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STUDIES IN THE LABOR MARKET FOR VETERINARIANS

By

David M. Smith

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ABSTRACT

STUDIES IN THE LABOR MARKET FOR VETERINARIANS

By

David M. Smith

This dissertation analyzes the labor market for veterinarians, and in the course investigates three main topics that have relevance to the general labor market. Data utilized include three wage surveys conducted by two veterinary journals, and census data, along with other government published data. Cross-section as well as time-series regression estimation techniques are utilized.

The first topic explored is how human capital investors form earnings expectations. Other have shown that in labor markets for highly skilled individuals, human capital investors behave myopically, forming earnings expectations based on market conditions that exist years prior to entry into the labor market. This behavior generates long periods of disequilibrium, with markets characterized by alternating periods of oversupply and undersupply of labor. A time-series analysis of the market for veterinarians provides evidence consistent with this theory. The veterinary labor market appears characterized by a seven-year lag between the time of occupational choice and entry into the labor market. Tests for competing rational expectations models provide further support for the myopic expectations model.

Second, I explore whether there exists evidence of wage discrimination in the veterinarian labor market. After a review of the wage discrimination literature, empirical evidence from wage-salary sector veterinarians is presented. The unadjusted gender gap in average earnings is 15 percent. After controlling for various observable

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characteristics, the adjusted earnings gap is 10 percent, based on the most conservative estimates. Utilizing unique productivity measures, I report women in parity with men in productivity, other factors held constant. Finding gender differences in earnings, but not in productivity, is evidence consistent with the existence of wage discrimination.

Last, I analyze gender differences in self-employment labor market outcomes. In the general labor market, females have lower self-employment rates and earnings, relative to males. After a review of existing models of self-employment choice, I test the predictions and implications of these models with self-employed veterinarians. Results find existing theories generally unable to explain the gender gap in earnings. Further analysis suggests a significant portion of the gender gap in earnings may be explained by the fact that female-owned firms tend to be smaller than male-owned firms.

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INTRODUCTION

This dissertation analyzes the labor market for veterinarians, and in studying this very specific labor market, explores various issues that have relevance to the general labor market. Three main topics are studied: human capital investment decisions, pay and productivity differences between men and women in the wage-salary sector, and gender differences in employment and earnings in the self-employment sector. Data utilized include a new wage survey conducted by Veterinary Economics, as well as US Census data, along with published data from the US Department of Commerce, US Department of Education, US Department of Labor, American Kennel Club, American Medical Association, American Veterinary Medical Association, Association of American Veterinary Medical Colleges, and the National Association of Colleges and Employers.

Chapter 1 studies human capital investment decisions among veterinarians. Human capital theory maintains that individuals invest in human capital based on expectations of future earnings. The way in which these expectations are formed is a disputable matter. While some claim that individuals are myopic in their investment choices, arriving at decisions based only on current market conditions, others contend that decisions are made in a much more sophisticated framework, based on predictions of future earnings streams. The issue is nontrivial, for if the investment period is relatively long, human capital decisions can have a significant impact on the operation of specific labor markets. Freeman (1975a, 1975b, 1976a, 1976b) provides evidence that in markets for highly skilled individuals such as engineers, physicists, and lawyers, ind

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individuals make human capital investment decisions based primarily on current market conditions. These decisions, in turn, generate systematic periods of oversupply and undersupply of labor, evidenced by sizable fluctuations in starting salaries. The labor market is thus characterized by a cobweb model, with myopic expectations on the part human capital investors as the factor that generates fluctuations in supply. If agents were able to perfectly forecast future market conditions, predicted by a competing rational expectations model, employment and wages would adjust instantaneously to changes in supply and demand.

Beyond Freeman's research, the evidence on whether agents behave myopically in forming their earnings expectations is mixed. In a competing model, Zarkin (1985) provides evidence that public school teachers forecast future market conditions. In an analysis of how students arrive at the choice of a college major, Berger (1988) also provides evidence against myopic expectations. Additional support for rational expectations is offered by Siow (1984) and Hoffman and Low (1983). However, in accordance with Freeman's findings, Leffler and Lindsay (1979) provide evidence for myopic expectations in the labor market for physicians. In addition, Leonard (1982) offers evidence against rational expectations on the part of personnel executives, individuals who might be expected to have the capacity to make accurate forecasts of future market conditions.

Utilizing various time series data, including a series of starting salary data published by the American Veterinary Medical Association, I test the predictions and implications of the cobweb model on the labor market for veterinarians. The cobweb model should only apply to labor markets where there is a close link between education and occupation, and thus the veterinarian labor market is a valid place to test this model. My findings support the cobweb model, with the veterinary labor market appearing as characterized by a seven-year lag between the time of occupational choice and entry into the labor market. Tests for competing rational expectations models provide further support for the myopic expectations model.

In Chapters 2 and 3, I study pay differences between male and female veterinarians. Chapter 2 reviews the literature, both theoretical and empirical, on labor market discrimination by gender. The publication of Becker's (1971) *The Economics of Discrimination* was the beginning of what is now a large literature exploring the issue of labor market discrimination. Motivating factors for this literature include the stylized facts of females earning less than males and blacks earning less than whites, along with the apparent incompatibility of the competitive model with the existence of labor market discrimination. Given the empirical evidence and the history of blacks in the United States, there seems to be a consensus supporting the existence of labor market discrimination by race. However, the issue with regard to gender is more controversial, particularly when focusing on the labor market experience of men and women during the past fifty years.

Although numerous theories of labor market discrimination have been developed, along with a significant amount of empirical evidence offered, there exist alternative theories that claim to explain the lower earnings of females relative to males. There is a subset of literature that uses human capital theory to explain the gender gap in earnings. It is theorized that women obtain less human capital in the labor market than men, and these differences in human capital, often unobserved, may account for a significant portion of the gender gap in earnings. Goldin and Polachek (1987) claim that women anticipate future child-related career interruptions, and thus invest less in human capital than do men, even early on in their careers. Lazear and Rosen (1990) contend that employers, in consideration of more career interruptions that occur to women, may be reluctant to hire and promote women into jobs that require a great deal of training and acquisition of firm-specific human capital. Thus, in reaction to the imperfect information they face, employers are said to statistically discriminate against women. Chapter 2 reviews both discrimination-based and human capital explanations for observed gender differences in earnings.

In Chapter 3, I present my own evidence on this issue, utilizing a new wage survey on veterinarians. The advantage of using these data is that they examine a relatively homogenous group of professionals, minimizing the personal and employment differences that exist between men and women. Gender differences in human capital should be less important in explaining earnings differences among veterinarians, relative to the general population. First, schooling is virtually identical among female and male veterinarians. In order to become a veterinarian, one must graduate from one of the twenty-seven accredited veterinary schools in the United States. Second, the analysis takes place over a self-selected group of females, one that behaves much like the group of males to whom they are being compared. Thus, there should be fewer differences in motivation, skills, and training among this group than among workers in general. In addition, employers should recognize the high opportunity costs of career interruptions faced by female veterinarians, making statistical discrimination a less likely scenario in this labor market.

An additional advantage of this data set is that it includes valuable proxy measures of productivity. Data on individual worker productivity is generally lacking in the empirical research on wage discrimination. Without productivity controls, it may always be contended that unobserved productivity differences cause observed differences in earnings. Thus, the ability to control for productivity differences between men and women significantly strengthens any evidence that is consistent with the presence of wage discrimination.

The method of analysis employed is the standard wage decomposition, due to Oaxaca (1973). Briefly, the unadjusted earnings gap is 15 percent. After controlling for various observable characteristics, the earnings gap narrows to 10 percent, based on the most conservative estimates. In addition, I find women in parity with men in productivity, other factors held constant. Finding gender differences in earnings, but not in productivity, is evidence consistent with the existence of wage discrimination. Other potential explanations for this finding are also explored.

The analysis in Chapter 3 is focused on wage-salary workers, veterinarians who have no ownership stake in their firms. In Chapters 4, 5, and 6, I study some of the same issues with self-employed veterinarians. After a period of decline following World War II, the population of self-employed in the United States has steadily increased. Particularly notable is a recent trend, with the percentage of self-employed among all workers increasing from 6.7 percent in 1970 to 8.8 percent in 1988 (Aronson, 1991). The increase in nonfarm self-employment during this period was led primarily by women, with increases in female self-employment rates exceeding increases in female labor force participation rates. Devine (1994) reports that the female nonfarm self-employment rate increased from 4 percent in 1975 to 6.6 percent in 1990, which represents almost one-eighth of the total increase in female nonfarm employment during this period.

Even after these gains, female self-employment rates lag well behind male self-employment rates, a relationship that has held true ever since the US government has kept statistics on the self-employed (Blau, 1987). This gap exists even within specific occupations, and on average, self employment rates among men are approximately twice those of women. Not only do women enter self-employment less frequently than men, they also earn less. Available data sources report that self-employed females earn significantly less than self-employed males, as well as considerably less than males and females in the wage-salary sector.

Self-employment, as a labor market phenomenon, is not a topic that has received much attention in the economic literature. There does exist a small literature that studies gender differences in self-employment labor market outcomes. Chapter 4 reviews this literature, both theoretical and empirical, that attempts to explain the lower earnings and lower rates of self-employment among females. Five models are reviewed, three of which offer discrimination-based explanations: Employer discrimination (Moore, 1983), employer discrimination with spillovers (Coate and Tennyson, 1992), and a customer discrimination model (Borjas and Bronars, 1989). Also reviewed are models of compensating differentials (Lombard, 1996) and capital investments (Faucher, 1996).

In Chapter 5, I test the implications and predictions of these five models on my sample of veterinarians. Using veterinarians to study the issue of self-employment has three advantages. As mentioned previously, veterinarians are a relatively homogenous group, with essentially identical training. Therefore, differences in earnings and self-employment behavior are not likely to be derived from differences in human capital. Second, veterinarians have relatively high rates of self-employment, giving a large number of observations to utilize. Approximately fifty percent of the sample studied here is self-employed. Last, the data contain valuable proxy measures of productivity, in addition to detailed firm-level data. Such measures allow for a careful analysis of the mechanisms that generate the gender differences in self-employment that are observed.

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Generally, I find all five models unable to account for the significant gender gap in earnings that exists between self-employed male and female veterinarians. In Chapter 6 I explore this issue further, utilizing detailed firm-level data that is reported from the self-employed. Specifically, I study the impact of firm scale, or size, on the earnings of self-employed veterinarians. Scale is defined in terms of output, or total revenue. Longstreth, Stafford, and Mauldin (1987) report that female-operated firms tend to be smaller and have lower revenues than male-operated firms, and this is reflected in my sample of self-employed veterinarians. Consistent with this finding, I report that, on average, self-employed female veterinarians employ less labor and capital than self-employed male veterinarians. Firm scale is found to be positively correlated with earnings, and a significant portion of the earnings gap is shown to be explained by gender differences in this characteristic. Last, I offer suggestions as to the underlying factors that form the basis for gender differences in firm scale.

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Chapter 1

THE LABOR MARKET FOR VETERINARIANS

Human capital theory maintains that individuals invest in human capital based on expectations of future earnings. The way in which these expectations are formed is the subject of some debate. While some claim that individuals are naïve in their investment choices, arriving at decisions based only on current market conditions, others contend that decisions are made in a much more sophisticated framework, based on predictions of future earnings streams. The issue is nontrivial, for if the investment period is relatively long, human capital decisions can have a significant impact on the operation of specific labor markets. Freeman (1975a, 1975b, 1976a, 1976b) provides evidence that in markets for highly skilled individuals, such as engineers, physicists, and lawyers, individuals make human capital investment decisions based primarily on current market conditions. These decisions, in turn, generate systematic periods of oversupply and undersupply of labor, evidenced by sizable fluctuations in starting salaries.

Freeman utilizes a cobweb model to explain how these systematic fluctuations in supply and starting wages are generated. The model presumes that individuals must undergo a training period in order to become a particular highly skilled worker. Underlying the model is the key assumption that an individual decides whether or not to become a highly skilled worker by examining the conditions in the labor market at the start of their training program. The model also makes the implicit assumption that after entry, individuals do not drop out of a highly skilled occupation, given the extensive investment required. Given this, any changes in labor supply, beyond general attrition, must come from the entry-level market.

