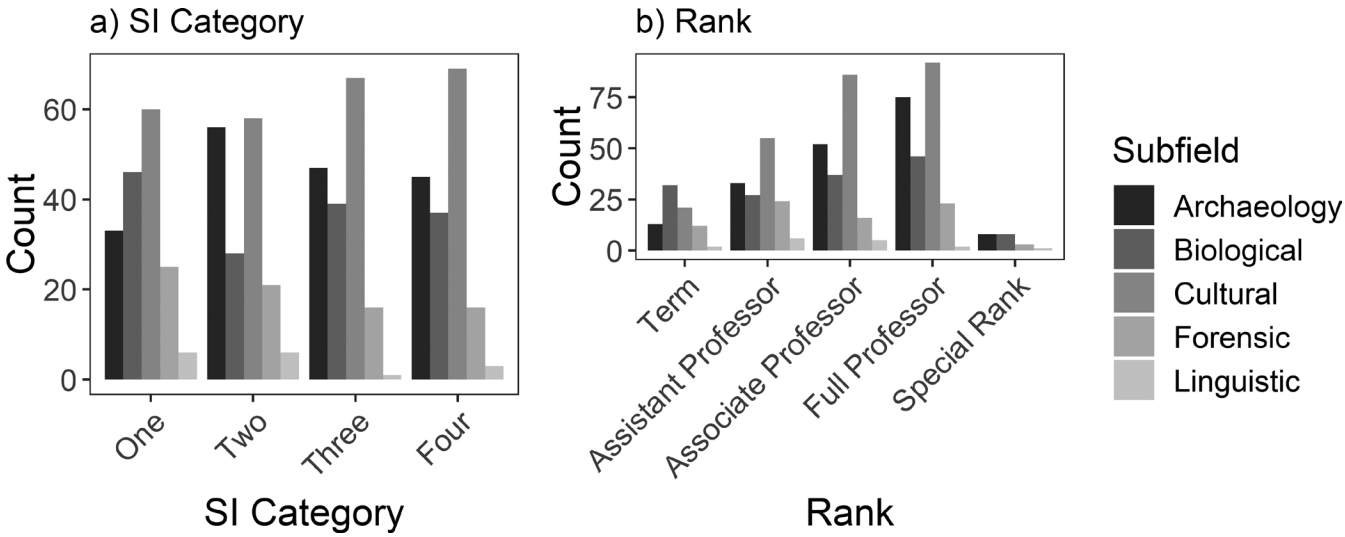

FIG. 9—*Distribution of individuals in each (a) SI category by subfield, and (b) rank by subfield.*

Discussion

Salaries in Forensic Anthropology

An overall view of the distribution of SI categories (and therefore, salaries) of forensic anthropologists shows a slight skew toward the first two SI categories, representing 68.42% of the sample (see Fig. 3). From the tests of association, the only strong correlation found using Cramer's V was between SI category and rank (Cramer's V = 0.5463). While the classification accuracy for each RFM ranged between 41.56% (academic-only model) to 62.16% (applied-only model), the classification errors associated with the confusion matrices are worth noting. The high levels of classification error for the first three SI categories in the academic forensic anthropology model allude to inconsistencies in salaries for the academic sector. The confusion matrix for academic forensic anthropologists (see Table 5) indicates that there seems to only be a clear distinction between those in SI category Four (i.e., the highest earners) and all others, where

there is significant overlap in misclassifications between SI categories One, Two, and Three and less overlap in SI category Four.

While no significant differences in forensic anthropologists' salary were found based on gender using the present data set, gender-based salary differences have been found in other applied forensic science positions (Dawley et al. 2014). Using survey data collected from 65 forensic scientists employed at crime labs throughout the United States, Dawley et al. (2014) found that the average woman forensic scientist was paid $59,500 while the average male forensic scientist was paid $74,000, a difference of 19.6%. Previous research in both the academic and applied sectors have found significant differences in salary between men and women (e.g., Barbezat & Hughes 2005; Burke et al. 2005). Such studies examined individuals in broader contexts (across departments and colleges at universities) and had additional data available (e.g., seniority, experience, accumulated merit, etc.). Similarly, others have found that the number of publications in top-tier journals is an important contributing factor to faculty salaries as well (Gomez-Mejia & Balkin 1992). However, as has been demonstrated recently (Pilloud & Passalacqua In press), women make up a large majority of the forensic anthropology workforce, so the findings here may be more specific to anthropology in comparison with other research.

