A Bayesian Decomposition Approach to Gender Wage Gaps

Clinton L. Neill*

Assistant Professor
Department of Agricultural and Applied Economics
Virginia Tech

Mariah Beverly

Graduate Research Assistant
Department of Agricultural and Applied Economics
Virginia Tech

Kimberly L. Morgan

Associate Professor
Department of Agricultural and Applied Economics
Virginia Tech

*Corresponding Author Address: Agricultural and Applied Economics, Hutcheson Hall 206-A, Blacksburg, VA 24060 telephone: 540–231–0770, e-mail: *cneill@vt.edu*. Data and financial support for this work was provided by the American Veterinary Medicine Association (AVMA). The authors are not at liberty to divulge the data, but a request to the AVMA can be submitted for access.

A Bayesian Decomposition Approach to Gender Wage Gaps

Abstract

Workers in professional service industries (doctors, lawyers, veterinarians, etc.) are characterized by highly specialized skillsets. This type of skill development requires standardized education across all accredited institutions. Yet, a wage gap still persists within these industries. Professional service education is also notorious for high debt to income ratios. A persistent wage gap confounds the problem of student loan debt repayment. This study discusses the conceptual and empirical quandary of gender wage gaps within professional services. Specifically, we focus on new entrants with an application to veterinary medicine. This study presents a Bayesian decomposition framework, where the overlap between male and female wage distributions can be examined within the highest density posterior intervals. The findings suggest that wage growth over time, presence of children, and practice type explain a significant part of the wage gap in veterinarians. Moreover, in recent years, an increasing percentage of new female veterinarians are earning similar or higher wages than their male counterparts.

1 Introduction

Evidence of gender wage gaps have been found in multiple industries. Since World War II, female participation in the labor force has increased such that the United States work force is equally comprised of both male and female workers. This is especially true for professional service industries such as medical doctors, lawyers, dentists, and veterinarians. Many wage inequality studies (Michelmore and Sassler, 2016; Kuhn and Weinberger, 2005; Bertrand, Goldin, and Katz, 2010; Dunn and Shapiro, 2014; Rosen, 1992) have used individual professional services industries as case studies for numerous theories. These industries have a high degree of standardization, which helps to highlight inequalities such as the gender wage gap. However, professional services typically require advanced schooling from a nationally accredited program, licensing (typically, done by exam and varies by state), selection of a well-defined specialty field, and continuing education throughout one's career. As such, expected earning paths and factors affecting inequalities are unique.

The Higher Education Act of 1973 allowed for certain aspects of the Civil Right Acts and Equal Pay Act of 1963 to prohibit discrimination by gender (Houghton, 1999). Thus, the share of female professional service providers has increased exponentially since 1972 (Hegewisch and Hartmann, 2014). Yet, very few professional service populations are comprised of greater than 50% female. Perhaps the only two such fields are pharmacists and veterinarians (Hegewisch and Luyri, 2010). Further, the growth in the number of women in professional services has stalled in recent years (Hegewisch and Hartmann, 2014). Thus, the literature is rife with new studies and press coverage about the gender wage gap. For example, a recent article highlighted the fact that women are more likely to leave STEM (Science, Technology, Engineering, and Mathematics) fields after they have children (Cech and Blair-Loy, 2019).

While laws have been put in place to discourage gender pay discrimination in the workplace, they often fail to do so due to cumbersome requirements for the plaintiff to follow in order to pursue a complaint (Canales, 2017). Title VII of the Civil rights act requires the plaintiff to file a formal charge within the first 180 to 300 days after the unlawful practice occurred. Since pay secrecy is often strongly encouraged or employees sign a contract forbidding them to discuss pay, discovering pay rate information could take months or even years. The Equal Pay Act requires the plaintiff to provide proof of different wages paid to someone of the opposite gender in the same position or performing a job of equal skill within two years. The Equal Employment Opportunity Commission (EEOC) oversees the enforcement of both Acts and determines what qualifies as a violation (Houghton, 1999). According to the national enforcement plan issued in 1996, only cases where "egregious violations are found" will be pursued (Houghton, 1999). By tasking the plaintiff with providing evidence needed to prosecute, and the overwhelming number of claims handled by the EEOC, there is reason to suspect many cases are not reported (Canales, 2017). Since professional services operate in a monopolistically competitive market, there are often non-disclosure and non-compete clauses in contracts that exaggerate this issue. Even those working in academic positions are vulnerable to gender wage gaps (Chen and Crown, 2019). As professional services span different types of labor markets, it is imperative to better understand the gender wage gap on a deep level.

The remainder of this article will review the underlying economic theory of professional service industries, develop a mixed methods approach to determine the gender wage gap in professional services with an application to veterinarians, and develop a Bayesian decomposition approach to analyzing gender wage gaps. We focus on a mixed methods approach (qualitative and quantitative) to better understand the gender wage gap and validate our results.

2 Conceptual Framework

As with any individual investment decision, people invest in education (also known as human capital) to increase their expected wages. Typically, one can observe this human capital investment in a two period framework. The individual's lifetime wealth, V, equals the discounted value of their earnings' stream net the investment in their education (Laing, 2011):

$$V = (w_0 - s_0) + \frac{w_1}{(1+r)^1} + \frac{w_2}{(1+r)^2} + ... + \frac{w_T}{(1+r)^T} \tag{1}$$

where w_0 are any earnings received during their time in college, s_0 is the cost of college, w_t is the expected earnings after they graduate in each of the years $t = 1, 2, ..., T$, and r is the interest rate. The first part of the equation $(w_0 - s_0)$ represents the time in which a person is in college, while the rest of the equation is the working life. If one chooses to attend college, then the present discounted value of lifetime wealth $(V(s))$ would be:

$$V(s) = (w_0 - s_0) + \frac{w_s}{(1+r)}. \tag{2}$$

However, if they do not choose to attend college, they earn a a constant w_n in each period. Thus, the wealth equation would transform to

$$V(n) = w_n + \frac{w_n}{(1+r)}. \tag{3}$$

The individual would choose to attend college if $V(s) \geq V(n)$. These expressions have underscored the human capital framework as developed by Becker (1962).

Professional service industries require additional schooling beyond an undergraduate degree. Thus, one expects a higher expected wage from the additional investment in human capital. A two-period model could be used to demonstrate the additional costs beyond an undergraduate degree, but a three-period framework represents the problem more fully. As represented in Figure 1, one must make two decisions about educational investment: (1) Attend college to receive an undergraduate degree, and (2) upon completion of an undergraduate degree, attend a professional service education program. It is important to discuss both investment decisions, as one must have an expected wage great enough to cover the cost of attending both college and professional service education.

With the addition of the second human capital investment decision, present discounted values presented in equation (2) is now altered to

$$V(s_1) = (w_0 - s_1) + \frac{w_s}{(1+r)}. \tag{4}$$

where s_1 represents the investment cost of attending an undergraduate degree program and w_s is the wage after (s)he graduates their undergraduate program. Now that a second investment cost exists, we have a third discounted value

$$V(s_2) = (w_0 - s_1 - s_2) + \frac{w}{(1+r)}. \tag{5}$$

where s_2 is the investment cost of attending a professional service education program, and w is the expected wage earned as a result of completing professional service education. This type of three-period model could be used for any advanced education beyond the undergraduate level. Thus, a professional service education decision requires the unique view of the three-period model to understand the complete human capital investment decision.

One could argue, that the investment cost is a sunk cost upon completion of the professional degree. While we assume this in our later application, the expectation of investment cost relative to expected wage is imperative to the decision of whether or not to pursue further education. If the investment cost, often measured as student debt, is significantly higher than wages one should not choose to attend professional education. Similarly, if discrimination exist, one group would experience a higher debt, and thus may choose not to invest in further education. As Sunstein (1991) notes, discrimination has a large effect on human capital and markets, alone, cannot be used as an anti-discrimination policy.

2.1 Gender Wage Gaps in a Principal-Agent Framework

Assume that there are two workers entering into a profession - one male and one female. Also, assume that these workers are treated equally (i.e. no discrimination exists). Upon entering a professional service industry (or any industry), the male and female workers invest approximately equal amounts of capital into their education. They both attended the same program, graduated with the same proficiency in skills, and both possess high recommendations from other professionals within the industry. Thus, *ceterus paribus*, both workers should receive equal wages. More formally, a female worker is expecting the same wage as her male counterpart

$$\int w_F(X, \psi) = \int w_M(X, \psi) \tag{6}$$

where $w_F = w_M = w$ from equation (5); X is a vector of individual and educational characteristics (which have been assumed equal between workers); and ψ represents the difference in gender identity.