Figure 1, depicting the entry-level market for some highly skilled occupation, summarizes how the model works. Starting at an initial equilibrium, E_0 and w_o, a shock to demand occurs, shifting the demand curve to D'. Firms would like to hire E^* workers at a wage of w^*, but since it takes time to train a highly skilled worker, supply is perfectly inelastic at E_o workers. The market clears, therefore, at w_1. Individuals facing occupational choice decisions respond to the higher starting salaries, and a total of E_1 individuals enroll in training programs. Assuming a training time that is four periods in length, the E_1 individuals who enroll in training programs in time t will not enter the market until t+4. Thus, assuming that demand remains unchanged, a total of E_1 individuals enroll in training programs for period's t+1, t+2, and t+3. In t+4, a total of E_1 new highly skilled workers enter the market, and the supply becomes perfectly inelastic at E_1 workers. At the new market situation, equilibrium will occur at w_2, substantially below the wage new entrants in the market planned to attain upon entering their training program. At w_2, only E_2 individuals decide to become highly skilled workers, and this will occur in period's t+4 through t+7. When the individuals who enrolled in t+4 complete their training program in t+8, the wage will increase to w_3 because there now exists an undersupply of highly skilled workers. This relatively high wage will induce the next cohort to oversupply the market, and so on.

The force that generates these fluctuations in supply is the shortsighted expectations on the part of agents facing occupational choice decisions. If agents were able to perfectly forecast future market conditions, employment and wages would adjust instantaneously to changes in supply and demand. Beyond Freeman, the evidence on whether agents are myopic in forming their earnings expectations is mixed. In a competing model Zarkin (1985) provides evidence that public school teachers forecast future market conditions. In an analysis of how students arrive at the choice of a college major, Berger (1988) also provides evidence against myopic expectations. Additional support for rational expectations is offered by Siow (1984) and Hoffman and Low (1983). However, in accordance with Freeman's findings, Leffler and Lindsay (1979) provide evidence for myopic expectations in the labor market for physicians. In addition, Leonard (1982) offers evidence against rational expectations on the part of personnel executives, individuals who might be expected to have the capacity to make accurate forecasts of future market conditions.

In this chapter, I test the implications and predictions of the cobweb model on a market of highly skilled individuals, veterinarians. The cobweb model should only apply to labor markets where there is a close link between education and occupation, and thus the veterinarian labor market is a valid place to test this model. First, I provide a description of the labor market for veterinarians since 1900. I apply an econometric analysis over the time period for which starting salary data is available (1978-95); the framework and results are discussed in sections II and III, respectively. In section IV, I examine more closely the issue of how expectations are formed and offer a test for competing expectations models.

I. The Market for Veterinarians over Time

Training for a veterinarian entails a minimum of six years, including at least two years of study in a preveterinary program and four years in a college of veterinary medicine.[1] The great majority of successful applicants to veterinary programs attain a bachelor's degree prior to attending veterinary school. After obtaining a Doctor of Veterinary Medicine (D.V.M.) degree and passing a national board examination, most states allow individuals to apply for licensure without further training (U.S. Department of Labor, 1995). In 1993, according to the American Veterinary Medical Association (1994), 81% of veterinarians were employed in the private clinical sector, and 19% in the public and corporate sector. Of those in the private clinical sector, 69% were employed in small animal practices, 19% in large animal practices, and the remainder in "mixed" (small and large) practices.

A. Supply of Veterinarians

Table 1 reports census data on veterinary employment since 1900. The data report varying periods of growth and decline in both the number of total veterinarians and veterinarians as a percentage of the total labor force. After growing from 1900 to 1920, the number of veterinarians actually declined from 1920 to 1950. In part, this may be explained by farmers depending less on animals, and more on tractors, in production. Since 1950, the number of veterinarians as a percentage of the labor force has steadily increased, with a particularly high growth period from 1970 to 1980, when veterinary employment grew by 76%.

To examine the supply of new veterinarians to the labor market, Figure 2 reports the number of first-year veterinary students as a proportion of annual bachelor's degree recipients, for the period 1950-95. The figure shows much variability over the period:

[1] There are 27 colleges of veterinary medicine, all accredited by the American Veterinary Medical Association: Auburn, California-Davis, Colorado State, Cornell, Florida, Georgia, Illinois, Iowa State, Kansas State, Louisiana State, Michigan State, Minnesota, Mississippi State, Missouri, North Carolina State, Ohio State, Oklahoma State, Oregon State, Pennsylvania, Purdue, Tennessee, Texas A & M, Tufts, Tuskegee, Virginia-Maryland, Washington State, and Wisconsin.

the proportion of bachelor degree recipients enrolling in veterinary school increased from .2% in 1950 to .32% in 1955, falling back to .25% in 1960; after rising modestly in the early 60's, the rate fell to a low of .17% in 1970; after increasing to .24% in 1980, the proportion of bachelor degree recipients entering veterinary school has slowly declined. While these peak-to-trough fluctuations do not follow a rigid pattern, they do suggest that the cobweb model might be applied successfully to the veterinarian labor market.

It is important to note that the supply of new veterinarians is constrained by the capacity of veterinary colleges to enroll new students. The Association of American Veterinary Medical Colleges (1996) reports that for the entering class of 1996, among all veterinary colleges, only 35.7 percent of applicants were accepted for enrollment. Given this constraint, cobweb fluctuations in supply may be dampened, or even be nonexistent, in this labor market. Therefore, as an alternative measure of supply when estimating the cobweb model, I will utilize data on applicants provided by the Association of American Veterinary Medical Colleges.[2] Given constrained supply, an analysis of the variability in applicant data will provide a more direct test for the existence of myopic expectations.[3]

B. Earnings and Demand for Veterinarians

Table 2 reports census data on the earnings of veterinarians, along with physicians and the total labor force for the period 1950-90. From 1950 to 1960 veterinarian earnings increased, in real terms, by 77.1%, far outpacing the increase in earnings for physicians and the total labor force. After continuing to increase from 1960 to 1970, veterinarian earnings fell from 1970 to 1980, both in real terms and

[2] This does not measure applications, but applicants, which is more desirable given that some applicants apply to more than one college.

[3] Unfortunately, data on applicants is available only over a 16 year period (1980-95).

relative to physicians and the total labor force. Real earnings recovered somewhat from 1980 to 1990, but lagged behind earnings gains made by physicians and the general labor force.[4] Over this entire period, fluctuations in veterinarian earnings are notably greater than fluctuations in total labor force earnings. Once again, this evidence is consistent with a cobweb model applied to the veterinary labor market. However, the evidence is not compelling, since other explanations could be offered for the observed changes in relative earnings. In addition, the cobweb model is most relevant to the market for new entrants and starting salaries, and thus, it is this market that warrants closer examination.

Since 1978, the American Veterinary Medical Association (AVMA) has conducted an annual survey on veterinary graduates' employment and starting salaries.[5] Figure 3 reports the mean starting salary for veterinary graduates entering private practice for the period 1978-95. For comparison, young physician median salaries are reported for the period 1973-95.[6] Since physicians and veterinarians have similar college training, it seems appropriate to consider young physician salaries as the opportunity wage for veterinarians.

Figure 3 shows real starting salaries for veterinarians falling from 1978-86, at which point they start a slow recovery that continued through 1995. Relative to young physician earnings, the earnings position of veterinarians has fallen over the period 1982-95. Once again the evidence presented in Figure 3 is consistent with a cobweb model applied to the veterinary labor market. Falling real earnings from 1978-86 could

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[4] Deflated by the Consumer Price Index, real earnings for veterinarians were greater in 1970 than in 1990. However, given increasing evidence that the CPI overstates the rate of price inflation, changes in relative earnings should receive greater consideration.

[5] The response rate is relatively high for these surveys. In 1995, 68.7% of all graduates responded to the survey.

[6] The American Medical Association has conducted an annual earnings survey on physicians since 1973. Young physician earnings are defined as earnings for physicians less than 36 years of age.

be result of an "oversupply" of veterinary graduates due to relatively large first-year enrollments for the period 1974-82 (see Figure 2). Increasing real earnings since 1986 could be the result of an "undersupply" of veterinary graduates due to declining first-year enrollments for the period 1983-91.[7] However, it is important to note that other factors could be generating these results. Specifically, changing demand for veterinary services could be the basis of these changes in veterinary salaries and employment.

In a quantitative examination of a particular labor market, a crucial part of the analysis is obtaining a convincing measure of labor demand. For lawyers, engineers, and physicists, Freeman (1976) utilized various government data on national output, consumer spending, and government budget outlays. For veterinarians, this task presents a challenge, for the government keeps few statistics relevant to the veterinary profession. Although the U.S. Department of Agriculture conducts annual surveys on the livestock population, the AVMA (1994) estimates that only 12% of veterinarians directly care for the livestock population. Since the majority of veterinarians care for small animals, a more direct measure of demand for veterinary services would be based on the pet population.

I report two such measures of demand in Figure 4. The first measure is an estimation of the pet population, based on statistics of annual dog registrations reported by the American Kennel Club. Although registered dogs are only a subset of the pet population, dog registration data may be used to estimate the dog population, which in turn may be used to proxy the total population of pets. I develop a crude

[7] In a study of 193 occupations from 1989-93, utilizing a variety of employment indicators, Cohen (1995) ranks veterinarians as the second highest occupation demonstrating a shortage of labor.

estimator of the dog population for the years 1950-95, by assuming that all dogs are registered at birth and then live for 10 years.[8]

As an alternative measure of demand, I utilize the total value of shipments for the dog and cat food industry, as reported in the US Department of Commerce's *Annual Survey of Manufacturers*, for the years 1972-94. Figure 4 reports both measures of demand over time. The estimated dog population reveals some variation, but the long-run trend has been one of steady growth. However, a stagnant pet population in the late 70's and early 80's may have contributed to falling starting salaries for veterinarians during this time period (see Figure 3). The measure of pet food shipments exhibits relatively greater variability, but has also trended upward over time. In an attempt to separate supply and demand effects on earnings, I turn now to an econometric analysis of the veterinarian labor market.

II. Estimation of the Cobweb Model

The cobweb model may be represented by the following three equations:

(1) Supply of first-year enrollments:

$$Fresh_t = a_1 Start_t - a_2 Alter_t + a_3 Bach_t + u_1$$

where $Fresh_t$ = First-year enrollments in year t
$Start_t$ = Starting salaries for veterinarians in year t
$Alter_t$ = Alternate starting salary in year t (young physician salaries)
$Bach_t$ = Bachelor degree recipients

(2) Supply of graduates:

$$Grad_t = b_1 Fresh_{t-4} + u_2$$

where $Grad_t$ = Number of graduates in year t

[8] For this estimator to be well correlated with the demand for veterinary services, two assumptions must be met. First, spending on dogs must make up a significant proportion of pet veterinary care expenditures. In 1991, the AVMA (1993) estimates that spending on dogs made up approximately 70% of pet veterinary care expenditures. Second, registered dogs must not exhibit a trend as a proportion of the total dog population over time. This assumption may not hold: utilizing dog population estimates by the AVMA, 1 out of every 4.96 dogs was registered in 1987, while this number increased to 1 out of every 4.5 dogs in 1991.

(3) Salary Determination:

$$Start_t = c_1 Pets_t - c_2 Grad_t + u_3$$

where $Pets_t$ = Measure of Demand derived from the pet population

Equation (1) relates the enrollment decision in year t to starting veterinarian and alternative salaries in year t[9,10]. An alternate specification to equation (1) will also be considered:

(1') Supply of first-year enrollments:

$$Fresh_t = a_1 Start_{t-3} - a_2 Alter_{t-3} + a_3 Bach_t + u_1$$

This equation assumes that decisions to attend veterinary schools are not made the year of enrollment, but three years before. Equation (1') seems a plausible alternative to equation (1), given the significant prerequisite training and preparation needed to attend veterinary school.