Salaries of forensic anthropologists working in applied positions were examined separately from those in academic positions, because little research has been conducted on the salaries of forensic scientists in applied positions and much of the research indicates that forensic scientists are underpaid (Albert et al. 2017; Becker et al. 2003, 2005; Dale & Becker 2003, 2004; Dawley et al. 2014; Higgins & Selavka 1988; Kemp 2014; Speaker 2009; Speaker & Fleming 2010). Of course, forensic anthropologists typically have advanced graduate degrees (master's and/or doctoral), are more closely associated with medicolegal death investigations, and are employed in ME/C offices rather than crime labs. Thus, as a point of comparison, Kemp (2014) examined the salaries of 337 forensic pathologists working in the United States using a similar approach as was taken here. Kemp (2014:509) found that when salaries were adjusted for COL, the median salary for chief medical examiners was $198,404 and for forensic pathologists was $164,548. When compared to forensic anthropologists from this sample employed full time at ME/C offices ($n = 37$), the median SI was 61.84 and the mean SI was 65.93, which corresponds to an adjusted median salary of $61,840. Based on these results, it appears that forensic anthropologists are paid barely one-third ($61,840/$164,548 = 37.5%) of what forensic pathologists earn.

Many ME/C offices do not employ forensic anthropologists as full-time staff. Instead, many offices hire forensic anthropologists as consultants on a case-by-case basis, or employ forensic anthropologists with terminal master's degrees in other, lower-level staff positions, such as a medicolegal death investigator or autopsy technician, with the expectation that these individuals will perform forensic anthropology casework as needed. While the data are not currently available for consulting fees and their impact on overall salaries, linking salary/consult fees to forensic anthropology caseload may provide further information regarding the value added by employing forensic anthropologists full time at ME/C offices, even though caseload will vary depending on staffing, jurisdiction, crime rate, and other factors (Speaker 2009).

Considering applied positions, the Defense POW/MIA Accounting Agency (DPAA) has two forensic anthropology laboratories and a current staff of approximately ninety anthropologists and archaeologists, making it the largest employer of forensic anthropologists in the world. The DPAA employs two classes of staff: government employees (in General Schedule [GS] positions) and contractors employed via a contracting agency. While GS salaries can be found for general steps and grades, these data do not account for any cost-of-living allowances (COLA) or other pay adjustments these individuals may earn, nor are the precise steps and grades of each GS anthropologist employed at the DPAA publicly available. Therefore, for both classes of employment category, the only way to get specific salaries would be to file a successful FOIA request, and thus this salary information was not included here.

Factors Affecting Academic Salaries in General

Ransom (1993) examined salary versus seniority and found that higher levels of seniority were associated with higher salaries for all occupations *except college/university professors* (Duncan et al. 2004:295). This finding was attributed to academic institutions having monopsony power, or a monopoly of the job market. Essentially the argument is that academic institutions are geographically separated, which requires longer-distance relocations and associated uprooting of families, while the tenure system disincentivizes faculty from moving institutions, as they are often forced to add time toward obtaining tenure or may need to start the tenure process over again. Other work has suggested that while academic monopsony is likely a contributing factor to issues related to faculty salaries, faculty salaries are more associated with market conditions, with entry-level faculty salaries subject to competitive market rates at the time of hire (Baker et al. 1994; Caplow & McGee 1958; Duncan et al. 2004).

Senior faculty often earn less than junior faculty due to a lack of salary increases in comparison with the market, which may disincentivize individuals of all ranks from working harder after tenure. This is largely because salary compression and salary inversion are extremely common in academia (Burke et al. 2005; Duncan et al. 2004; Twigg et al.

2002). These factors arise when entry-level employees are hired with similar (compression) or higher salaries (inversion) in comparison to preexisting senior-level employees. Compression and inversion likely contribute to the limited predictive power of the modeling attempted here.

In both academic and applied positions, there are often limited avenues for increasing one's salary aside from structured salary increases. These increases are often available to all employees in the form of timed grade or step increases (e.g., moving from a GS12-01 to a GS12-02 for federal employees) or rank-based promotion (e.g., moving from assistant to associate to full professor, which can be considered step increases). Outside of such structures, individuals typically lack access to merit-based salary increases (Campbell et al. 2010; Heneman & Cohen 1988) and are often forced to apply for other jobs in hopes of receiving a better offer elsewhere or a counteroffer by their current employer (O'Meara 2015; Siow 1998). The failings of such a system result in faculty salaries declining over time as they fail to get raises simply to adjust for inflation (Burke et al. 2005; Siow 1998).

While some argue that individuals should not apply to positions they are uninterested in solely in hopes of obtaining a counteroffer at their current institution (Dubrow 2013), Siow (1998:163–164) argues that this is simply an expression of market forces upon faculty in academia. Essentially, academic institutions can only offer faculty salaries based on their expected outputs (in terms of teaching, scholarship, and service), and it is not until a faculty member's output has been demonstrated to be above his or her institutional average that the faculty member can obtain a counteroffer, and thus obtain a more appropriate (i.e., market-adjusted) salary.