Now assume that discrimination exists. Discrimination is characterized as a market failure due to asymmetric information. As is well established in the literature, most industries experience a gender wage gap. Within a principal-agent framework, the principal (the firm/hiring manager) discriminates between the two agents and opts to pay the female agent less. This decrease in expected wage creates an inequality:

$$\int w_F(X, \psi_F) < \int w_M(X, \psi) \tag{7}$$

where ψ_F represents the discounted wage received by the female worker due to discrimination. The discrimination factor could be a function of sexism, expected work hours, child-rearing and caring expectations, or a host of other factors. The issues affecting the discrimination factor is the primary focus of previous gender wage gap research and is the focus of this study.

2.2 Gender Wage Gaps in Service Industries

Service industries are less prone to "brawn" skills than product producing industries which makes them more predisposed to women workers as compared to the production of goods (Ngai and Petrongolo, 2017). Thus, Ngai and Petrongolo (2017) suggest that women have a comparative advantage in service industries. This advantage increases the relative wage and total market work hours of women.

In general, high skill, integrated (not heavily dominated by males or females) occupations have lower median hourly earnings for women than men. However, if the occupation is predominately female, women actually earn higher median hourly earnings than men (Hegewisch and Hartmann, 2014). As previously mentioned, most professional service industries are not predominately female. In addition, professional services are classified as high skilled since they require advanced education and specialized training. Hegewisch and Hartmann (2014) suggests that women may not actually be paid less, but rather work less hours in high skilled occupations. For some professional service industries, evaluation of the wage rate between male and female workers is apparent. For instance, the performance of lawyers is calculated by the number of hours billed to clients and the amount of new client revenue generated (Azmat and Ferrer, 2017). High skilled occupation pay and promotion are explicitly tied to performance evaluations and lead to pay transparency (Lemieux, MacLeod, and Parent, 2009; Lazear and Shaw, 2007; Azmat and Ferrer, 2017). However, this is not standard across all professional service industries because of nondisclosure clauses within a monopolistically competitive market (Neill et al., 2019).

2.2.1 The Role of Parenting in Wage Disparities

As Cech and Blair-Loy (2019) report, nearly half of all female scientist in the United States leave full-time science after their first child. In addition, nearly a quarter of new fathers leave full-time science after the birth or adoption of their first child. This disparity has been noted for the lack of representation of women in traditional science, technology, engineering, and mathematics fields. As Goldin (2006) finds, women with children have a mean out-of-work period about five times higher than those women without children (2.08 years versus 0.41 years, respectively). When comparing women with children to men, the average is approximately 8.5 times as high. The literature is consistent in the finding that the presence of children has a negative effect on both parents' earnings, but women experience a heftier discount.

It is clear that employer decision making on who to hire and how much to pay is conditionally based on future expected work hours. If employers believe women will eventually choose to have children, the expected returns gained from hiring a woman is lower than that of hiring a man. Whether this thought process is ethical is another topic. However, this asymmetry in principal versus agent optimization is seen as the driver of the gender wage gap.

3 Application to the Veterinary Medicine Industry

As Hegewisch and Luyri (2010) discuss, gender wage disparities are specific to the occupation. When analyzing different professional services, veterinary medicine presents an interesting problem: the profession has recently transformed from predominately male to predominately female. This change in industry gender composition is, likely, the result of the High Education Act of 1973. In 1970, only 7.8% of Doctor of Veterinary Medicine (DVM) graduates were female, while in 2008 almost 80% of graduates were female (Irvine and Vermilya, 2010).

This study focuses on the gender wage gap between graduating veterinary medicine students. New veterinarians have not experienced absences from the work force, and they have equal amounts of experience as a DVM. This eliminates some of the potential wage disparity explanations discussed in previous literature. So, this application focuses on family situations, age, school choice, location of job, specialty (practice area) choice, and time as explanatory factors affecting gender wage disparities among new veterinarians.

3.1 Data

Between 2009 and 2017, the American Veterinary Medical Association conducted an annual survey of fourth-year veterinary medical students in conjunction with the 28 U.S. schools and colleges of veterinary medicine. Surveys have been collected since 2000, but we focus on the later surveys for three reasons: (1) the surveys significantly changed in 2009 and have remained relatively consistent, so we are able to have more explanatory variables; (2) we wanted to analyze incomes after the Great Recession, as there is a structural shift in incomes after 2008; (3) the veterinary industry shifted from an integrated workforce to predominately female during this time period. Surveys were sent to all veterinary medical students expected to graduate in each year approximately 4 weeks before graduation. The survey remained active until graduation. The respondents gave information relating to their employment choices, expected salaries, and estimated debt amount upon graduation (Shepherd and Pikel, 2012). Several students did not report a starting salary. Summary statistics for the survey results are reported in Table 1 by gender.

Not every student had a pending job, which in turn means that not all students participating in the survey reported a starting salary. In total, 22,902 graduating seniors responded to the surveys. Of those that responded to the survey, 15,969 reported a starting salary. The average response rate across years is about 95% and about two-thirds of the new veterinarian population reported a salary.

3.2 Methods

In order to analyze gender wage disparities within new veterinarians, we focus on the demographics, practice type choice, and school choice of the new veterinarian. As discussed in previous literature, specialty choice plays a significant role in salaries and can impact lifetime earnings (Neill et al., 2019; Neill, Holcomb, and Brorsen, 2017, 2018). In addition, literature suggests that demographic information (outside of gender), like children in the household and marital status, explain a significant proportion of the gender wage gap (Bertrand and

Hallock, 2001). Institution choice also likely plays a role in returns to education. Based on the work of Arias, Hallock, and Sosa-Escudero (2002), returns to education vary significantly depending on where in the conditional distribution of wages an individual is located.

As Blinder (1973) and Oaxaca (1973) discovered, decomposing a sample into male and female respondents, distinct differences among demographics and practice type choice will be revealed. While this is not traditional Blinder-Oaxaca decomposition, it does expand upon the work of DiNardo, Fortin, and Lemieux (1996) and Radchenko and Yun (2003) to examine posterior densities and the amount of overlap in the highest density posterior intervals. DiNardo, Fortin, and Lemieux (1996) seminal work focused on applying kernel density measures to analyze the effects of labor market factors. Their work highlights the need for more flexible approaches to measuring labor market issues. Our work builds upon these previous approaches by estimating the overlap in distributions in addition to traditional decomposition measures. This adaptation of the Bayesian decomposition presents a richer understanding of the gender wage gap. Further, the quantitative results are validated with a qualitative study (i.e. focus group) to validate econometric findings.

3.2.1 Examining the Gender Wage Gap

As previously noted, a large sample of the population of interest responded to the yearly survey. However, about a third of the respondents did not report a salary which creates a selectivity bias. As such, a Tobit model is used to handle the censoring of starting salaries. Within this application, a Bayesian Tobit model is used due to the high dimensionality of the data and the small sample sizes within specific practice types. Some practice types are only slightly above 1% of the total sample. These small samples within practice types increases the dimensionality problem as the number of observable variables increases. Further a Bayesian Tobit, as compared to a frequentist version, allows for the distribution of the posterior values to be viewed in full. This approach identifies the extent of overlap between male and female predictive wage distributions with less distributional assumptions than a frequentist version.

The structural model is given as

$$
\begin{aligned}
y^*_{ikt} = \boldsymbol{x'_{ikt}}\boldsymbol{\beta} + \xi_{ikt} \qquad\qquad & \xi_{ikt} \sim N(0,\rho^2) \\
y_{ikt} = y^*_{ikt} \qquad if \qquad & y^*_{ikt} > 0 \\
y_{ikt} = 0 \qquad\qquad\qquad & otherwise.
\end{aligned} \tag{8}
$$

The likelihood function can be expressed as (Chib, 1992):

$$
p(\boldsymbol{y}|\boldsymbol{\beta},\tau^2,\boldsymbol{X}) = \prod_{i,y_i>0} \Phi\left(\frac{x_i\beta}{\rho}\right) \prod_{i,y_i>0} \frac{1}{\rho}\phi\left(\frac{y_i - \boldsymbol{x'_i}\boldsymbol{\beta}}{\rho}\right) \tag{9}
$$

where $\phi(.)$ and $\Phi(.)$ denote the standard normal pdf and cdf, respectively. We assign the normal and inverse-gamma priors to $\boldsymbol{\beta}$ and τ^2, respectively.

$$
\begin{aligned}
p(\boldsymbol{\beta} = (2\pi)^{-k/2}|\boldsymbol{Z_0}|^{-1/2} exp\left(-\frac{1}{2}(\boldsymbol{\beta}-\boldsymbol{\mu_0})'\boldsymbol{Z}_0^{-1}(\boldsymbol{\beta}-\boldsymbol{\mu_0})\right), \\
p(\rho^2) = \frac{\tau_0^{z_0}}{\Gamma(z_0)}(\rho^2)^{(z_0+1)}) exp\left(-\frac{\tau_0}{\rho^2}\right)
\end{aligned} \tag{10}
$$