Equation (2) makes the number of graduates four years later a function of first-year enrollments. The coefficient on $Fresh_{t-4}$ should approximate unity, assuming that individuals do not drop out of veterinary school after enrollment. This appears a reasonable assumption, given the significant investment veterinary students have made in their training, whose value presumably depends upon completion of their program.[11]

The demand side of the market is represented by equation (3), which treats

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[9] It should be noted that this specification does not imply the exclusion of nonpecuniary considerations in occupational choice decisions. I am unable to control for these factors, but as long as they are uncorrelated with the pecuniary variables, estimates of the coefficients in the supply equations will not be biased by the absence of these omitted variables.

[10] Berger (1988) argues that it is more appropriate to frame the occupational choice decision in a life-cycle model, in terms of earnings streams, rather than starting salaries. The data do not permit this approach, but estimation of equation (1) should yield results consistent with a life-cycle model, since starting salaries are highly correlated with lifetime earnings profiles for both veterinarians and physicians.

[11] For the period 1950-95, analysis of first-year enrollment figures with graduation rates four years later confirms that the attrition rate in veterinary school is very low.

starting salaries as a function of the number of veterinary graduates in year t, along with an exogenous demand-shift variable. The estimated dog population and pet food shipments are employed as alternative measures of demand. Equation (3) implicitly assumes that starting veterinarians do not substitute well for experienced veterinarians. An alternative assumption, embodied in equation (3'), is that there is perfect substitution between young and old veterinarians:

(3') Salary Determination:

$$Start_t = c_1 Pets_t - c_2 Vets_t + u_3$$

where $Vets_t$ = Total number of veterinarians in year t

The error terms in equations (1) - (3) are assumed to be independent of each other. Because of potential serial correlation in the error terms, a Durbin-Watson test is applied to each equation. If no evidence of serial correlation is found, estimation by OLS is appropriate; if evidence of serial correlation is found,[12] a Cochrane-Orcutt correction is applied (see Kmenta, 1986).

III. Results of Estimation

A. Supply Equations

Table 3 reports estimates of the enrollment equations (1 and 1'). In the first three specifications, I test whether individuals respond to market conditions in year t (the year of enrollment), or in year t-3, three years prior to enrollment. Given the required preveterinary training period, it seems reasonable to postulate that individuals decide to attend veterinary school three years before their first year of enrollment.[13] The results in Table 3 support this hypothesis. In the first specification, starting and

[12] If the estimated d was less than d_u at the 5% significance level, the hypothesis of no serial correlation was rejected, and the Cochrane-Orcutt procedure was utilized.

[13] Davis (1965) reports that over 95 percent of applicants to medical school made the decision to apply at least three years prior to submission of their application.

alternate salaries in year t have almost no power to explain enrollment in year t. However, in the second specification, starting and alternate starting in t-3 are both highly statistically significant. In the third specification, when I include salary data from both years t and t-3 as regressors, the coefficients on the salary variables in t-3 remain statistically significant, while those on variables in t remain insignificant. As all variables are in log form, the coefficient on starting salary (t-3) in the third specification suggests that a 10% increase in veterinarian starting salaries leads to a 5.0% increase in first-year enrollments *three years later.* A 10% increase in young physician salaries leads to a 1.9% *decrease* in first-year veterinary school enrollments three years later. The fourth specification estimates equation (1') and reports that the number of bachelor degree recipients in year t has a positive and statistically significant effect on veterinary school enrollments in year t. Note that controlling for bachelor degree recipients strengthens the statistical significance of the salary variables. In addition, this specification reports a higher degree of explanatory power (R^2=.67) than the previous specifications.

Up to this point, the analysis has assumed that expected salaries equal current salaries. The fifth specification tests for the possibility of adaptive expectations, where expected salaries are some combination of current salaries and past expectations. By allowing for adaptive expectations, equation (1') is modified as follows:

$$Fresh_t = a_1 Start^*_{t-3} - a_2 Alter^*_{t-3} + a_3 Bach_t + u_1 \qquad (1'')$$

where $Start^*_t$ = Expected started salaries in time t
$Alter^*_t$ = Expected alternate salaries in time t

Following Freeman (1975a), suppose adaptive salary expectations are represented by the following:

$$Start^*_t = \lambda\ Start_t + (1-\lambda)\, Start^*_{t-1} \qquad (4)$$

$$Altern_t^{*} = \lambda \; Altern_t + (1-\lambda)\, Altern_{t-1}^{*} \tag{5}$$

Substituting equations (4) and (5) into (1") yields the following:

$$Fresh_t = a_1\lambda \; Start_{t-3} - a_2\lambda \; Alter_{t-3} + a_3 Bach_t - a_3 a_4 Bach_{t-1} - (1-\lambda) Fresh_{t-1} + e_1 \quad (1''')$$

This adds a lagged enrollment term to the right hand side of the equation, and a statistically significant coefficient on this variable would suggest that expectations are adaptive in nature. However, the fifth specification in Table 3 reports the coefficient on the lagged dependent variable is statistically insignificant, and in addition, the point estimates on the remaining coefficients do not vary much from the fourth specification.[14]

Assuming that individuals attend veterinary school immediately after graduation from a four-year undergraduate program, the estimates so far suggest that individuals decide to become veterinarians at the start of their sophomore year of undergraduate training (t - 3). If alternative occupations had become relatively more attractive upon graduation (year t), it would be expected that some individuals would change their occupational choice and not enroll in veterinary school. Although the estimates in Table 4 suggest that young physician salaries in year t have no impact on veterinary school enrollments in year t, this should be expected. The decision to enter medical school must also be made prior to year t, given the required premedical training, testing, and application process. While in year t-3, medical school is an alternative for agents considering veterinary school, it is "too late" in year t to decide enter medical school. However, other occupational alternatives do exist upon graduation, and the

[14] For an equation with a lagged dependent variable, the Durbin-Watson statistic is not a valid test for serial correlation. I utilize Durbin's h test (Kmenta, 1986), and I was unable to reject the hypothesis of no serial correlation at the 5% level. As long as no serial correlation exists, OLS yields somewhat biased though consistent and relatively efficient estimates on coefficients in equations with lagged dependent variables (Malinvaud, 1970).

sixth specification in Table 3 tests whether these alternatives may have an impact on veterinary school enrollments. Utilizing data gathered by the National Association of Colleges and Employers, I test whether starting salaries in year t for individuals with a bachelor's degree in Chemistry have a significant impact on veterinary enrollments. Although the coefficient on this variable the expected sign (-.17), it is only marginally significant (p = .13).

Table 4 reports reestimations of the supply equations utilizing applicant data as the dependent variable. Noted earlier, analysis of applicant variability provides a more direct test of expectations behavior, given the constraints on supply that exist in this particular labor market. Changing the dependent variable does impact the results. From columns (1) - (3), the only variable demonstrating statistical significance is starting salary in (t - 3) in the second specification. In addition, the coefficient on the lagged dependent variable term in column (5) is statistically significant, suggesting that expectations may be adaptive in nature. These results demonstrate that the estimates are sensitive to alternative specifications, and may also be hindered by limited degrees of freedom.

Results from columns (4) and (6) in Table 4 are consistent with those reported in Table 3. Note that the relatively greater magnitudes of the coefficient estimates reflect the supply constraints in this labor market. For example, the coefficient estimates from column (6) indicate that a 10% increase in veterinarian starting salaries in (t - 3) would induce a 31.6% increase in applicants. However, estimates from column (6) in Table 3, suggest that freshman veterinary enrollments, in response to such an increase in starting salaries, would increase by only 5.6%.

Overall, the results in Tables 3 and 4 indicate that the supply of new enrollees into veterinary school is best explained by veterinary and physician starting salaries three years prior to enrollment. The link between enrollments and number of degree recipients four years later is examined in Table 5, which records the coefficients for the regression of veterinary graduates in year t on first-year veterinary students in year t-4. As expected, the coefficient on first-year veterinary students is not significantly different from unity, suggesting a very low attrition rate in veterinary colleges.

B. Salary Equations

Estimates of salary determination equations for starting veterinarians are given in Table 6. Specifications (1-3) employ the estimated dog population as the demand variable, while specifications (4-6) utilize reported pet food shipments. The first and fourth specifications estimate Equation (3). Veterinary school graduates are the quantity variable, reflecting the assumption of a distinct labor market for starting veterinarians, or very little substitution between less-experienced and experienced veterinarians. In both specifications, the estimated coefficients on the demand-shift variables are positive and statistically significant. As an example, the fourth specification indicates that a 10% increase in reported pet food shipments would increase starting salaries for veterinarians by .9%. In both specifications, the coefficient on veterinary school graduates is highly statistically significant, and as expected, a large class of veterinary graduates is correlated with lower starting salaries. According to the estimate in column (4), an increase in the number of veterinary graduates by 10% would lower starting salaries by 5.5%.

In the second and fifth specifications (Equation 3'), the total number of veterinarians serves as the quantity variable, consistent with the assumption of perfect substitutability between new and experienced veterinarians. Only in the second column is it reported that the total number of veterinarians has a negative and statistically significant impact on starting salaries, indicating that there may exist some substitution between less and more experienced veterinarians. This does not hold true in the fifth specification, where pet food shipments are used as the demand variable. In addition, note that the explanatory power of the specifications in columns (2 and 4) is significantly lower than the estimates in columns (1 and 3). To explore this further, the third and sixth specifications include both quantity variables as regressors. The results from these specifications indicate veterinary school graduates as the appropriate quantity variable, as the coefficient on this variable remains negative and highly statistically significant, while the coefficient on the total number of veterinarians falls to zero. Unfortunately, the coefficients on the demand variables are also insignificant, possibly reflecting limited degrees of freedom or problems inherent with the demand variables themselves.

C. Complete Cobweb Model

By substituting (3) into (1'), the overall operation of the veterinarian labor market may be summarized by the following cobweb supply equation:

$$Fresh_t = a_1 c_1 Pets_{t-3} - a_1 c_t Grad_{t-3} - a_2 Alter_{t-3} + a_3 Bach_t + u_1 + a_1 u_3 \qquad (6)$$

This equation models the decision to become a veterinarian based on the balance between forces creating job opportunities (increases in the pet population), and forces depressing job opportunities (increases in recent graduates). Estimation of equation (6) has an advantage, for by not including starting salaries as an independent variable, the available data allow estimation over a longer time series.

Estimates of the cobweb model are reported in Table 7. Specifications (1 and 2) employ the estimated dog population as the demand variable, while specifications (3 and 4) utilize reported pet food shipments. Columns (1 and 3) report estimates of equation (6). The key coefficient is that for graduates in t-3, which according to the model should be negative and the basic cause of cyclical fluctuations in the labor market for veterinarians. A large graduating class in year t-3 will negatively impact starting salaries, inducing a smaller supply of first-year students in year t (and a smaller graduating class in t+4, seven years after the enrollment decision). The coefficient is negative and statistically significant in both specifications, indicating that a 10% increase in graduates in year t-3 reduces first-year enrollments in year t by 1.5% or 2.0%, depending on the specification. In both specifications, the coefficient on the alternative salary variable is negative, and statistically significant. Estimates of the coefficient on the demand variable differ. While column (3) reports the coefficient on the pet food shipments' variable as positive and significant, the coefficient on the estimated dog population in column (1) is statistically insignificant. This may be a reflection of the limitations of this variable discussed earlier. Columns (2) and (4) add the starting salaries for graduates with a bachelor's degree in chemistry in year t. The coefficients are negative, but statistically insignificant.

Table 8 reports estimates of the cobweb model with applicants as the supply variable. Results are consistent with those reported in Table 7, where enrollments were utilized as the dependent variable. In fact, the estimates in Table 8 report a higher degree of explanatory power, relative to corresponding estimates in Table 7. In addition, the coefficients on both demand variables are positive and statistically significant. The relatively greater magnitudes of the coefficient estimates reflect the supply constraints in this labor market. For example, the coefficient estimates from column (4) indicate that a 10% increase in demand for veterinarians in (t - 3), as proxied by the pet food shipments variable, would induce a 7.7% increase in applicants. However, estimates from column (4) in Table 7, suggest that freshman veterinary enrollments, in response to such an increase in demand, would increase by only .9%.