O'Meara (2015) examined impacts relating to academic institutional policies that essentially require faculty to obtain "outside offers" in order to increase their salary at their current institution. O'Meara found consensus between faculty who departed, faculty who were retained, and administrators that such policies resulted in negative influences on institutional retention efforts as well as faculty organizational commitment (i.e., "the relative strength of an individual's identification with and involvement in a particular organization" [Mowday et al. 1982:226]). O'Meara argued that the policy was effective in a broad economic sense, in that the policy forced organizations to pay individuals what they are worth based on the free market, but that it also resulted in institutions losing individuals they would have liked to retain. Recommendations for revising such practices included providing counteroffers to faculty upon confirmation of an on-campus interview request, creating institutional reward programs to increase faculty salaries based on performance (such as merit pay), increasing transparency and shared governance into the entire process, and investing in faculty via on-campus awards, benefits, and other services (O'Meara (2015). Other research has found that factors such as promotion and tenure, merit pay, allocation of space, and travel funds influence faculty retention/departure (e.g., Daly & Dee 2006; Johnsrud & Rosser 2002; Rosser 2004; Smart 1990).

Conclusions

This project examined salary data for forensic anthropologists specifically as well as academic anthropologists in general. Results found that in all models there were no differences in salary between men and women. Further, no significant differences were found between anthropology subfields in academia. Importantly, years in the discipline was the most important variable in all models for forensic anthropologists, with rank being the most important variable for all academic anthropologists.

The results of this study are promising in that there is gender parity in salaries among forensic anthropologists. However, it would appear that forensic anthropologists (and anthropologists in general) are underpaid professionals. In the academic sector, anthropology salaries are below the national average in all categories (American Association of University Professors 2018). In the applied sector, on average forensic anthropologists are paid less than half of what forensic pathologist are paid, with forensic pathology being known for its relatively poor salary in comparison to its education and training requirements. We argue that continued salary transparency is important to for salary equity among forensic anthropologists and may also have an impact on increasing forensic anthropology salaries in general.

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References

Albert A, Schwartz J, Arnold A. Forensic science curricular and career planning: A modified system theory-based model for student advising. *Journal of Forensic Science and Criminology* 2017;5:403.

American Association of University Professors. *Annual Report on the Ecomonics Status of the Profession: 2017–2018*, https://www.aaup.org/sites/default/files/ARES_2017-18.pdf, 2018.

Azfar O, Nelson WR. Transparency, wages, and the separation of powers: An experimental analysis of corruption. *Public Choice* 2007;130:471–493.

Baker G, Gibbs M, Holmstrom B. The wage policy of a firm. *Quarterly Journal of Economics* 1994;109:921–955.

Barbezat DA, Hughes JW. Salary structure effects and the gender pay gap in academia. *Research in Higher Education* 2005; 46:621–640.

Becker WS, Dale WM, Lambert A, Magnus D. Letter to the editor—Forensic lab directors' perceptions of staffing issues. *Journal of Forensic Science* 2005;50:JFS2005201–2005203.

Becker WS, Lambert A, Magnus D. *Staffing Issues in the Crime Lab: National Survey of Forensic Science Lab Directors*, Southern Management Association 2003 Meeting, 2003. 273–279.

Bivand R. classInt: Choose univariate class intervals. R package version 0.4-2. https://CRAN.R-project.org/package=classInt. 2019.

Breiman L. Random forests. *Machine Learning* 2001;45:5–32.

Burke K, Duncan K, Krall L, Spencer D. Gender differences in faculty pay and faculty salary compression. *Social Science Journal* 2005;42:165–181.

Burroughs JD. Pay secrecy and performance: The psychological research. *Compensation Review* 1982;14:44–54.

Campbell A, Lindsay DH, Garner DE, Tan KB. The impact of merit pay on research outcomes for accounting professors. *Contemporary Issues in Education Research* 2010;3:55–62.

Caplow T, McGee RJ. *The Academic Marketplace*. New York: Transaction Publishers; 1958.

Card D, Mas A, Moretti E, Saez E. Inequality at work: The effect of peer salaries on job satisfaction. *American Economic Review* 2012;102:2981–3003.

Cullen Z, Perez-Truglia R. *How Much Does Your Boss Make? The Effects of Salary Comparisons*, National Bureau of Economic Research, https://www.nber.org/papers/w24841, 2018;1–52.

Dale W, Becker W. A case study of forensic scientist turnover. *Forensic Science Communications* 2004;6.

Dale W, Becker W. Strategy for staffing forensic scientists. *Journal of Forensic Sciences* 2003;48:465–466.

Daly CJ, Dee JR. Greener pastures: Faculty turnover intent in urban public universities. *Journal of Higher Education* 2006;77: 776–803.

Dawley DD, Houck MM, Gupta S. Women, forensic science, and STEM: An initial inquiry. *Forensic Science Policy and Management* 2014;5:70–75.