Thus, the joint posterior kernel is (Koop, Poirier, and Tobias, 2007)

$$
\begin{aligned}
p(\boldsymbol{\beta},\rho^2|\boldsymbol{y},\boldsymbol{X}) = exp\left(-\frac{1}{2}(\boldsymbol{\beta}-\boldsymbol{\mu_0})'\boldsymbol{Z}_0^{-1}(\boldsymbol{\beta}-\boldsymbol{\mu_0})\right) * (\rho^2)^{-(v_0+1)} exp\left(-\frac{\tau_0}{\rho^2}\right) * \\
\prod_{i,y_i>0} \Phi\left(\frac{x_i\beta}{\rho}\right) \prod_{i,y_i>0} \frac{1}{\rho}\phi\left(\frac{y_i - \boldsymbol{x'_i}\boldsymbol{\beta}}{\rho}\right)
\end{aligned} \tag{11}
$$

This posterior kernel would not lead to well-understood conditional posteriors due to censoring, so we introduce a latent vector $\boldsymbol{y^*}$ as augmented data:

$$
p(\boldsymbol{\beta},\rho^2,\boldsymbol{y^*}|\boldsymbol{y},\boldsymbol{X}) \propto p(\boldsymbol{\beta},\rho^2,\boldsymbol{y^*}|\boldsymbol{X})p(\boldsymbol{y}|\boldsymbol{\beta},\rho^2,\boldsymbol{y^*}) = p(\boldsymbol{\beta})p(\rho^2)p(\boldsymbol{y^*}|\boldsymbol{\beta},\rho^2,\boldsymbol{X})p(\boldsymbol{y}|\boldsymbol{\beta},\rho^2,\boldsymbol{y^*}). \tag{12}
$$

The latent vector, $\boldsymbol{y^*}$, is conditioned only on $\boldsymbol{\beta}$ and ρ^2 and follows the normal density as given in (13). So, we have

$$p(\boldsymbol{y^*}|\boldsymbol{\beta},\rho^2,\boldsymbol{X}) = (2\pi)^{-n/2}(\rho^2)^{-n/2}exp\left(-\frac{1}{2\rho^2}\left((\boldsymbol{y^*}-\boldsymbol{X\beta})'(\boldsymbol{y^*}-\boldsymbol{X\beta})\right)\right) \tag{13}$$

For the second term, $p(\boldsymbol{y}|\boldsymbol{\beta},\rho^2,\boldsymbol{y^*})$, given a latent observation y_i^*, the value of y_i is determined with certainty, regardless of $\boldsymbol{\beta}$ and ρ^2:

$$p(\boldsymbol{y}|\boldsymbol{y^*},\boldsymbol{\beta},\rho^2) = p(\boldsymbol{y}|\boldsymbol{y^*}) = \prod_{i=1}^{n}\left(I(y_i=0)I(y_i^*\leq 0)+I(y_i=y_i^*)I(y_i^*>0)\right). \tag{14}$$

Note the decoupling of the likelihood function from the main model parameters $\boldsymbol{\beta}$ and ρ^2. This increases the efficiency of the Gibbs sampler. Thus, the augmented joint posterior kernel takes the following form:

$$p(\boldsymbol{\beta},\rho^2,\boldsymbol{y^*}|\boldsymbol{y},\boldsymbol{X})exp\left(-\frac{1}{2}(\boldsymbol{\beta}-\boldsymbol{\mu_0})'\boldsymbol{Z}_0^{-1}(\boldsymbol{\beta}-\boldsymbol{\mu_0})\right)*(\rho^2)^{-\frac{-n-2z_0-2}{2}}exp\left(-\frac{\tau_0}{\rho^2}\right)$$
$$exp\left(-\frac{1}{2\rho^2}\left((\boldsymbol{y^*}-\boldsymbol{X\beta})'(\boldsymbol{y^*}-\boldsymbol{X\beta})\right)\right)*\prod_{i=1}^{n}\left(I(y_i=0)I(y_i^*\leq 0)+I(y_i=y_i^*)I(y_i^*>0)\right). \tag{15}$$

We leave the $y_i^*>0$ cases untouched and draw the $y_i^*\leq 0$ cases from the truncated-from-above-at-zero normal density:

$$y_i^*|\boldsymbol{\beta},\rho^2,y_i=0,\boldsymbol{x_i}(\boldsymbol{x_i'\beta},\rho,-\infty,0). \tag{16}$$

The primary posterior construct of interest in the Tobit model is the expected value of the outcome variable under censoring:

$$p\left(E(y_p|\boldsymbol{x_p},y_p^*>0)\right) = \int_{\theta}\left(\boldsymbol{x_p'\beta}+\rho\frac{\phi\left(\frac{\boldsymbol{x_p'\beta}}{\rho}\right)}{\Phi\left(\frac{\boldsymbol{x_p'\beta}}{\rho}\right)}\right)d\boldsymbol{\theta}. \tag{17}$$

These posterior constructs will better show the disparity between the male and female predictive distributions, thereby quantifying the unexplained gender wage gap.

To better examine the relative differences in veterinarian wage gap, the overlap in the highest density posterior densities (HDPIs) to the full range of HDPIs is estimated for each practice type for a particular school (Moeltner et al., 2009). Moeltner et al. (2009) develop this overlap, henceforth defined as OLR, to estimate the *smallest possible* interval to contain 95% of the density mass of a given distribution. OLR is calculated as

$$OLR_{FM} = (min(u_F, u_M) - max(l_F, l_M))/(max(u_F, u_M) - min(l_F, l_M)) \tag{18}$$

where F and M are the corresponding male and female wage distributions and $l_{(.)}$ and $u_{(.)}$ represent the lower and upper limits of the respective 95% HDPIs. The resulting overlap (or lack thereof) gives a more complete understanding of the gender wage gap across practice types. Further, this is examined at the beginning and end of the time span to determine how the overlap has changed over time.

4 Results

Table 2 reports the means of the parameter estimates from each of the gender specific Bayesian Tobit models. From the demographic variables, female veterinarians see higher returns from having children in the household and are not as heavily discounted for increases in age as compared to males. In contrast, males have higher returns from being self-employment and being married. Both genders see similar increases in salary from expected work hours per week and prior debt accumulation. Interestingly, male veterinarians experience a larger return from higher cost of living states than females. The interaction between expected work hours and children in the household was insignificant and small.

When comparing salary returns from practice type choice, females see higher returns from every practice type as compared to those pursuing advanced education. Note that equine practitioners have lower incomes as compared to those pursuing advanced education, but male veterinarians are more heavily discounted. This is an indicator that female veterinarians are not discounted for their practice type choice. Rather, females are better off in all practice types, relative to males.

Perhaps the most heterogeneous results between male and female veterinarians are the school and year fixed effects. While not all school fixed effects are significant, females experience a salary discount across most of the schools. The exceptions are University of Florida, Ohio State University, and Purdue University. The only statistically significant positive school effect for females is Ohio State University. As for the year fixed effects, both genders see similar year to year trends, but the results are mixed. Between 2010 and 2014, the yearly differences between genders are within one to two standard deviations. In 2015, males experienced a significantly larger return to salaries as compared to females. In 2016 and 2017, females experienced a significantly larger return. Across both genders, there is not much growth in real incomes across time.

To investigate the effects of school and practice type choice on mean starting salaries across time, posterior predictive distribution (PPD) means and standard deviations are constructed for each gender and practice type. Specifically, martial status, gender, and presence of children are used to analyze the differences in posterior mean starting salaries at two schools at the beginning (2009) and end (2017) of time series within the analysis. While PPDs could be constructed for every school and combination of other attributes, we focus on the schools that have the largest, positive effects on male and female starting salaries (Colorado State and Ohio State, respectively), marriage and children. By constructing PPDs for two separate years, we are able to observe how the mean gender wage gap by practice type has changed over time. Other variables in the construct are assumed to be the means of those who reported a starting salary: graduating debt ($131,150), expected weekly work hours (55 hours), age (27.6 years of age), cost of living ($79,800), and the veterinarians were assumed to be working for someone rather than be self-employed.

The 2009 PPDs (Table 3a) for graduates from Colorado State show that the single women without children have higher predictive means in companion animal, food animal, mixed animal, and other practices than single males. In 2009, men with no children graduating from Colorado State had higher predictive means for Equine practices and Uniform services. However, married women without children graduating from Colorado State in 2009 only had higher predictive means in companion and mixed animal practices. When comparing to a school with a larger return for women (Ohio State) in 2009, we find that single men without children only had a higher predictive mean in other practices and married men without children only had higher means in uniformed services and other practices. When considering those veterinarians with children in the household (Table 3b), single women veterinarians graduating from Colorado State have a higher predictive mean in the same practice types as single women without children. Married women with children graduating from Colorado State have higher predictive means for companion, food, and mixed animal practice. For single women with children graduating from Ohio State, their predictive means are higher for every practice type compared to single men with children. Similarly, married men with children only have a higher predictive mean for the other practice type.