Overall, the results in Tables 7 and 8 provide support for the operation of cobweb models in the veterinary labor market. In addition, the estimated seven-year lag between undersupply and oversupply of veterinarians is consistent with the observed changes in the supply of veterinarians over time (see Figure 2). However, two caveats apply. First, the equations are estimated over a relatively short time period, and the coefficient estimates appear sensitive to different specifications. Second, as it was noted earlier, supply is constrained in the veterinary market by the enrollment capacities of veterinary schools, and thus, the magnitudes of disequilibrium in the veterinary market will be mitigated by this factor.[15] However, results from Tables 7 and 8 provide evidence that agents are shortsighted in their formation of earnings expectations, in that they respond primarily to market conditions that occur seven years prior to entry into the labor market. This is an issue that has relevance to the general labor market, and in the next section I explore this topic in further detail.

IV. Expectations

Evidence of myopic expectations in the veterinary labor market conflicts with the findings of some researchers, who report evidence of forward-looking expectations in the area of occupational choice. For instance, Zarkin (1985) demonstrates that public school teachers do not behave shortsightedly, but are able to forecast future demand conditions. In his study on the market for school teachers from 1950-80, Zarkin found that enrollment in teacher education programs would fall years prior to a decline in student enrollments.

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[15] It could be suggested that veterinary colleges, by not completely accommodating fluctuations in demand, play an important role in dampening periods of disequilibrium in the labor market for veterinarians.

When discussing forward-looking expectations it is important, as Siouw (1984) notes, to distinguish between rational expectations, in the sense of Muth (1961), and perfect foresight. An agent with rational expectations makes forecasts of future market conditions, based on current and past information. This agent is aware of the general nature of markets and effects of entry of future cohorts. Alternatively, an agent with perfect foresight is able to perfectly predict future market conditions. In the present analysis, the following two equations distinguish the models:

$$Fresh_t = b_1 Pets_{t+4} - b_2 Alter_{t+4} + b_3 Bach_t + v_1 \qquad (7)$$

$$Fresh_t = a_1 Pets_{t-3} - a_2 Grad_{t-3} - a_3 Alter_{t-3} + a_4 Start_{t-3} + a_5 Bach_t + e_1 \qquad (8)$$

Equation (7) assumes that first-year enrollees exhibit perfect foresight, responding to job opportunity conditions in t+4.[16,17] The first specification in Table 9 reports the estimation of this equation, utilizing pet food shipments as the demand variable. Note that the all the coefficients are statistically insignificant, and the equation exhibits very little explanatory power. This should be expected, for there is little economic reason to believe that agents should be able to predict demand conditions for veterinary services several years into the future.[18]

Equation (8) is a cobweb supply equation, with the addition of the starting salary variable as a regressor. Estimation of this equation will test if agents respond to demand conditions, *independent* of starting salary information. Up to this point, it has been assumed that agents respond to only starting salaries and alternative salaries. If agents occupational choices are independently affected by demand conditions, it may

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[16] The graduation variable is not included in equation, since if included, graduates in t+4 almost perfectly predict first-year enrollments in time t.

[17] Equations (7) and (8) are not estimated with applicants as the dependent variable, due to the short time series over which applicant data is available.

[18] Although Zarkin (1985) reports evidence consistent with perfect foresight model in the market for school teachers, it is much easier to forecast student enrollment figures than demand for veterinary services.

indicate that agents are making forecasts of future market conditions, based on current information sets. Such forecasting would be consistent with Muth's rational expectations theory. Equation (8) is estimated in the second specification of Table 9, once again utilizing pet food shipments as the demand-shifter variable. The estimates indicate that individuals respond as expected to the starting salary variables, and the coefficient on veterinarian starting salaries is statistically significant at the 10% level. However, the coefficients on the demand variables in year t-3 are statistically insignificant. Thus, the estimates in Table 9 provide further evidence that veterinarians behave myopically in their formation of earnings expectations, responding primarily to information on starting salaries at the time of their decision to enroll in veterinary school. As noted previously, Leffler and Lindsay (1979) reach the same conclusion in a study of the physician labor market.

V. Conclusion

Cobweb models in labor markets are generated by earnings expectations that are formed years prior to entry into the market. A labor market following a cobweb model is characterized by alternating periods of oversupply and undersupply of labor. These trends may be identified by sizable fluctuations in starting salaries. In the qualitative analysis undertaken in the first portion of this chapter, trend data on veterinarians suggests the appropriateness of applying a cobweb model to the labor market for veterinarians. Econometric estimation of demand and supply equations further supports the results that Freeman obtained with engineers, lawyers, and physicists with an important exception: the veterinary labor market appears to be characterized by a *seven-year* lag between the time of occupational choice and graduation. Such a lag would induce an even longer period of disequilibrium than estimated by Freeman.

The time series in the econometric models are relatively short (ranging from 15 to 20 years), and the equations are sensitive to different specifications. Thus, inferences from such estimates need to be made with caution. In addition, fluctuations in supply are dampened by the constraints imposed by veterinary colleges. With these caveats in mind, the estimations provide support for the hypothesis that individuals in highly skilled professions respond to market conditions long before entry into the labor market. This myopic behavior, in turn, can have an important impact on the operation of specific labor markets over time.

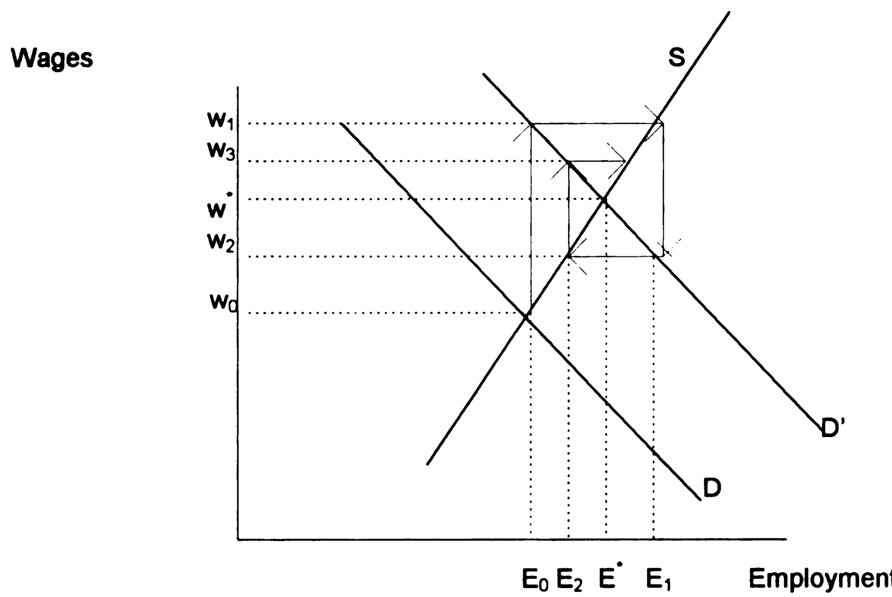


Figure 1: The Cobweb Model

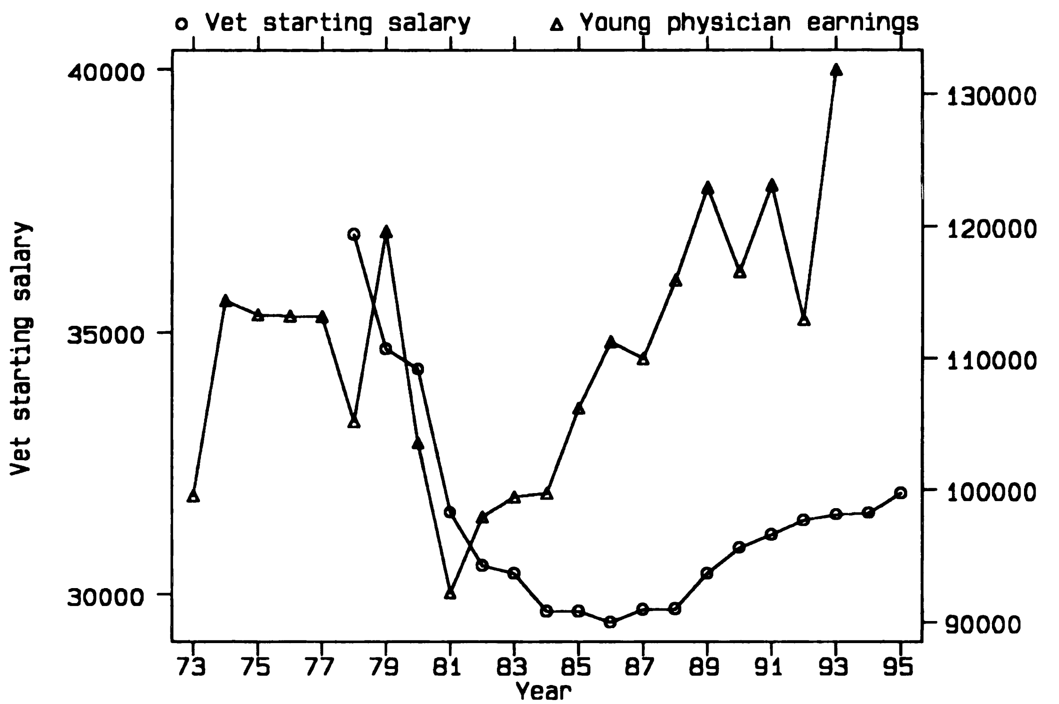
Represents the ratio of the ratio of first year veterinary students over bachelor degree recipients for the period 1950 - 1995.

Sources:

U.S. Department of Education, *Digest of Education Statistics* and *Earned Degrees Conferred*, (various years).

American Veterinary Medical Association. "Student Enrollment Statistics," Journal of the American Veterinary Medical Association, (1950-95).

Figure 2: Supply of New Veterinarians, 1950 - 1995



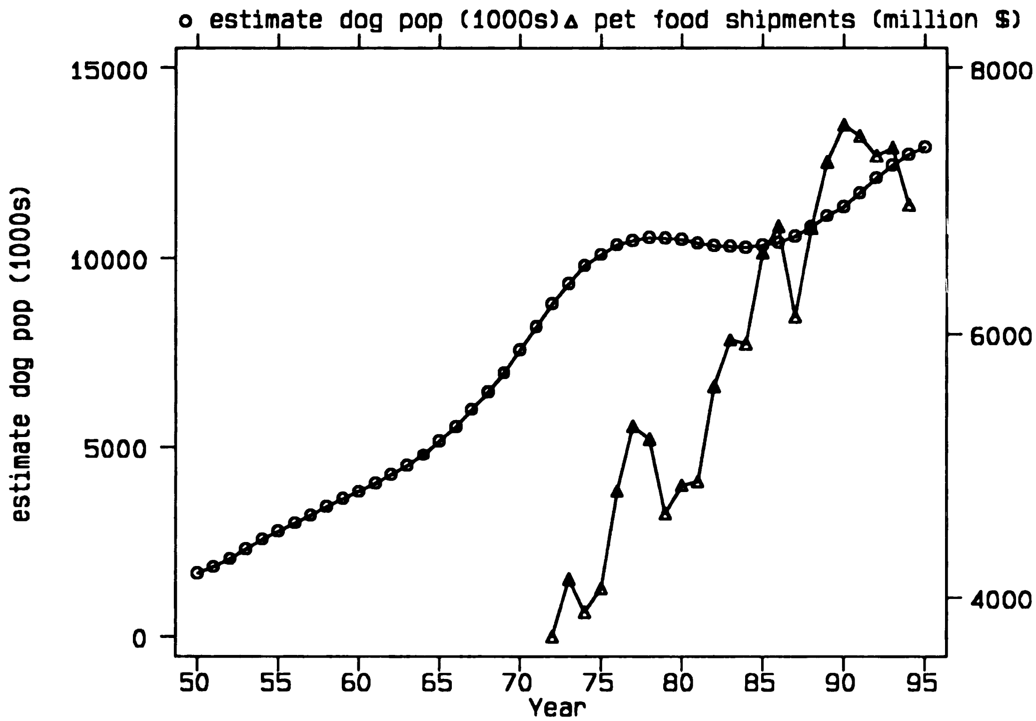
All earnings figures are deflated by the Consumer Price Index, and expressed in 1995 dollars. Veterinary starting salaries are reported as means. Young physician earnings are defined as income for physicians less than 36 years of age, reported as medians. Young physician earnings data are lacking for 1976 and 1980, and thus the median value between neighboring years is imputed.