Dubrow H. *The Counteroffer Game*, Inside Higher Ed, https://www.insidehighered.com/advice/2013/08/26/essay-calling-end-counteroffer-strategies-academic-hiring, 2013.

Duncan KC, Krall L, Maxcy JG, Prus MJ. Faculty productivity, seniority, and salary compression. *Eastern Economic Journal* 2004;30:293–310.

Estlund C. Extending the case for workplace transparency to information about pay. *UC Irvine Law Review* 2014;4:781–800.

Estlund C. Just the facts: The case for workplace transparency. *Stanford Law Review* 2010;63:351–408.

Gardner TM, Stansbury J, Hart D. The ethics of lateral hiring. *Business Ethics Quarterly* 2010;20:341–369.

Gomez R, Wald S. When public-sector salaries become public knowledge: Academic salaries and Ontario's Public Sector Salary Disclosure Act. *Canadian Public Administration* 2010; 53:107–126.

Gomez-Mejia LR, Balkin DB. Determinants of faculty pay: An agency theory perspective. *Academy of Management Journal* 1992;35:921–955.

Heneman RL, Cohen DJ. Supervisory and employee characteristics as correlates of employee salary increases. *Personnel Psychology* 1988;41:345–360.

Higgins KM, Selavka CM. Do forensic science graduate programs fulfill the needs of the forensic science community? *Journal of Forensic Science*. 1988;33:1015–1021.

Houck MM, Siegel JA. *Fundamentals of Forensic Science,* 2nd ed. Burlington, MA: Academic Press; 2010.

Janićijević N. Pay secrecy: Pros and cons. *Ekonomika preduzeća* 2016;64:225–238.

Johnsrud LK, Rosser VJ. Faculty members' morale and their intention to leave: A multilevel explanation. *Journal of Higher Education* 2002;73:518–542.

Kemp WL. Forensic pathologist salaries in the United States: The results of internet data collection. *Academic Forensic Pathology* 2014;4:505–513.

Kuhn M. Classification and regression training. R package version 6.0-8.5. https://CRAN.R-project.org/package=caret. 2020.

Liaw A, Wiener M. Classification and regression by random forest. *R news* 2002;2:18–22.

Marutho D, Handaka SH, Wijaya E. *The Determination of Cluster Number at k-mean Using Elbow Method and Purity Evaluation on Headline News*. 2018 International Seminar on Application for Technology of Information and Communication, IEEE, 2018. 533–538.

Missouri Economic Research and Information Center. 2019. https://meric.mo.gov/data/cost-living-data-series. Last accessed 4/28/20.

Mowday R, Porter L, Steers R. *Employee-Organization Linkages*. New York: Academic Press; 1982.

O'Meara K. Half-way out: How requiring outside offers to raise salaries influences faculty retention and organizational commitment. *Research in Higher Education* 2015;56:279–298.

Passalacqua NV, Pilloud M, Belcher WR. Scientific integrity in the forensic sciences: Consumerism, conflicts of interest, and transparency. *Science and Justice* 2019;59:573–579.

Pilloud MA, Passalacqua NV. "Why are there so many women in forensic anthropology?": An evaluation of gendered experiences in forensic anthropology. *Forensic Anthropology*. In press.

Raileanu LE, Stoffel K. Theoretical comparison between the gini index and information gain criteria. *Annals of Mathematics and Artificial Intelligence* 2004;41:77–93.

Ramachandran G. Pay transparency. *Penn State Law Review* 2011; 116:1043–1080.

Ransom MR. Seniority and monopsony in the academic labor market. *American Economic Review* 1993;83(1):221–233.

R Core Team. *R:* A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna Austria, 2019. ISBN 3-900051-07-0, http://www.R-project.org.

Rosenfeld J, Denice P. The power of transparency: Evidence from a British Workplace Survey. *American Sociological Review* 2015;80:1045–1068.

Rosser VJ. Faculty members' intentions to leave: A national study on their worklife and satisfaction. *Research in Higher Education* 2004;45:285–309.

R Studio Team. RStudio: Integrated development for R. RStudio, Inc. http://www.rstudio.com/, Boston; 2018.

Siow A. Tenure and other unusual personnel practices in academia. *Journal of Law, Economics, and Organization* 1998;14: 152–173.

Smart JC. A causal model of faculty turnover intentions. *Research in Higher Education* 1990;31:405–424.

Speaker PJ. The decomposition of return on investment for forensic laboratories. *Forensic Science Policy and Management* 2009;1:96–102.

Speaker PJ, Fleming AS. Benchmarking and budgeting techniques for improved forensic laboratory management. *Forensic Science Policy and Management* 2010;1:199–208.

Twigg NW, Valentine SR, Elias RZ. A comparison of salary compression models and pay allocation in academia over time. *Review of Higher Education* 2002;26:81–96.