When examining the PPDs without children in 2017, it is evident that female veterinarians without children at both schools are better off in terms of starting salaries. For Colorado State in 2017, both single and married women have higher predictive mean salaries across all practice types except for uniformed services. Female graduates from Ohio State in 2017 had higher predictive mean starting salaries across every practice type. However, when children enter the equation, the results are mixed for Colorado State. Single women with children only have higher predictive means in companion animal, equine, mixed animal, and other practice types. Married women with children have higher predictive means in all practice types other than uniform practices. For a school with a larger return for women (Ohio State), single women with children have higher predictive means for every practice type other than uniform practices. Married women with children have higher predictive means across all practice types.

The 95% HDPIs (Table 4) reflect a similar story as starting salaries have clearly increased across time for males and females for most practice types. It is evident that the overlap between genders at the beginning of the time series (2009) is greater than the overlap at the end of time series (2017) for those without children. Further, women veterinarians without children tend to have a higher upper bound on the 95% HDPIs in 2017. However, the results are mixed one children enter the equation. The interplay between marital status and children seems to have the opposite effect as women with children were closer to equivalence in lower and upper bounds in 2009, but in 2017 women with children have higher lower bounds across most practice types. The upper bounds in 2017 are far more mixed.

From the OLR calculations, a more exact estimate of the percentage overlap is possible. Figure 2 shows the overlap in predicted wage distributions by practice type and the change between 2009 and 2017 only for those veterinaians without children in the household. Within Figure 2, it is clear that new female veterinarians have had greater increases in wages. Figure 2 also shows that new male veterinarians tend to have a wider variance across the different practice types. This shows that the top percent of male wages are likely greater than those of the top percent of female wages.

Tables 5a and 6a are the actual percentage of overlap between all genders, without children, and scenarios in 2009 and 2017 that reflect Figures 2 and 3, respectively. Over time, the percentage overlap between genders within the same practice type supports the results of the Bayesian Tobit model. For example, the percentage overlap between genders for single, companion animal veterinarians decreases over time, with the female veterinarian distribution experiencing faster wage growth (see Figure 2a and 3a). Similarly, there is an increase in the overlap over time between genders for married equine veterinarians, again with female veterinarians experiencing faster wage growth (see Figure 2b and 3b). On the other hand, female uniformed service veterinarians experienced slower wage growth than male uniformed service veterinarians since the overlap decreased and the female mean did not surpass the male mean (see Figure 2f and 3f). The combination of Figures 2 and 3 with Tables 5a and 6a, create a clearer understanding of the gender wage gap and the differences between practice type earnings. Similarly, Tables 5b and 6b contain the percentage overlap within practice types for veterinarians with children. Again, there are significant increases in the female distributions for most practice types over time. The most prominent exception is veterinarians in uniformed services. The results show a widening gap between male and female veterinarians in uniformed services, with males distribution increasing at a faster rate across time. When comparing the overlap between those with and without children in household, certain practice types are more affected than others. For example, other practice types have much more overlap in male and female veterinarians with children compared to those without children in 2009 (Tables 5a and 5b). This highlights the significant interplay between marital status and children.

5 Focus Group of Hiring Managers

To verify the quantitative results, a focus group of hiring managers was performed to determine if the statistically significant factors are also qualitatively identified. On July 18, 2018, we conducted a focus group of 7 veterinarians and/or practice managers who are in charge of hiring for their respective practices. Three of the veterinarians participating in the focus group were female and four were male. In addition, one of the participants was a female practice manager without a DVM. Focus Pointe Global (FPG) managed the focus group at their Atlanta, Georgia Buckhead facility. FPG recruited and pre-screened all participants and hosted the meeting in their facility. All seven veterinarians participated in the focus group and received compensation for their time. To respect the rights of our participants, we received approval of our moderator's guide and informed consent process through our respective Institutional Review Board (IRB).

Through the course of the focus group, three main areas were discussed: general personnel management procedures, performance measures (including negotiation of job offer), and retention. Under current practice composition for the participating veterinarians, a large majority have females and/or underrepresented minorities on staff. Two of the veterinarians participating were foreign born. The largest clinic represented had seven full time veterinarians on staff and the smallest clinic represented was a single veterinarian, who is also the practice owner. Only two clinics employed part time veterinarians, with one clinic only using part time work occasionally. The specific questions we will discuss in the results is the following:

> "Suppose you have two job openings for veterinarians to join your growing companion animal practice. Suppose you came across two individuals with identical training, live nearby, and are available to start immediately (graduated from same vet school in May 2018, five years' experience working in a similar practice as technician) except for the following differences..."

The attributes of the candidates varied by gender, age, presence of children and the relative age of the children, marital status, willingness to work weekends, and primary interest (surgical vs. serving clinic clientele).

5.1 Focus Group Discussions

From the focus group, many of the hiring managers were focused on soft skills (communication skills, confidence, compassion for animals and clients, etc.) rather than the variables of interest from the quantitative analysis. When directly asked about physical characteristics within the context of our hiring situation questions, we did discover an important factor for hiring and salary offers. Outside of specific needs of the clinic (some candidates' hours did not work), the largest contributing factor was the presence of young children.

Panelist stated that they expect job candidates to be parents first and believe that "young, married women are likely to have young children in the near future" and will have to budget time for children. One quote was, "kids lead to distractions." The hiring managers stated issue was not necessarily a gender an issue of young children in the household. There may be some unconscious bias as to gender roles and parenting, but we were unable to gain any insight into this topic within this focus group. Moreover, the participants noted that the age of children is important as those under 10 years of age need more attention. This is a key point point that was previously unknown, and has not been explicitly asked on the senior surveys used in this quantitative analysis.

6 Conclusions

Professional services are unique in the sense that they require additional, skill-specific education beyond the undergraduate level. This type of education requires an additional human capital investment(s) with an expectation to earn cumulative lifetime wealth above the cost of the investment. The decision to pursue professional service investments are carefully weighed as students choose undergraduate degrees as most require specific prerequisite coursework in order to enter professional education programs. Professional education programs are regulated by state and national associations that require standardized education in order for students to acquire certifications. This standardization creates an ideal sample to examine for gender discrimination because educational differences are minimized, yet institutional differences still exist.

Veterinarians, like many other professional services, experience a gender wage gap. Unlike other professional services, veterinary medicine has recently become a predominately female workforce. This study has investigated the gender wage gap among new veterinarians between the years of 2009 and 2017 using a Bayesian decomposition method that estimates predictive distribution overlap. Over time, new female veterinarians have experienced a reduction in the wage gap across most practice types. This result is consistent with Hegewisch and Hartmann (2014) findings that women in predominately female occupations experience higher median earnings than men. However, a wage gap is still present for a percentage of new female veterinarians, albeit it is decreasing every year.

At the same time, this result is mixed when it comes to the interplay between marital status and the presence of children in the household. The presence of children affects the mean of predictive posterior densities depending on the institution of interest (i.e. Colorado State versus Ohio State). The percentage of overlap in the HDPI also varies between veterinarians with and without children depending on the veterinarian's chosen practice type. The dynamic relationship between marital status, the presence of children, and institutions proves that gender wage gaps are multifaceted and require multiple analyses that create a more holistic view of the problem.

By calculating the overlap between the posterior densities across time, we have shown the extent to which the male and female predicted wage distributions are attributed to discrimination by practice type. This creates a fuller picture of wage disparities and has the potential to better estimate the proportion of unexplained wage gaps. Thus, the decomposition method presented here not only identifies factors that affect the wage gap, but to what extent this affects the population of interest.

We verified our results using qualitative methods via a focus group of hiring managers for veterinary clinics. As we found quantitatively, the presence of children in the household has a significant effect on earnings for both genders. Furthermore, married women, while earning more than single women, do not receive as large of a salary increase as their married, male counterparts. Within the focus group, hiring managers were concerned about female practitioners' availability to work full time if they had young children. The perceived likelihood of young, married women to have children in the future was also a concern. Hiring managers within our focus group predominately intend for new hires to work full time and understand that family commitments are sometimes a priority over work.

This mixed-methods approach to understanding the gender wage gap among veterinarians, and more generally among professional services, has highlighted the need for more family-centered work place policies. This study has also highlighted the potential for expected gender roles in parenting and childcare. While this is difficult to fully quantify, it was clearly highlighted qualitatively. At the same time, veterinary clinics are typically privately owned small businesses. This means that, even when operating profitably, the ability to offer services that are family-centered may not be economically feasible. There is need for a balance between eliminating discrimination of marginalized populations (i.e. women) and meeting employee needs in mind. Since professional service industries require highly-skilled workers, the need more more inclusive work-life policies will continue to be a topic of interest.

Bibliography

Arias, O., K.F. Hallock, and W. Sosa-Escudero. 2002. "Individual heterogeneity in the returns to schooling: instrumental variables quantile regression using twins data." In *Economic Applications of Quantile Regression*. Springer, pp. 7–40.

Azmat, G., and R. Ferrer. 2017. "Gender gaps in performance: Evidence from young lawyers." *Journal of Political Economy* 125:1306–1355.

Becker, G.S. 1962. "Investment in human capital: A theoretical analysis." *Journal of political economy* 70:9–49.