Sources:

American Veterinary Medical Association, "Starting Salaries for Veterinary College Graduates," *Journal of the American Veterinary Medical Association*, (1986-95).

American Medical Association, *Socioeconomic Characteristics of Medical Practice*, annual reports, (1973-94).

Figure 3: Veterinarian Starting Salaries vs. Young Physician Earnings 1973 - 1995



The dog population is estimated from registration statistics reported by the American Kennel Club, for the period 1950-95. Pet food shipments is obtained from the *Annual Survey of Manufacturers*, for the period 1972-94. The measure of pet food shipments has been deflated by the corresponding producer price index and is expressed in 1995 dollars..

Sources:

American Kennel Club, "Dog Registration Statistics," *AKC Gazette*, (1985-95) and *The American Kennel Club, 1884-1984, A Source Book*, (1950-1984).

U.S. Department of Commerce, Bureau of the Census, *Annual Survey of Manufacturers*, (1972-94).

Figure 4: Veterinary Demand, 1950 - 1995

Table 1: Veterinary Employment 1900 - 1990

Census Year	Veterinarians	% Change in Employment	(Veterinarians/ Labor Force) x 10,000	% Change in (Veterinarians/ Labor Force)
1900	5,149	-	1.77	-
1910	11,652	126.3	3.12	76.2
1920	13,494	15.8	3.20	2.3
1930	11,863	-12.1	2.44	-23.8
1940	10,717	-9.7	2.07	-15.0
1950	11,460	6.9	1.96	-5.5
1960	15,365	34.1	2.26	15.4
1970	19,176	24.8	2.39	6.0
1980	33,746	76.0	3.48	45.4
1990	48,258	43.0	4.17	19.9

Sources:
U.S. Department of Commerce, Bureau of the Census, *Subject Reports*, *Occupational Characteristics,* (1900-1970).
U.S. Department of Commerce, Bureau of the Census, *Earnings by Occupation and Education*, (1980 and 1990).

Table 2: Earnings of Veterinarians, Physicians, Total Labor Force, 1950-90

Census Year	Veterinarian Earnings[1]	% Change	Physician Earnings	% Change	Total Labor Force Earnings	% Change
1950	26,685	-	52,496	-	14,923	-
1960	47,252	77.1	74,253	41.4	20,445	37.0
1970	62,395	32.0	92,838	25.0	23,978	17.3
1980	54,073	-13.3	98,136	5.7	24,605	2.6
1990	59,500	10.0	131,156	33.6	27,882	13.3

[1]Earnings as defined by the Census Bureau, for the year preceding the census. Earnings figures for 1950, 1960 and 1970 are medians, and for 1980 and 1990, means. All earnings figures are deflated by the Consumer Price Index and expressed in 1995 dollars.

Sources:
U.S. Department of Commerce, Bureau of the Census, *Subject Reports*, *Occupational Characteristics,* (1900-70) and *Earnings by Occupation and Education*, (1980 and 1990).

Table 3: Supply Equations

Dependent Variable: Ln First Year Veterinary School Enrollments in year (t)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Starting Salary (t)[1]	.14 (.64)		.32 (1.08)			
Physician Salary[2] (t)	-.07 (1.10)		.01 (.22)			
Starting Salary (t - 3)		.53 (3.45)	.50 (2.75)	.37 (3.70)	.25 (4.39)	.56 (3.63)
Physician Salary (t - 3)		-.16 (3.66)	-.19 (3.33)	-.19 (4.33)	-.22 (3.60)	-.17 (4.08)
Bachelor Recipients (t)				.22 (3.28)	.64 (1.92)	.06 (.60)
Bachelor Recipients (t - 1)					-.39 (1.17)	
First Year Veterinary Students (t - 1)					.33 (1.55)	
B.S. Salary (t + 3)[3]						-.17 (1.69)
Constant	7.02 (3.11)	4.04 (2.53)	1.32 (.46)	3.09 (2.38)	1.61 (.98)	4.76 (2.71)
Rho[4]	.53 (4.60)	.67 (9.94)	.59 (7.95)	.39 (2.41)	-	.58 (9.73)
Estimation Technique	Cochrane -Orcutt	Cochrane -Orcutt	Cochrane -Orcutt	Cochrane -Orcutt	OLS	Cochrane -Orcutt
Time Period	1978-93	1981-95	1981-93	1981-95	1981-95	1981-95
Adjusted R^2	-.05	.60	.55	.67	.69	.70

t-statistics are in parentheses. All variables are in log form. [1]All salary figures are deflated by the Consumer Price Index. [2]Median earnings for physicians under the age of 36. [3]Mean starting salary for graduates with a B.S. in Chemistry. [4]Rho = measure of the serial correlation between error terms, estimated from a first-order autoregressive equation.

Sources:

American Veterinary Medical Association, "Student Enrollment Statistics," *Journal of the American Veterinary Medical Association*, (1950-95). [First Year Enrollments]

American Veterinary Medical Association, "Starting Salaries for Veterinary College Graduates," *Journal of the American Veterinary Medical Association*, (1986-95). [Starting Salary]

American Medical Association, *Socioeconomic Characteristics of Medical Practice*, annual reports, (1973-94). [Physician Salary]

U.S. Department of Education, *Digest of Education Statistics* and *Earned Degrees Conferred,* (various years). [Bachelor Recipients]

National Association of Colleges and Employers, *CPC Salary Survey* and *National Association of Colleges and Employers Salary Survey*, (various years). [B.S. Salary]

Table 4: Supply Equations

Dependent Variable: Ln Applicants in year (t)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Starting Salary (t)[1]	.35 (.38)		-1.31 (.83)			
Physician Salary[2] (t)	.02 (.07)		-.06 (.20)			
Starting Salary (t - 3)		1.65 (2.15)	1.52 (1.43)	2.79 (7.52)	-.43 (.59)	3.16 (8.01)
Physician Salary (t - 3)		-.13 (.47)	.08 (.32)	-.82 (2.39)	.11 (.40)	-1.06 (3.45)
Bachelor Recipients (t)				1.45 (3.50)	2.42 (1.68)	1.48 (3.09)
Bachelor Recipients (t - 1)					-1.41 (.97)	
Applicants (t - 1)					1.25 (4.37)	
B.S. Salary (t + 3)[3]						-.36 (.56)
Constant	4.58 (.56)	-6.14 (.76)	6.08 (.47)	-30.84 (4.74)	-12.80 (2.31)	-28.68 (2.13)
Rho[4]	.80 (12.65)	.98 (43.83)	.79 (3.97)	-	-	-.35 (1.65)
Estimation Technique	Cochrane -Orcutt	Cochrane -Orcutt	Cochrane -Orcutt	OLS	OLS	Cochrane -Orcutt
Time Period	1980-93	1981-95	1981-93	1981-95	1981-95	1981-95
Adjusted R^2	-.17	.17	-.19	.79	.94	.90

t-statistics are in parentheses. All variables are in log form. [1]All salary figures are deflated by the Consumer Price Index. [2]Median earnings for physicians under the age of 36. [3]Mean starting salary for graduates with a B.S. in Chemistry. [4]Rho = measure of the serial correlation between error terms, estimated from a first-order autoregressive equation.

Sources:

Association of American Veterinary Medical Colleges, "Historical Summary of Applications and Applicants," (1980-95). [Applicants]

American Veterinary Medical Association, "Starting Salaries for Veterinary College Graduates," *Journal of the American Veterinary Medical Association*, (1986-95). [Starting Salary]

American Medical Association, *Socioeconomic Characteristics of Medical Practice*, annual reports, (1973-94). [Physician Salary]

U.S. Department of Education, *Digest of Education Statistics* and *Earned Degrees Conferred*, (various years). [Bachelor Recipients]

National Association of Colleges and Employers, *CPC Salary Survey* and *National Association of Colleges and Employers Salary Survey*, (various years). [B.S. Salary]

Table 5: Graduation Equation

Dependent Variable: Veterinary School Graduates in year (t)

Variable	(1)
First Year Veterinary Students (t - 4)	1.01 (44.46)
Constant	-119.75 (3.15)
Rho[1]	.25 (1.62)
Estimation Technique	Cochrane-Orcutt
Time Period	1956-93
Adjusted R^2	.98

t-statistics are in parentheses. [1]Rho = measure of the serial correlation between error terms, estimated from a first-order autoregressive equation.

Sources:
U.S. Department of Education, *Digest of Education Statistics* and *Earned Degrees Conferred,* (various years). [Graduates]
American Veterinary Medical Association, "Student Enrollment Statistics," *Journal of the American Veterinary Medical Association*, (1950-95). [First Year Enrollments]

Table 6: Salary Equations

Dependent Variable: Ln Starting Salary for Veterinarians in year (t)[1]

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Estimated Dog Population[2] (t)	.16 (2.95)	1.21 (7.68)	.14 (.53)			
Pet Food Shipments (t)				.09 (3.34)	-.10 (.39)	.06 (.65)
Veterinary School Graduates (t)	-.44 (14.62)		-.45 (3.83)	-.55 (13.47)		-.54 (11.68)
Number of Veterinarians[3] (t)		-.58 (9.88)	.01 (.07)		-.13 (.47)	.03 (.38)
Constant	11.07 (12.31)	-3.21 (1.52)	11.35 (3.03)	13.72 (67.86)	12.64 (12.59)	13.60 (38.40)
Rho[4]	-.12 (.86)	-	-.13 (.93)	-.26 (1.74)	-	-.24 (1.65)
Estimation Technique	Cochrane -Orcutt	OLS	Cochrane-Orcutt	Cochrane -Orcutt	OLS	Cochrane-Orcutt
Time Period	1978-93	1978-93	1978-93	1978-93	1978-93	1978-93
Adjusted R^2	.94	.86	.93	.95	.26	.95

t-statistics are in parentheses. All variables are in log form. [1]Starting salary figures are deflated by the Consumer Price Index, and expressed in 1995 dollars. [2]Dog population is proxied and estimated using dog registration statistics. [3]The total number of veterinarians is estimated by the following equation: $V_t = (1 - \delta)V_{t-1} + G_t$, where V_t is the total number of veterinarians, δ is the rate of depreciation, and G_t is the number of new graduates. The base year is taken as 1950, when the census reports 11,460 veterinarians, and δ was estimated as .017 in order to obtain a close approximation to subsequent census figures. [4]Rho = measure of the serial correlation between error terms, estimated from a first-order autoregressive equation.

Sources:
American Kennel Club, "Dog Registration Statistics," *AKC Gazette*, (1985-95) and *The American Kennel Club, 1884-1984, A Source Book*, (1950-1984). [Dog Population]
U.S. Department of Commerce, Bureau of the Census, *Annual Survey of Manufacturers*, (1972-94). [Pet Food Shipments]
U.S. Department of Education, *Digest of Education Statistics* and *Earned Degrees Conferred,* (various years). [Graduates]
U.S. Department of Commerce, Bureau of the Census, *Subject Reports*, *Occupational Characteristics,* (1900-70) and *Earnings by Occupation and Education*, (1980 and 1990). [Number of Veterinarians]

Table 7: Cobweb Supply Equations

Dependent Variable: Ln First Year Veterinary School Enrollments in year (t)

Variable	(1)	(2)	(3)	(4)
Estimated Dog Population[1] (t - 3)	-.09 (.35)	-.13 (.53)		
Pet Food Shipments (t - 3)			.09 (2.48)	.09 (2.29)
Veterinary School Graduates (t - 3)	-.15 (2.39)	-.15 (2.41)	-.20 (4.21)	-.19 (3.88)
Physician Salary[2] (t - 3)	-.20 (4.40)	-.20 (4.29)	-.22 (5.62)	-.22 (5.36)
Bachelor Recipients (t)	.31 (1.67)	.32 (1.72)	.16 (1.94)	.15 (1.82)
B.S. Salary[3] (t)		-.08 (.88)		-.04 (.47)
Constant	8.36 (3.76)	9.73 (3.56)	8.80 (9.31)	9.21 (7.05)
Rho[4]	.57 (17.50)	.57 (18.43)	.54 (18.60)	.54 (18.74)
Estimation Technique	Cochrane-Orcutt	Cochrane-Orcutt	Cochrane-Orcutt	Cochrane-Orcutt
Time Period	1976-95	1976-95	1976-95	1976-95
Adjusted R^2	.50	.49	.66	.64

t-statistics are in parentheses. All variables are in log form. All salary figures are deflated by the Consumer Price Index. [1]Dog population is proxied and estimated using dog registration statistics. [2]Median earnings for physicians under the age of 36. [3]Mean starting salary for graduates with a B.S. in Chemistry. [4]Rho = measure of the serial correlation between error terms, estimated from a first-order autoregressive equation.

Table 8: Cobweb Supply Equations

Dependent Variable: Ln Applicants in year (t)

Variable	(1)	(2)	(3)	(4)
Estimated Dog Population[1] (t - 3)	3.95 (4.77)	4.05 (5.41)		
Pet Food Shipments (t - 3)			.78 (2.24)	.77 (2.28)
Veterinary School Graduates (t - 3)	-.80 (4.13)	-.71 (3.78)	-2.12 (7.59)	-2.05 (6.33)
Physician Salary[2] (t - 3)	-.48 (2.73)	-.43 (2.63)	-.75 (2.27)	-.85 (2.77)
Bachelor Recipients (t)	-1.31 (1.98)	-1.62 (2.68)	.64 (1.30)	.63 (1.30)
B.S. Salary[3] (t)		-.50 (1.50)		-.24 (.41)
Constant	-25.76 (3.83)	-19.09 (2.50)	17.61 (3.05)	20.96 (2.45)
Rho[4]	.06 (.39)	-.14 (.82)	-	-.35 (1.28)
Estimation Technique	Cochrane-Orcutt	Cochrane-Orcutt	OLS	Cochrane-Orcutt
Time Period	1980-95	1980-95	1980-95	1980-95
Adjusted R^2	.94	.96	.86	.91

t-statistics are in parentheses. All variables are in log form. All salary figures are deflated by the Consumer Price Index. [1]Dog population is proxied and estimated using dog registration statistics. [2]Median earnings for physicians under the age of 36. [3]Mean starting salary for graduates with a B.S. in Chemistry. [4]Rho = measure of the serial correlation between error terms, estimated from a first-order autoregressive equation.

Table 9: Tests of Expectations Models

Dependent Variable: Ln First Year Veterinary School Enrollments in year (t)

Variable	(1)	(2)
Pet Food Shipments (t + 4)	.03 (.39)	
Physician Salary[1] (t + 4)	-.15 (1.82)	
Pet Food Shipments (t - 3)		.09 (1.59)
Veterinary School Graduates (t - 3)		-.10 (1.33)
Physician Salary (t -3)		-.21 (4.63)
Veterinarian Starting Salary (t - 3)		.33 (1.96)
Bachelor Recipients (t)	-.31 (.85)	.11 (.98)
Constant	13.53 (2.72)	5.29 (2.45)
Rho[2]	.87 (46.63)	.48 (4.30)
Estimation Technique	Cochrane-Orcutt	Cochrane-Orcutt
Time Period	1969-89	1981-95
Adjusted R^2	.10	.68

t-statistics are in parentheses. All variables are in log form. All salary figures are deflated by the Consumer Price Index. [1]Median earnings for physicians under the age of 36. [2]Rho = measure of the serial correlation between error terms, estimated from a first-order autoregressive equation.

Chapter 2

LABOR MARKET DISCRIMINATION BY GENDER: THEORY AND EVIDENCE

The publication of Becker's (1971) *The Economics of Discrimination* was the beginning of what is now a large literature exploring the issue of labor market discrimination. Motivating factors for this literature include the stylized facts of females earning less than males, and blacks earning less than whites, along with the apparent incompatibility of the competitive model with the existence of labor market discrimination. Given the empirical evidence and history of blacks in the United States, there is strong evidence supporting the existence of labor market discrimination by race. However, the issue with regard to gender is more controversial, particularly when focusing on the labor market experience of men and women during the past fifty years.[1] Although numerous theories of labor market discrimination have been developed, and a significant amount of empirical evidence offered, there exist alternative theories that attempt to explain the lower earnings of females relative to males.

This chapter surveys the theory and evidence offered on the topic of labor market discrimination by gender. In section I, I define concepts and present some summary statistics. In section II, I cover the existing theories of labor market discrimination, along with alternative explanations. I examine the way in which

[1] Few would claim that the "marriage bars," described in Goldin (1990), were not prejudicial. These policies, instituted by firms and public agencies, prevented the hire of married women, and prescribed the firing of single women at the time of marriage. Evidence indicates such bars covered a significant portion of the female labor force. Marriage bars were not completely abandoned until the 1950's.

discrimination is measured in the third section, while in section IV, I summarize some of the empirical evidence that exists on this issue.

I. Concepts and Summary Statistics

Generally and broadly defined, labor market discrimination refers to participants in the labor market taking into account such factors as race and gender when making economic decisions. Thus, labor market discrimination could result on the part of an employer in the hiring, promotion, or wage-setting processes. Most theoretical and empirical work focuses on discrimination in wages, since wages are convenient to measure.[2] The concept of wage discrimination, thus, is more specific than labor market discrimination, and refers to discrimination in the wage-setting process. Specifically, wage discrimination can be defined as occurring when individuals of equal productivity receive unequal wages.

Wage discrimination by gender is evidenced in the following model if δ is estimated as less than zero:

$$W_i = \beta X_i + \delta F_i + e_i \tag{1}$$

where W = wages for individual i
X = vector of productivity characteristics for individual i
F = gender dummy variable, where F=1 for female

Implicit in the above model is the assumption that the variables in the X vector are exogenous and not the result of labor market discrimination. If occupation is included as a control variable, the assumption of exogeneity becomes more doubtful, for individuals may be crowded into certain occupations as a result of labor market discrimination. In addition, some would argue that all of the variables included in vector

[2] This may ignore, as Lazear (1991) points out, that significant discrimination occurs in the hiring and promotion process. However, if a minority group is discriminated against in the hiring and promotion process, they are crowded into less desirable firms and occupations, and their wages will be lowered relative to the majority group. Hence, wages should reflect the reduced demand for the minority group.

X could be considered endogenous, as a result of discrimination apart from the labor market. For instance, if labor market experience is included as a variable in X, it could be argued that females have, on average, less labor market experience due to a socialization process that requires more household production on the part of females. Such concerns, although important, are generally considered as outside the scope of economics. Thus, a distinction is made between discrimination within the labor market, which is the current topic of study, and other potential forms of discrimination.

Before examining recent estimates of the disparity between female and male earnings, a historical perspective proves helpful. Claudia Goldin (1990), has published an important volume on the economic history of women in America. Using early manufacturing censuses, Goldin reports that the female-male earnings ratio stood at approximately .35 in 1830, and increased to .50 by 1850, its greatest increase in such a short period. Goldin theorizes that this increase in the earnings ratio, since it occurred during a period of industrial growth, resulted from the escalating division of labor and use of machinery, both of which reduced the need for skill and strength. These changes mitigated differences in productivity between females and males, thereby narrowing the earnings gap.

Goldin reports a relatively unchanging earnings ratio from 1850 to 1890, followed by an increase in the ratio from 1890 to 1930, where it reached .64. From 1930 to 1980, the earnings gap remained relatively unchanged. This does not imply that the economic status of women did not improve during this period. As O'Neill (1985) points out, the female labor force participation rate rapidly increased during this time period, and new entrants in the labor market were relatively inexperienced. New entrants received lower wages, thereby reducing the average wage of the female work force and masking wage gains made by more experienced females.

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After fifty years of relative stability, the gender gap in earnings has resumed its long-run decline. Table 1 reports the female-male earnings ratio from 1982 to 1995 among full-time wage and salary workers. From 1982 to 1992 the female-male earnings ratio increased from .65 to .75. Since 1992, the earnings ratio has remained relatively constant. Table 1 also reports labor force participation rates for males and females. Note that the female labor force participation rate continues to steadily increase, while the corresponding measure for males has slightly fallen. In 1995, the difference in labor force participation rates was only 16 percent (76 percent for males, 59 percent for females).

Since men and women differ in various characteristics relevant to the labor market, the gender earnings gap does not serve as a reliable measure of wage discrimination.[3] A more useful measure of wage discrimination must take into account differences in individual characteristics, and this issue will be explored further in section III. Nevertheless, the persistent gap in earnings over time does present a challenge to economic theory. In addition as shown in section IV, existing empirical work, controlling for various gender differences in observed characteristics, falls short in its effort to explain the entire gender gap in earnings. In an attempt to address these challenges various theories of discrimination have been developed, which are surveyed in the next section.

II. Theories of Wage Discrimination

Prior to an exploration of the existing theories of wage discrimination, a review of the neo-classical model will prove useful. Assuming labor as the only factor of

[3]In fact, a decline in the gender gap in earnings does not necessarily imply a decline in wage discrimination. Goldin (1990) reports evidence of wage discrimination rising in the early 1900s, even as the earnings gap was declining.

production, and assuming that male and female workers are perfect substitutes in production, a firm's production function may be expressed as:

$$Y = F(m + f) \tag{2}$$

where m = male labor
f = female labor

The profit function may be expressed as:

$$\pi = F(m+f) - w_m m - w_f f \tag{3}$$

where w_m = male wage
w_f = female wage

Maximization of the profit function leads to the condition, $MP_L = w_m = w_f$, where MP_L is the marginal product of labor. Thus, the competitive model predicts equivalent wages for males and females of equal productivity. Note that this result does not change if there exists imperfect competition in the product market, as long as the assumption of profit maximization is maintained.[4]

A. Employer Discrimination

Adding labor market discrimination to the analysis alters the firm's profit-maximizing condition. The key assumption of Becker's theory of employer discrimination is that some employers suffer a disutility in hiring females, measured by d_i, a discrimination coefficient. The total cost of hiring a female, thus, is $(w_f + d_i)$. The profit maximization condition may now be expressed as $MP_L = w_m = w_f + d_i$. As d_i differs for each individual employer, the decision rule for the profit-maximizing employer that discriminates against females is:

Hire all females if $(w_f + d_i) < w_m$

[4] In the case of imperfect competition in the *labor* market, or monopsony, profit maximization by a monopsonistic firm may result in the condition $w_f<w_m$. Necessary for this to occur, as described in Madden (1973), is that the female labor supply be less elastic than the male labor supply. However, as pointed out in Cain (1986), not only is prevalence of monopsony thought to be rare, most empirical evidence suggests that the female labor supply is *more* elastic than the male labor supply.

Hire all males if $(w_f + d_i) > w_m$

Thus, the employer discrimination model predicts a perfectly segregated work force. The fact that this is not encountered in the US labor force forms the basis of a major criticism against Becker's model. Arrow (1972) answers this criticism by modifying the model, allowing discriminatory tastes to be an increasing function of the ratio of female-to-male employees, thus depending on the *relative* amount of female employees, rather than the *absolute* number of female employees. Allowing this modification, the model still predicts some segregation, but not perfect segregation.

A second prediction of the employer discrimination model is that discrimination should disappear in the long-run. In exchange for avoiding disutility in hiring females, discriminatory firms sacrifice profits. Non-discriminatory firms, making relatively greater profits, would be expected to expand production and drive out discriminatory firms.[5] Thus, the fact that discrimination should be competed away in the long-run is an additional charge against the employer discrimination model. A first response to this criticism is that some non-competitive forces are thought to exist in the long-run. In the case of oligopolistic or regulated industries, firms are under less competitive pressure to maximize profits, which may allow employers to engage in discriminatory practices in the long-run.