Bertrand, M., C. Goldin, and L.F. Katz. 2010. "Dynamics of the gender gap for young professionals in the financial and corporate sectors." *American Economic Journal: Applied Economics* 2:228–55.

Bertrand, M., and K.F. Hallock. 2001. "The gender gap in top corporate jobs." *ILR Review* 55:3–21.

Blinder, A.S. 1973. "Wage discrimination: reduced form and structural estimates." *Journal of Human resources*, pp. 436–455.

Canales, B. 2017. "Closing the Federal Gender Pay Gap through Wage Transparency." *Hous. L. Rev.* 55:969.

Cech, E.A., and M. Blair-Loy. 2019. "The changing career trajectories of new parents in STEM." *Proceedings of the National Academy of Sciences* 116:4182–4187.

Chen, J.J., and D. Crown. 2019. "The Gender Pay Gap in Academia: Evidence from the Ohio State University." *American Journal of Agricultural Economics* 101:1337–1352.

Chib, S. 1992. "Bayes inference in the Tobit censored regression model." *Journal of Econometrics* 51:79–99.

DiNardo, J., N.M. Fortin, and T. Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." *Econometrica* 64:1001–1044.

Dunn, A., and A.H. Shapiro. 2014. "Do physicians possess market power?" *The Journal of Law and Economics* 57:159–193.

Goldin, C. 2006. "The Quiet Revolution That Transformed Women's Employment, Education, and Family." *American Economic Review* 96:1–21.

Hegewisch, A., and H. Hartmann. 2014. "Occupational segregation and the gender wage gap: A job half done.", pp. .

Hegewisch, A., and H. Luyri. 2010. "The Workforce Investment Act and Women's Progress: Does WIA Funded Training Reinforce Sex Segregation in the Labor Market and the Gender Wage Gap?" *Briefing Paper C* 72.

Houghton, K.J. 1999. "The equal pay act of 1963: Where did we go wrong." *Lab. Law.* 15:155.

Irvine, L., and J.R. Vermilya. 2010. "Gender work in a feminized profession: The case of veterinary medicine." *Gender & Society* 24:56–82.

Koop, G., D.J. Poirier, and J.L. Tobias. 2007. *Bayesian econometric methods*. Cambridge University Press.

Kuhn, P., and C. Weinberger. 2005. "Leadership skills and wages." *Journal of Labor Economics* 23:395–436.

Lazear, E.P., and K.L. Shaw. 2007. "Personnel economics: The economist's view of human resources." *Journal of economic perspectives* 21:91–114.

Lemieux, T., W.B. MacLeod, and D. Parent. 2009. "Performance pay and wage inequality." *The Quarterly Journal of Economics* 124:1–49.

Michelmore, K., and S. Sassler. 2016. "Explaining the gender wage gap in STEM: Does field sex composition matter?" *RSF: The Russell Sage Foundation Journal of the Social Sciences* 2:194–215.

Moeltner, K., R.J. Johnston, R.S. Rosenberger, and J.M. Duke. 2009. "Benefit transfer from multiple contingent experiments: A flexible two-step model combining individual choice data with community characteristics." *American journal of agricultural economics* 91:1335–1342.

Neill, C.L., R.B. Holcomb, and B.W. Brorsen. 2018. "Current market conditions for veterinary services in the US." *Applied Economics* 50:6501–6511.

—. 2017. "Starting on the Right Foot: Does School Choice Affect Veterinarian Starting Salaries?" *Journal of Agricultural and Applied Economics* 49:120–138.

Neill, C.L., R.B. Holcomb, K.C. Raper, and B.E. Whitacre. 2019. "Effects of spatial density on veterinarian income: where are all of the veterinarians?" *Applied Economics* 51:1532–1540.

Ngai, L.R., and B. Petrongolo. 2017. "Gender gaps and the rise of the service economy." *American Economic Journal: Macroeconomics* 9:1–44.

Oaxaca, R. 1973. "Male-female wage differentials in urban labor markets." *International economic review*, pp. 693–709.

Radchenko, S.I., and M.S. Yun. 2003. "A Bayesian approach to decomposing wage differentials." *Economics Letters* 78:431–436.

Rosen, S. 1992. "The market for lawyers." *The Journal of Law and Economics* 35:215–246.

Shepherd, A.J., and L. Pikel. 2012. "Employment, starting salaries, and educational indebtedness of year-2012 graduates of US veterinary medical colleges." *Journal of the American Veterinary Medical Association* 241:890–894.

Sunstein, C.R. 1991. "Why markets don't stop discrimination." *Social Philosophy and Policy* 8:22–37.

7 Tables and Figures

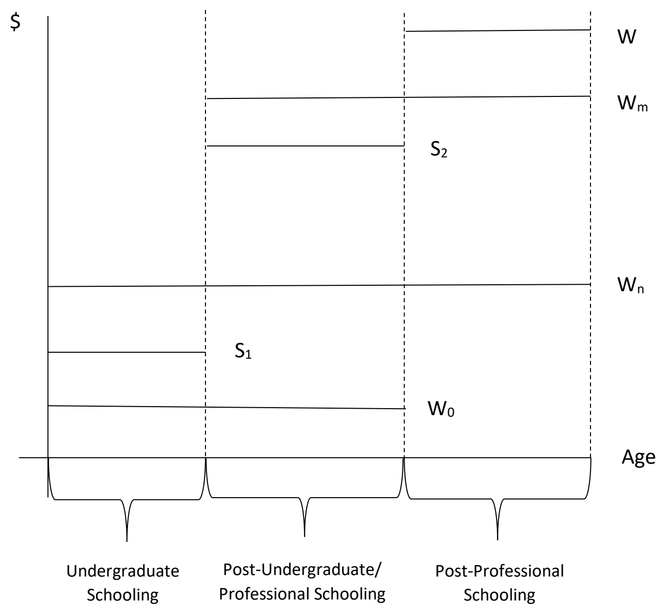
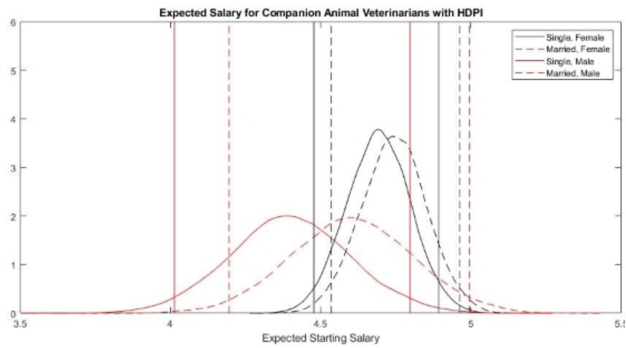
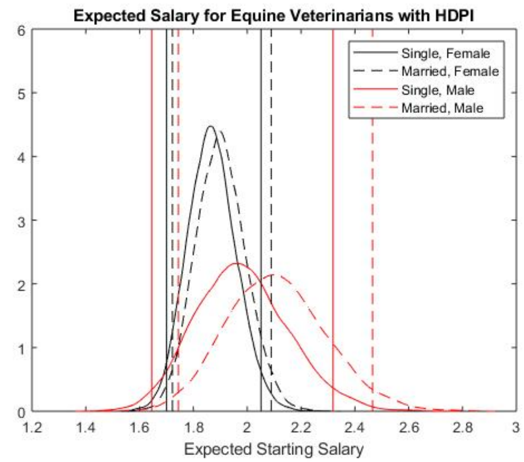


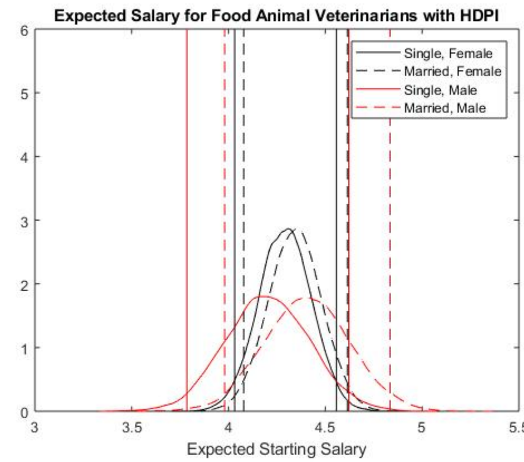
Figure 1: Three Period Human Capital Investment Framework



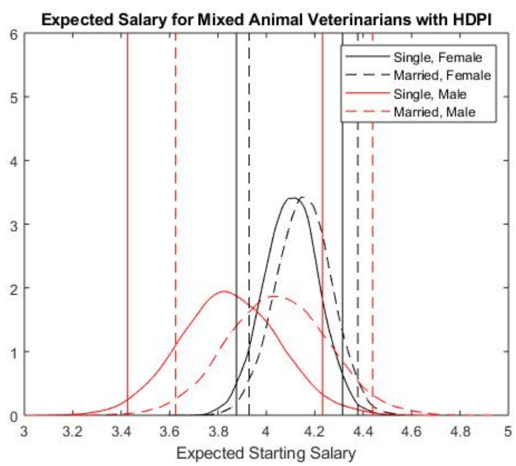
(a) Companion Animal Veterinarian HDPI Overlap



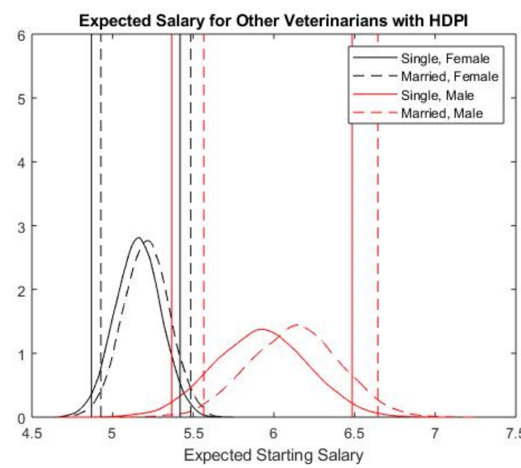
(b) Equine Veterinarian HDPI Overlap



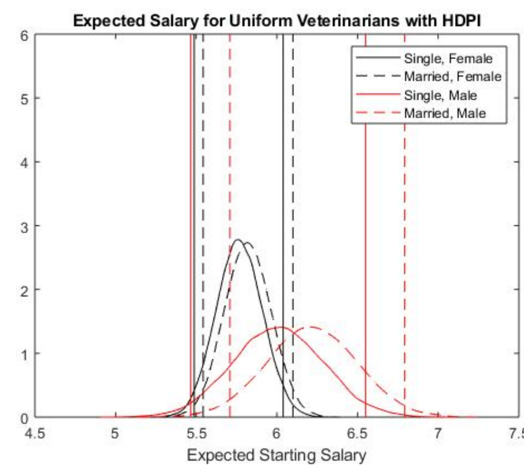
(c) Food Animal Veterinarian HDPI Overlap



(d) Mixed Animal Veterinarian HDPI Overlap

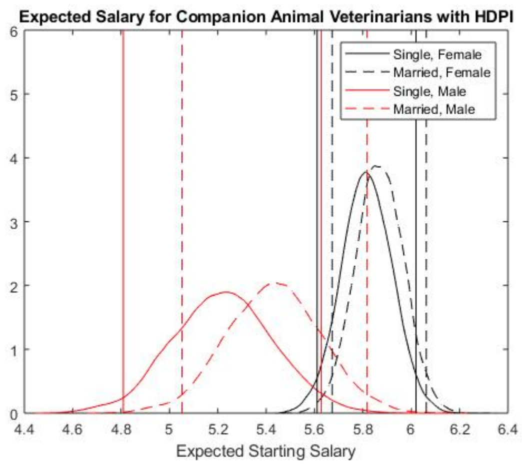


(e) Other Practice Type Veterinarian HDPI Overlap

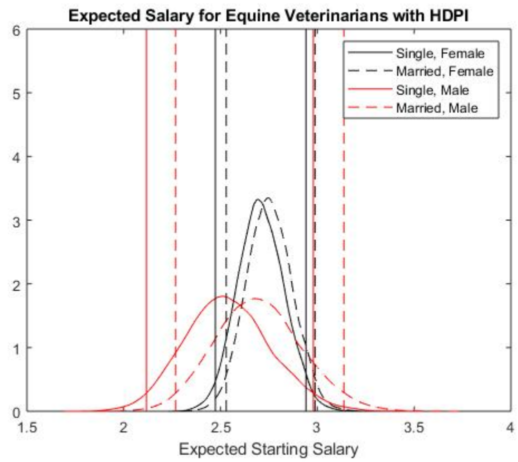


(f) Uniformed Services Veterinarian HDPI Overlap

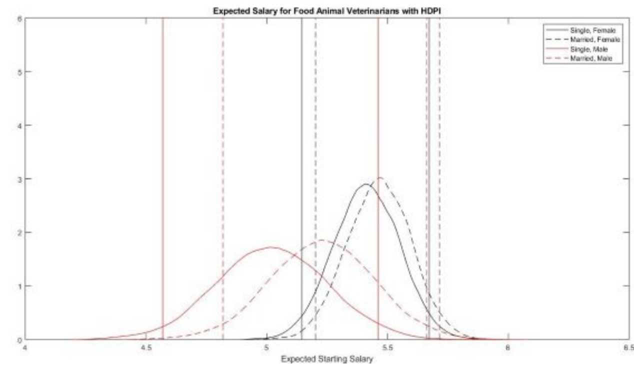
Figure 2: 2009 HDPI Overlaps for the Various Veterinary Practice Types



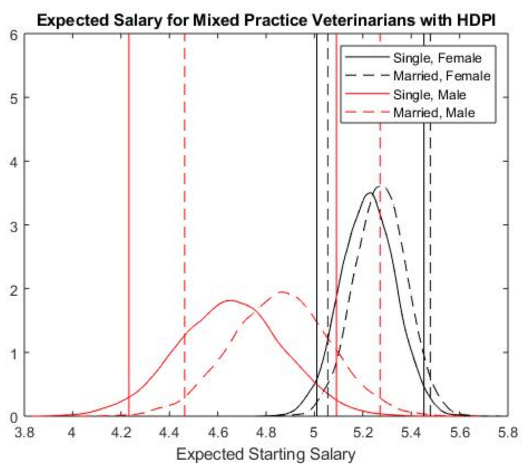
(a) Companion Animal Veterinarian HDPI Overlap



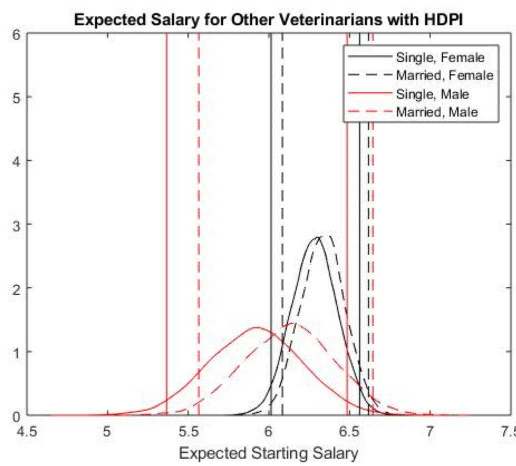
(b) Equine Veterinarian HDPI Overlap



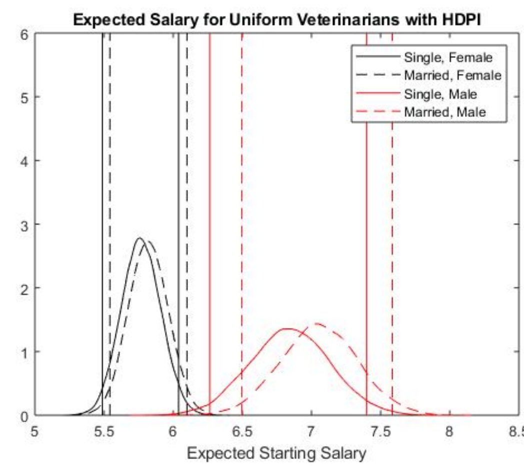
(c) Food Animal Veterinarian HDPI Overlap



(d) Mixed Animal Veterinarian HDPI Overlap



(e) Other Practice Type Veterinarian HDPI Overlap



(f) Uniformed Services Veterinarian HDPI Overlap

Figure 3: 2017 HDPI Overlaps for the Various Veterinary Practice Types

Table 1. Summary Statistics for New Veterinarians by Gender

Variable	Mean/Percent Male	Female
Graduating Debt	$125,609.20	$133,081.40
Food Animal	6.82%	1.53%
Mixed Animal	8.64%	5.70%
Companion Animal	23.54%	25.56%
Equine	1.23%	1.18%
Uniformed Services	1.18%	1.01%
Other Practices	1.13%	1.03%
Advanced Education	57.43%	63.97%
Expected Work Hours	55.08	56.08
Self employed	38.41%	31.89%
Age	27.88	28.88
Married	55.64%	51.53%
Children	31.13%	27.73%
Auburn	4.350%	3.79%
Colorado State	2.81%	2.37%
Cornell	5.64%	4.87%
Cummings	4.45%	4.02%
Iowa State	3.54%	3.40%
Kansas State	4.44%	3.72%
Louisiana State	3.63%	3.90%
Michigan State	4.98%	4.69%
Mississippi State	3.85%	3.61%
North Carolina State	3.29%	3.15%
Oklahoma State	2.76%	3.20%
Oregon State	3.34%	3.75%
Purdue	2.95%	3.60
Texas A&M	2.80%	3.04%
Ohio State	2.78%	2.75%
Tuskegee	3.17%	3.59%
University of California - Davis	3.29%	3.26%
University of Florida	2.70%	3.40%
University of Georgia	5.08%	4.88%
University of Illinois	3.58%	3.88%
University of Minnesota	3.13%	3.52%
University of Missouri	4.69%	5.13%
Pennsylvania State	1.51%	1.92%
University of Tennessee	2.76%	3.05%
University of Wisconsin	3.81%	3.82%
Virginia-Maryland Regional College	3.60%	3.07%
Washington State	3.29%	2.95%
Cost of Living	$78,594.16	$80,112.82