An additional response to the aforementioned criticism is offered by Goldberg (1982), who modifies Becker's model in two ways. First, the employer's problem is expressed in the context of maximizing utility, rather than maximizing profits. Second, the employer derives utility from hiring males, instead of sustaining a disutility in hiring

[5] This statement assumes that decreasing returns to scale are not operative. However, even in the presence of decreasing returns to scale, non-discriminatory firms could expand production by "buying out" discriminatory firms.

females. Goldberg's model is referred to as the "nepotism model." The utility function may therefore be expressed as:

$$U_i = \pi_i + d_i m \tag{4}$$

Maximization of the utility function leads to the condition, $MP_L = w_m - d_i = w_f$. Therefore, for positive d_i, $w_m > w_f$. Although Goldberg's modification of the employer discrimination model appears minor, the change in results is significant. By framing the model in a utility maximizing framework, employers who show favor toward males may earn less pecuniary profits relative to nondiscriminating employers; however, to offset those losses, they obtain an additional amount of utility by hiring males. As a result, discrimination may continue to exist, even in the long-run.[6]

As Cain (1986) points out, one problem with the nepotism model is that it seems unrealistic to regard employers as finding "extra utility" in hiring males, which make up a majority of the work force. The issue appears more appropriately framed in the context of disutility in hiring females, which are a minority in the labor force. However, Goldberg's contribution is important, and it points out, along with the other considerations mentioned, that the employer discrimination model should not be summarily dismissed.

B. Employee Discrimination

Females may encounter labor market discrimination that originates from fellow employees. In Becker's theory of employee discrimination, male workers demand extra compensation, d, for employment alongside female workers. Thus, their wage rate may be expressed as $(w_m + d)$. Predictions of the model follow from an examination of the profit functions of the three different types of firms:

All male: $\pi_m = F(m+f) - w_m m$

[6] In the context of the previous footnote, discriminating employers would refuse to be "bought out" by nondiscriminating employers, since they receive extra utility from hiring males.

All female: $\pi_f = F(m+f) - w_f f$
Integrated: $\pi_{mf} = F(m+f) - w_f f - w_m m - df$

Since π_m, $\pi_f > \pi_{mf}$, this model also predicts perfect segregation with profit-maximizing firms. In addition, this simple model does not predict $w_m > w_f$, but instead $w_m = w_f$. Once again, modification of the model is necessary to alter these predictions.

Arrow (1973) points out that it is unrealistic to assume that there are no adjustment costs in reallocating labor. If the wage rate changes for an all-male firm so that $w_m > w_f$, the firm may not immediately become an all-female firm, given fixed costs in training and hiring. Thus, firms may be integrated over a long period of time, and may never reach the long run equilibrium of perfect segregation if relative wages constantly fluctuate.

In order to modify the model's prediction of equivalent wages, consider the following: Assume that the labor force is either skilled or unskilled, with skilled workers receiving higher wages. Due to assumed pre-labor market discrimination, all females are unskilled. Existing technology requires that the skilled and unskilled are complementary in production. Skilled males require a premium, d, when working with unskilled females. Thus, unskilled females are paid less than equally productive unskilled males, in order to offset the high wage rate they "impose" on their complementary factor of production, skilled males. Thus, the employee discrimination model, modified in this manner, predicts wage discrimination.

A criticism of the modified employee discrimination model is that it rests on the assumption of pre-labor market discrimination. Indeed, under the above assumptions, females would have a significant incentive to become skilled, and employers would desire the same. Females would seek to receive the higher wages received by skilled workers, and employers would want to hire skilled females, since they would not have to pay the premium that they are required to pay skilled males. Eventually, as more skilled females become hired, the underlying source of discrimination would disappear. Thus even after modification, the employee discrimination model is lacking in its ability to predict long-run differences in wages between equally productive males and females.

C. Customer Discrimination

The last of the "taste" discrimination models introduced by Becker is the customer discrimination model. The model is based on the assumption that male customers suffer disutility when purchasing goods or services from female sellers. Female customers are assumed indifferent regarding from whom they make their purchases. If female sellers wish to sell to male customers, they must charge $P_f^* = (1-d)P_m^*$, where P_m^* is the price that male sellers charge all customers, and d is the disutility that male customers incur when purchasing from female sellers. Female sellers may charge $P_f^* = P_m^*$, but then they will only sell to female customers. It follows from this that male sellers will have greater earnings than female sellers, since they are able to charge higher prices to all customers.

An underlying assumption of the customer discrimination model is that customer contact is necessary for discrimination to occur. Females, facing discrimination in jobs with high levels of customer contact, would be expected to select into occupations with low levels of customer contact. Thus, as in the other taste discrimination models, there exists a prediction of segregation. In this case, it is a prediction of occupational segregation.[7]

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[7] The degree of occupational segregation could vary, since some female sellers may stay in jobs with customer contact, dealing with only nondiscriminating female customers.

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Given the predicted segregation, wage differences should disappear between males and females of equal productivity. Thus once again, a taste discrimination model, in its simplest form, may be better classified as a theory of segregation, rather than a theory of labor market discrimination. In addition, even in the absence of segregation, a large percentage of jobs have little or no customer contact, so the magnitude of customer discrimination in the aggregate should be small. Finally, there is little empirical evidence supporting the theory of customer discrimination, especially by gender, and thus the model has received a relatively minor role in the literature.

D. Statistical Discrimination

In the three taste discrimination models presented, discrimination originates from prejudice on the part of labor market agents. Labor market discrimination may also arise as a result of imperfect information, which is referred to as statistical discrimination. The first models of statistical discrimination were formulated by Arrow (1973) and Phelps (1972). The following model is due to Phelps.

Suppose that q is the true measure of a worker's productivity, which is unknown to the employer, who relies on an imperfect indicator of productivity, y:

$$y = q + u \tag{5}$$

where $E(u) = Cov(q,u) = 0$; $E(y) = E(q) = \alpha$; $Var(u) = \sigma^2$; q, u ~ N. An estimate of true productivity may be expressed in regression form:

$$q = \alpha(1 - \gamma) + \gamma y + e \tag{6}$$

where γ measures the reliability of y as a predictor of q, and $0 \leq \gamma \leq 1$. Thus, the closer γ is to zero, the greater reliance an employer will place on the group average, α; the closer γ is to one, the greater weight an employer will place on the indicator, y. Employers will pay workers according to their expected productivity,

$$w = \alpha(1 - \gamma) + \gamma y \qquad (7)$$

Assume that males and females have equivalent average productivity, but that the productivity indicator for females is less reliable ($\gamma_f < \gamma_m$). Figure 1 illustrates this case. For a value of the indicator greater than the mean ($y > \bar{y}$), males will be paid more than females, since the employer places greater weight on the indicator for males, relative to females. For a value of the indicator less than the mean ($y < \bar{y}$), males will be paid less than females, as once again the employer relies more on the indicator for males compared to females.

Under these assumptions, wage discrimination will take place on an *individual* basis. High productivity females will be paid less than males with equivalent productivity. However to offset this, low productivity females are paid more than males, and thus, discrimination does not occur on a *group* basis. No evidence of wage discrimination will appear in the aggregate, since female and males workers are paid in accordance with their average productivity. This holds true regardless of the differences between gender differences in mean productivity ($\bar{y}_m, \bar{y}_f$) or reliability indicators (γ_m, γ_f).[8]

An implicit assumption of the above model is that employers are risk neutral. As Aigner and Cain (1977) show, by modeling risk aversion in the employer's utility function, statistical discrimination can lead to group discrimination. For example, suppose that an employer bases hiring decisions, at least in part, on expected job tenure. Other factors held constant, the employer desires longer tenure, in order to recoup training costs. Further, assume that there are two job applicants, one male and

[8] If, as in the above example, high productivity females are not rewarded with wages as great as high productivity males, they will have less incentive, relative to males, to train to become high productivity workers. Thus, statistical discrimination could have an impact on the distribution of ability over time.

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one female, who are alike in every respect, including expected job tenure. However, if job tenure is estimated with uncertainty, and females as a group experience greater variance in tenure, the risk-averse employer will hire the male applicant over the female applicant. Such group discrimination evident in the hiring process could be carried over into the wage-setting and promotion processes (see Lazear and Rosen, 1990).

A criticism of statistical discrimination models is that employers should be able to observe productivity over time and adjust wages accordingly. Therefore, as demonstrated in Figure 1, high productivity females may be hired in at lower wages than high productivity males, but after a trial period, employers would learn the productivity of workers and pay individuals according to their true productivity. This point is not trivial; however, some information about workers, such as job-quitting behavior, remains imperfect and could have a long term impact on wages.

Statistical discrimination models remain interesting and relevant, as labor market discrimination is reconciled with profit-maximizing behavior on the part of firms. However, the models are lacking in their ability to explain gender wage differences in the aggregate. Statistical discrimination may be most relevant in the hiring and promotion process, and there is a need for more empirical testing in these areas.

E. Occupational Crowding

As documented by Reskin and Roos (1990), though females have made recent gains in entering many male-dominated occupations, a great deal of occupational segregation by gender remains in the US labor market. A discrimination-based explanation of this segregation is known as the occupational crowding hypothesis. This theory contends that females are segregated into specific occupations, resulting from any of the types of discrimination covered up to this point. Alternatively, others argue that it results from pre-labor market discrimination, a social climate that teaches young females that certain occupations are for men and others for women. Regardless of the underlying basis, the theory contends that females are crowded into a relatively small number of occupations, and as a result earnings are depressed.

At the center of the discussion regarding occupational segregation is the issue of controlling for occupation in wage estimations. Although a significant amount of the gender gap in earnings may be explained by occupational differences, proponents of the occupational crowding hypothesis contend that it is inappropriate to control for occupation, since the choice of occupation is tainted by discrimination. It remains a controversial issue, since, as will be discussed in the next section, there are alternative theories that claim to explain occupational segregation.

In order to test for the existence of occupational segregation, consider the following equation:

$$w = \beta X + \delta p + e \qquad (8)$$

where w = wages (for individual i, subscripts omitted)
X = vector of control variables, including education, experience, industry, hours worked, marital status, and gender
p = proportion female in individual i's occupation
e = error term

δ is estimated as less than zero indicates that the proportion of female workers in an occupation has a negative impact on earnings. Given the human capital and productivity variables included as control variables, δ estimated as less than zero suggests a discriminatory process at work. Ferber and Green (1991) obtain this result in a data set of male and female managers. Not only is their estimate of δ negative and statistically significant, they employ a much richer set of independent variables than in equation (8), including controls for specific job responsibilities. Within their sample, the proportion female in an occupation has an average negative impact of 15 percent on earnings. Their work complements other work (see England, 1982; Reskin and Roos,

1990) which suggests that labor market discrimination may manifest itself, at least in part, in occupational segregation. However, as will be discussed in the next section, some researchers believe other factors form the basis for occupational segregation.

F. Human Capital Explanations

An alternate explanation for job segregation depends on differences in the continuity of labor force attachment for males and females. On average, women are more likely to have longer and more frequent interruptions in their lifetime pattern of labor force participation. As previously discussed, this may induce "demand-side" statistical discrimination on the part of firms. There is also theory and evidence, due primarily to Mincer and Polachek (1974; Polachek, 1981, 1993), that there is a "supply-side" response to intermittent labor force attachment on the part of females.

A consequence of a career interruption is a depreciation in human capital, both general and specific. This decline in human capital will negatively impact earnings upon reentry to the labor force. Females, therefore, have an incentive to choose occupations in which the earnings loss on their human capital is lowest. Occupations of this nature will have training that is general in nature, with short promotion ladders, and job skills that do not quickly become obsolete. Examples of such occupations are secretaries and school teachers, occupations that are predominantly female.[9]

Polachek (1981) provides evidence that the intermittent pattern of female labor force participation has a significant impact on occupational choice. Using NLS data, he

[9] A corollary argument is offered by Becker (1985). His theory begins with the premise that division of labor within the household is efficient. Becker argues that females have a comparative advantage in household production, and will concentrate their efforts and investments in household production. One result of this is occupational segregation, where females seek occupations that require lower levels of human capital investments, relative to males.

estimates that if females had the same commitment to the labor force as males, the number of female professionals would increase by 35%, and the number of female managers by more than 100%.