Table 2. Results of the Bayesian Tobit Model with Fixed Effects for School Choice, Practice Type, and Year

	Male			Female		
Variable	Mean	Std	P(>0)	Mean	Std	P(>0)
Constant	-3.294	0.280	0.000	-3.141	0.138	0.000
Graduating Debt	0.003	0.003	0.799	0.002	0.001	0.934
Cost of Living	0.000	0.002	0.592	-0.003	0.001	0.000
Expected Work Hours	2.310	0.093	1.000	1.610	0.046	1.000
Self employed	-0.016	0.007	0.019	-0.008	0.004	0.016
Age	0.211	0.058	1.000	0.052	0.028	0.971
Married	0.090	0.136	0.745	0.165	0.074	0.986
Children	0.238	0.188	0.897	0.199	0.093	0.983
Expected Work Hours*Children	0.000	0.002	0.592	-0.003	0.001	0.000
Practice type Fixed Effect: Base= Advanced Education						
Food Animal	1.965	0.122	1.000	2.353	0.096	1.000
Mixed Animal	1.589	0.114	1.000	2.161	0.061	1.000
Companion Animal	2.168	0.093	1.000	2.757	0.046	1.000
Equine	-0.794	0.227	0.000	-0.469	0.106	0.000
Uniformed Services	3.795	0.224	1.000	3.836	0.110	1.000
Other Practices	2.868	0.225	1.000	3.223	0.108	1.000
Advanced Education	0.027	0.002	1.000	0.028	0.001	1.000
School Fixed Effect: Base= Western University						
Auburn	0.708	0.208	1.000	0.399	0.104	1.000
Colorado State	0.318	0.174	0.965	0.085	0.087	0.838
Cornell	0.430	0.184	0.990	0.308	0.090	1.000
Cummings	0.371	0.197	0.971	0.345	0.093	1.000
Iowa State	0.320	0.187	0.958	0.155	0.092	0.952
Kansas State	0.417	0.191	0.983	0.281	0.090	0.999
Louisiana State	0.634	0.179	1.000	0.257	0.087	0.998
Michigan State	0.276	0.193	0.923	0.083	0.093	0.812
Mississippi State	0.591	0.195	0.999	0.325	0.096	1.000
North Carolina State	-0.013	0.211	0.472	-0.112	0.095	0.119

Table 2 Continued. Results of the Bayesian Tobit Model with Fixed Effects for School Choice, Practice Type, and Year

	Male			Female		
Variable	Mean	Std	P(>0)	Mean	Std	P(>0)
School Fixed Effect: Base= Western University						
Oklahoma State	0.123	0.197	0.736	-0.081	0.092	0.183
Oregon State	-0.017	0.201	0.470	0.023	0.091	0.606
Purdue	0.452	0.197	0.989	0.361	0.093	1.000
Texas A&M	0.209	0.209	0.843	0.279	0.099	0.998
Ohio State	0.022	0.200	0.545	-0.108	0.092	0.117
Tuskegee	0.340	0.198	0.959	0.096	0.094	0.845
University of California - Davis	-0.154	0.206	0.225	-0.037	0.093	0.343
University of Florida	0.206	0.178	0.878	0.190	0.087	0.986
University of Georgia	0.426	0.191	0.987	0.038	0.090	0.669
University of Illinois	0.432	0.200	0.983	0.317	0.091	0.999
University of Minnesota	0.391	0.182	0.982	0.218	0.084	0.994
University of Missouri	0.553	0.246	0.988	0.121	0.106	0.870
Pennsylvania State	0.334	0.203	0.950	0.196	0.096	0.978
University of Tennessee	0.173	0.191	0.818	0.133	0.090	0.933
University of Wisconsin	0.232	0.192	0.888	0.047	0.096	0.691
Virginia-Maryland Regional College	0.520	0.196	0.997	0.033	0.097	0.638
Washington State	3.170	0.157	1.000	3.058	0.074	1.000
Year Fixed Effect: Base= 2009						
Year=2010	0.517	0.121	1.000	0.557	0.057	1.000
Year=2011	0.616	0.115	1.000	0.647	0.058	1.000
Year=2012	0.685	0.118	1.000	0.650	0.057	1.000
Year=2013	0.442	0.122	1.000	0.581	0.057	1.000
Year=2014	1.950	0.132	1.000	1.515	0.062	1.000
Year=2015	0.423	0.183	0.989	0.869	0.128	1.000
Year=2016	0.838	0.131	1.000	1.127	0.062	1.000
Year=2017	0.468	0.016	1.000	0.415	0.007	1.000

Table 3a. Predictive Posterior Density Means for Colorado State and Ohio State in 2009 and 2017 by Practice Type and Gender Without Children in the Household

	Colorado State University								Ohio State University							
	Single, No Children				Married, No Children				Single, No Children				Married, No Children			
2009	Female	std	Male	std	Female	std	Male	std	Female	std	Male	std	Female	std	Male	std
Companion	4.692	0.106	4.299	0.200	4.744	0.109	4.604	0.204	4.573	0.099	3.922	0.199	4.625	0.101	4.121	0.206
Equine	1.869	0.091	1.981	0.173	1.902	0.093	2.109	0.185	1.794	0.084	1.708	0.149	1.826	0.086	1.818	0.161
Food	4.292	0.135	4.203	0.216	4.343	0.138	4.406	0.220	4.174	0.128	3.732	0.209	4.225	0.131	3.929	0.216
Mixed	4.104	0.112	3.847	0.205	4.155	0.115	4.046	0.208	3.987	0.105	3.392	0.198	4.037	0.107	3.581	0.206
Uniform	5.768	0.141	6.008	0.278	5.820	0.143	6.218	0.278	5.648	0.137	5.510	0.286	5.700	0.139	5.720	0.287
Other	5.157	0.14	5.086	0.279	5.208	0.142	5.295	0.282	5.037	0.136	5.422	0.289	5.089	0.138	5.631	0.28
2017																
Companion	5.817	0.104	5.222	0.209	5.869	0.099	5.431	0.195	5.697	0.096	4.729	0.207	5.749	0.091	4.937	0.196
Equine	2.709	0.12	2.538	0.221	2.753	0.118	2.697	0.224	2.609	0.113	2.192	0.194	2.652	0.111	2.332	0.200
Food	5.413	0.135	5.021	0.227	5.465	0.131	5.229	0.214	5.293	0.128	4.531	0.219	5.345	0.124	4.737	0.209
Mixed	5.222	0.112	4.651	0.219	5.274	0.108	4.858	0.206	5.102	0.104	4.168	0.213	5.154	0.099	4.371	0.203
Uniform	5.768	0.141	6.845	0.289	5.82	0.143	7.055	0.277	6.775	0.139	6.346	0.294	6.827	0.135	6.556	0.283
Other	6.283	0.141	5.919	0.289	6.335	0.137	6.129	0.279	6.163	0.137	5.422	0.289	6.215	0.133	5.631	0.280

Table 3b. Predictive Posterior Density Means for Colorado State and Ohio State in 2009 and 2017 by Practice Type and Gender With Children in the Household

	Colorado State University								Ohio State University							
	Single, With Children				Married, With Children				Single, With Children				Married, With Children			
2009	Female	std	Male	std	Female	std	Male	std	Female	std	Male	std	Female	std	Male	std
Companion	4.856	0.126	4.487	0.238	4.908	0.127	4.693	0.236	4.737	0.121	4.008	0.237	4.788	0.122	4.208	0.238
Equine	1.977	0.105	2.037	0.195	2.011	0.107	2.168	0.205	1.898	0.099	1.756	0.169	1.931	0.101	1.869	0.180
Food	4.455	0.152	4.290	0.252	4.506	0.153	4.494	0.249	4.336	0.146	3.817	0.244	4.387	0.147	4.015	0.245
Mixed	4.266	0.132	3.933	0.239	4.317	0.132	4.132	0.238	4.148	0.126	3.473	0.232	4.199	0.127	3.665	0.234
Uniform	5.933	0.157	6.098	0.308	5.985	0.158	6.308	0.303	5.865	0.154	5.600	0.316	5.865	0.155	5.810	0.313
Other	5.321	0.156	5.175	0.309	5.373	0.156	5.384	0.307	6.328	0.155	5.512	0.324	5.253	0.153	5.722	0.312
2017																
Companion	5.982	0.128	5.312	0.254	6.033	0.122	5.521	0.237	5.862	0.122	4.818	0.253	5.913	0.116	5.026	0.239
Equine	2.851	0.139	2.608	0.252	2.896	0.136	2.769	0.252	2.748	0.132	2.253	0.223	2.792	0.129	2.397	0.226
Food	5.578	0.154	5.110	0.270	5.629	0.150	5.319	0.253	5.458	0.148	4.619	0.263	5.509	0.144	4.826	0.249
Mixed	5.386	0.135	4.74	0.261	5.438	0.129	4.947	0.244	5.267	0.129	4.255	0.255	5.318	0.123	4.459	0.242
Uniform	5.933	0.157	6.935	0.325	5.985	0.158	7.146	0.309	6.94	0.158	6.436	0.329	6.992	0.153	6.647	0.315
Other	6.448	0.159	6.009	0.325	6.500	0.154	6.219	0.311	6.328	0.155	5.512	0.324	6.380	0.15	5.722	0.312

Table 4. 95% HDPI Lower and Upper Bounds for Male and Female Graduates from Colorado State University

	Female, No Children		Male, No Children		Female, With Children		Male, With Children	
2009	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Companion, Single	4.477	4.892	4.013	4.797	4.607	5.103	4.000	4.928
Companion, Married	4.534	4.962	4.195	4.994	4.664	5.161	4.232	5.155
Equine, Single	1.700	2.051	1.644	2.318	1.775	2.188	1.673	2.434
Equine, Married	1.722	2.089	1.744	2.465	1.806	2.226	1.779	2.574
Food, Single	4.031	4.557	3.784	4.621	4.171	4.769	3.805	4.779
Food, Married	4.078	4.614	3.979	4.834	4.195	4.795	3.997	4.966
Mixed, Single	3.876	4.314	3.427	4.231	4.015	4.527	3.474	4.404
Mixed, Married	3.928	4.377	3.625	4.438	4.058	4.572	3.660	4.588
Other, Single	4.869	5.418	5.865	6.484	5.014	5.617	4.558	5.762
Other, Married	4.927	5.484	4.565	6.644	5.067	5.674	4.783	5.979
Uniform, Single	5.487	6.038	5.465	6.550	5.636	6.252	5.479	6.684
Uniform, Married	5.542	6.099	5.708	6.792	5.675	6.290	5.711	6.905
2017								
Companion, Single	5.611	6.020	4.809	5.628	5.728	6.231	4.814	5.809
Companion, Married	5.673	6.062	5.052	5.817	5.788	6.266	5.059	5.985
Equine, Single	2.473	2.941	2.117	2.979	2.570	3.117	2.136	3.103
Equine, Married	2.530	2.988	2.267	3.137	2.623	3.153	2.292	3.270
Food, Single	5.145	5.672	4.569	5.460	5.291	5.839	4.585	5.644
Food, Married	5.201	5.714	4.818	5.662	5.341	5.922	4.819	5.816
Mixed, Single	5.009	5.452	4.232	5.090	5.121	5.664	4.248	5.266
Mixed, Married	5.054	5.479	4.463	5.271	5.184	5.683	4.454	5.415
Other, Single	6.014	6.562	5.365	6.484	6.141	6.753	5.362	6.627
Other, Married	6.083	6.617	5.565	6.644	6.204	6.798	5.599	6.806
Uniform, Single	5.487	6.038	6.264	7.397	5.636	6.252	6.313	7.593
Uniform, Married	5.542	6.099	6.496	7.584	5.675	6.290	6.519	7.749

Table 5a. 2009 HDPI Relative Overlap Within Practice Type Between Genders, Marital Status, and No Children in the Household for Colorado State Graduates

	Female, Single	Female, Married	Male, Single	Male, Married
Female, Companion, Single	1			
Female, Companion, Married	0.738	1		
Male, Companion, Single	0.363	0.277	1	
Male, Companion, Married	0.519	0.536	0.613	1
Female, Equine, Single	1			
Female, Equine, Married	0.846	1		
Male, Equine, Single	0.521	0.545	1	
Male, Equine, Married	0.401	0.464	0.700	1
Female, Food, Single	1			
Female, Food, Married	0.822	1		
Male, Food, Single	0.628	0.640	1	
Male, Food, Married	0.615	0.627	0.611	1
Female, Mixed, Single	1			
Female, Mixed, Married	0.768	1		
Male, Mixed, Single	0.400	0.318	1	
Male, Mixed, Married	0.538	0.551	0.599	1
Female, Other, Single	1			
Female, Other, Married	0.798	1		
Male, Other, Single	-0.276	-0.244	1	
Male, Other, Married	-0.082	-0.047	0.573	1
Female, Uniform, Single	1			
Female, Uniform, Married	0.811	1		
Male, Uniform, Single	0.508	0.513	1	
Male, Uniform, Married	0.253	0.313	0.634	1

Note: Negative values represent zero overlap between posterior densities.
Note: Columns represent the overlap within the practice types presented in each row.

Table 5b. 2009 HDPI Relative Overlap Within Practice Type Between Genders, Marital Status, and With Children in the Household for Colorado State Graduates

	Female, Single	Female, Married	Male, Single	Male, Married
Female Companion Single	1			
Female Companion Married	0.792	1		
Male Companion Single	0.291	0.227	1	
Male Companion Married	0.536	0.528	0.603	1
Female Equine Single	1			
Female Equine Married	0.847	1		
Male Equine Single	0.542	0.553	1	
Male Equine Married	0.511	0.529	0.725	1
Female Food Single	1			
Female Food Married	0.919	1		
Male Food Single	0.614	0.589	1	
Male Food Married	0.617	0.619	0.674	1
Female Mixed Single	1			
Female Mixed Married	0.841	1		
Male Mixed Single	0.369	0.315	1	
Male Mixed Married	0.552	0.553	0.668	1
Female Other Single	1			
Female Other Married	0.832	1		
Male Other Single	0.501	0.504	1	
Male Other Married	0.504	0.507	0.688	1
Female Uniform Single	1			
Female Uniform Married	0.883	1		
Male Uniform Single	0.511	0.509	1	
Male Uniform Married	0.426	0.470	0.682	1

Note: Negative values represent zero overlap between posterior densities.
Note: Columns represent the overlap within the practice types presented in each row.

Table 6a. 2017 HDPI Relative Overlap Within Practice Type Between Genders, Marital Status, and No Children in the Household for Colorado State Graduates

	Female, Single	Female, Married	Male, Single	Male, Married
Female, Companion, Single	1			
Female, Companion, Married	0.768	1		
Male, Companion, Single	0.014	-0.035	1	
Male, Companion, Married	0.213	0.142	0.571	1
Female, Equine, Single	1			
Female, Equine, Married	0.798	1		
Male, Equine, Single	0.542	0.516	1	
Male, Equine, Married	0.538	0.527	0.697	1
Female, Food, Single	1			
Female, Food, Married	0.827	1		
Male, Food, Single	0.285	0.226	1	
Male, Food, Married	0.605	0.514	0.587	1
Female, Mixed, Single	1			
Female, Mixed, Married	0.847	1		
Male, Mixed, Single	0.066	0.028	1	
Male, Mixed, Married	0.264	0.212	0.604	1
Female, Other, Single	1			
Female, Other, Married	0.792	1		
Male, Other, Single	0.393	0.319	1	
Male, Other, Married	0.508	0.494	0.718	1
Female, Uniform, Single	1			
Female, Uniform, Married	0.811	1		
Male, Uniform, Single	-0.118	-0.089	1	
Male, Uniform, Married	-0.218	-0.194	0.683	1

Note: Negative values represent zero overlap between posterior densities.
Note: Columns represent the overlap within the practice types presented each row.

Table 6b. 2017 HDPI Relative Overlap Within Practice Type Between Genders, Marital Status, and With Children in the Household for Colorado State Graduates

	Female, Single	Female, Married	Male, Single	Male, Married
Female, Companion, Single	1			
Female, Companion, Married	0.823	1		
Male, Companion, Single	0.057	0.014	1	
Male, Companion, Married	0.219	0.162	0.641	1
Female, Equine, Single	1			
Female, Equine, Married	0.848	1		
Male, Equine, Single	0.542	0.472	1	
Male, Equine, Married	0.558	0.542	0.714	1
Female, Food, Single	1			
Female, Food, Married	0.788	1		
Male, Food, Single	0.281	0.226	1	
Male, Food, Married	0.514	0.431	0.671	1
Female, Mixed, Single	1			
Female, Mixed, Married	0.852	1		
Male, Mixed, Single	0.102	0.056	1	
Male, Mixed, Married	0.242	0.187	0.696	1
Female, Other, Single	1			
Female, Other, Married	0.835	1		
Male, Other, Single	0.349	0.294	1	
Male, Other, Married	0.507	0.492	0.712	1
Female, Uniform, Single	1			
Female, Uniform, Married	0.883	1		
Male, Uniform, Single	-0.031	-0.012	1	
Male, Uniform, Married	-0.126	-0.111	0.748	1

Note: Negative values represent zero overlap between posterior densities.
Note: Columns represent the overlap within the practice types presented each row.