Intermittent labor force participation will not only impact occupational choice, but also returns to experience. It is important to note that most studies do not, or are unable to, control for differences in work histories. Wood, Corcoran, and Courant (1993) show that among lawyers with 15 years of experience, over half of the gender gap in earnings can be attributed to the differences in work histories between male and female lawyers. The impact of taking time off work to care for children is reported as particularly significant. For example, if a female lawyer worked part-time for one year to take care of children early in her career, the authors estimate that her annual earnings are reduced by 5.6% *for every year thereafter*.

Other researchers question the relevance of human capital explanations to explain occupational segregation and lower returns to experience for females. England (1982) reports that females who have intermittent work histories are no more likely to be employed in predominantly female occupations than are women who have continuous work histories. In addition, some argue that female intermittent labor force attachment *results* from labor market discrimination. In other words, the low wages that females receive as a consequence of discrimination leads to lower work force attachment. Regardless of which comes first, the potential feedback effects between the demand and supply of female labor could be significant: employers expect females to have higher quit rates and therefore provide them with only general training. Since women have only general training, they quit more frequently, and so on.

Although usually pitted against one another as alternative explanations for occupational segregation, there is evidence that both discriminatory and human capital forces are at work in generating occupational segregation. The extent to which each is responsible for the existing segregation is of course a matter for further study.

III. Measuring Wage Discrimination

The standard statistical model used to measure wage discrimination, referred to as a wage decomposition, is due to Oaxaca (1973). First, using OLS, separate earnings regressions are estimated for females and males:

$$\hat{W}_f = \sum B_f \cdot X_f \text{ and } \bar{\hat{W}}_f = \overline{W}_f = \sum B_f \cdot \overline{X}_f \tag{9}$$

$$\hat{W}_m = \sum B_m \cdot X_m \text{ and } \bar{\hat{W}}_m = \overline{W}_m = \sum B_m \cdot \overline{X}_m \tag{10}$$

The first term of each equation denotes the predicted value of wages, the mean of which, $\bar{\hat{W}}$, is equal to the overall mean, $\overline{W}$. The X variables include measures for various productivity-related characteristics.[10]

If $\sum B_m \cdot \overline{X}_f$ is added to both equations (9) and (10), and then equation (10) is subtracted from equation (9), the following decomposition is obtained:

$$\overline{W}_m - \overline{W}_f = \sum B_m(\overline{X}_m - \overline{X}_f) + \sum \overline{X}_f(B_m - B_f) \tag{11}$$

The first term on the right-hand side of equation (11) evaluates the difference in mean values of the X's using male coefficients. This is generally referred to as the "explained portion" of the wage gap. The second term on the right-hand side is the conventional measure of wage discrimination, with $B_m > B_f$ indicating a higher price received by a male worker relative to female worker for the same productivity characteristic. An alternative measure of wage discrimination evaluates the differences in mean characteristics using female coefficients:

[10] An intercept term is included in $\sum B \cdot \overline{X}$, for which $X_m = X_f = 1$.

$$\overline{W}_m - \overline{W}_f = \sum B_f(\overline{X}_m - \overline{X}_f) + \sum \overline{X}_m(B_m - B_f) \tag{12}$$

Defining the unadjusted earnings ratio as $\frac{\overline{W}_f}{\overline{W}_m}$, an "adjusted" earnings ratio can be obtained from (11) or (12): $A_r = \frac{\sum B_f \overline{X}_m}{\overline{W}_m}$. Conceptually, the numerator represents the earnings females would receive if their observable characteristics were equal to those of males, evaluated with female prices, or coefficients. Generally, an A_r of unity implies no wage discrimination.

As noted Cain (1991), the wage decomposition approach has weaknesses. One problem is how unobserved differences are dealt with in the model. It is not possible to control for all productivity differences between males and females, and these differences may reflect themselves in coefficient estimates. For example, Becker (1985) theorizes that males have a comparative advantage in market work and therefore place more investment and effort, relative to females, in market work. Such a difference may reflect itself in a greater coefficient on the variable "married" for males compared to females. According to the model, this price difference would be labeled "discrimination," while such a classification may not be appropriate.[11]

A related problem concerns mismeasured experience for females. As previously discussed, most studies are unable to control for work histories. If females have a more discontinuous pattern of labor force participation relative to males, this may reflect itself in a lower coefficient on an experience variable. Once again, it may be inaccurate to classify this as discrimination.[12] A final problem with Oaxaca's model

[11] Indeed, most studies show a marriage premium for males, but not for females. Additionally, there is evidence that the premium does not reflect discrimination, but a productivity effect from marriage (see Korenman and Neumark, 1991).

[12] Of course, there are some who argue that a discontinuous pattern of female labor force participation is a result of discrimination.

is the uncertainty regarding whether to control for occupation. As argued by some, if occupation is included as a control variable, the amount of discrimination may be underestimated by the decomposition.

Taken together, these concerns demonstrate that a wage decomposition, though a useful tool of analysis, should not be regarded as an exact measure of wage discrimination. Accordingly, many researchers regard the second term on the right-hand side of equations (11) and (12) as the "unexplained portion of the wage gap" rather than the "discrimination term."

Since the large majority of empirical work utilizes the wage decomposition approach, alternative methods in studying the gender gap in earnings can potentially make a significant contribution. Holzer (1990) utilizes supervisory ratings as a proxy for productivity, and examines gender differences in relative productivity and wages. Hellerstein, Neumark, and Troske (1995), utilizing detailed establishment-level data, estimate production functions and compare gender differences in marginal products versus gender differences in wages.[13] As more research is done utilizing alternative methods to the wage decomposition approach, greater insight into the issue of labor market discrimination may be offered.

IV. Empirical Evidence

Cain (1986) surveys twenty studies on gender differences in earnings, each using the wage decomposition method. Instead of detailing each study or conducting a similar survey, I believe it more useful to point out general characteristics that hold true for these studies, as well more recent work.

The studies surveyed by Cain utilize data from 1959 to 1977, and they report

[13] Although theoretically appealing, the data requirements of this approach will limit its widespread applicability.

unadjusted earnings (U_r) ratios ranging from .33 to .85, and adjusted earnings ratios (A_r) ranging from .39 to .93.[14] Samples that represent the full population generally report smaller earnings ratios than restricted samples, limited to a single occupation or small group of occupations. This should not be unexpected since full samples represent a more heterogeneous population than restricted samples, and there will be greater differences in unobserved characteristics in the general population.

Controlling for variables such as education, age, and location generally explains very little of the gender gap in earnings. This is expected, since males and females do not differ greatly in these characteristics. Controlling for work experience, such as years spent in the labor force and tenure, however, generally does explain a significant portion of the earnings gap. Mincer and Polachek (1974), utilizing NLS data on married individuals, report an U_r of .66, but after controlling for detailed work histories, report an A_r of .80. Wood, Corcoran, and Courant (1993), in a study previously referenced, report an U_r of .61 on lawyers with fifteen years of experience, but after controlling for very detailed work histories, report an A_r of .81.

Some would argue that a relatively small adjusted wage gap, such as .19 in the previous study, could be explained by measurement error or other omitted productivity variables. If corrected, the A_r would approach unity, and this would imply an absence of discrimination by gender. Once again, this assumes that the smaller investments, lesser experience, and greater time in the household work are voluntary choices made by women and are choices not impacted by labor market discrimination. Unfortunately, the statistical model does not reveal what is or what is not exogenous.

In an attempt to avoid the issue of human capital investment decisions made by

[14]The majority of studies utilize data on earnings versus data on wages; the latter measure is preferable since it holds constant the unit of time over which earnings are measured.

married women, it may be better to restrict samples to unmarried women and men. Utilizing NLS data on unmarried individuals, Mincer and Polachek report an A_r of .87. Although this restriction may provide a purer measure of labor market discrimination, uncertainty still remains. This could reflect employers statistically discriminating against young women with the expectation that they will become married. Alternatively, it may reflect young single women having an expectation of becoming married and investing in human capital accordingly. Once again, economic and statistical models are limited in identifying the underlying factors that generate wage differentials by gender.

V. Conclusion

In this chapter, I have outlined the major theories that claim to explain gender differences in earnings. Three theories first introduced by Becker (1971), which base themselves on a "taste" for discrimination, were surveyed: employer, employee, and customer discrimination. All of the models are somewhat unsatisfactory in that they predict segregation and are unable to explain the existence of discrimination in the long-run. However, the work of follow-up researchers has shown that some of these predictions may be modified, and thus the taste discrimination models should not be dismissed.

The statistical discrimination model by Phelps (1972), based on the market failure of imperfect information, reconciles profit-maximization with labor market discrimination. This model, although somewhat lacking in its ability to predict group discrimination, may be particularly relevant in employer hiring and promotion practices.

The occupational crowding hypothesis offers a discrimination-based explanation for occupational segregation by gender, something that is observed in the US labor force. As a result of discrimination, females are segregated into specific occupations and earnings are depressed. Although its claims are debatable, the fact that researchers have found a negative correlation between the percentage female in an occupation and earnings offers support for this theory.

Human capital theorists offer an alternative explanation for occupational segregation. Specifically, the theory contends that females are "crowded" into occupations as a result of their own choices. Considering their intermittent lifetime labor force participation, females choose jobs that have training that is general in nature, with relatively low penalties imposed for discontinuous participation. It is likely that both crowding on the part of firms and voluntary choices made by women contribute to occupational segregation. In addition, the potential feedback effects between these two factors could be significant.

The standard statistical technique used to measure wage discrimination, a wage decomposition, is a useful tool of analysis, but subject to various limitations. The numerous studies that report measurements of wage discrimination do not provide irrefutable proof on the existence of wage discrimination. However, over time, as more evidence is offered and new techniques are used to study and measure labor market discrimination, the issues should become more clear.

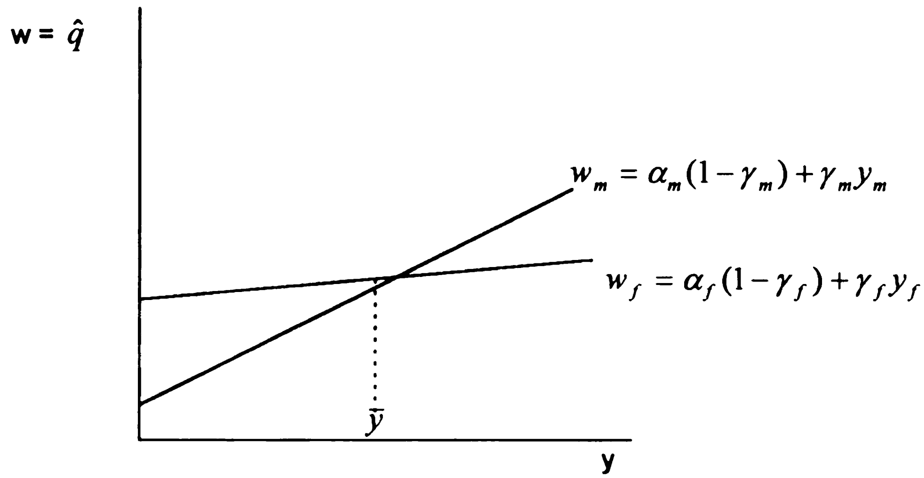

Figure 1: Statistical Discrimination

Table 1: Gender Earnings Ratio and Labor Force Participation, 1982-95

Year	Female Earnings/ Male Earnings[1]	Male Labor Force Participation Rate[2]	Female Labor Force Participation Rate
1982	.65	.77	.53
1983	.67	.76	.53
1984	.68	.76	.54
1985	.68	.76	.55
1986	.69	.76	.55
1987	.70	.76	.56
1988	.70	.76	.57
1989	.70	.76	.57
1990	.72	.76	.58
1991	.74	.76	.57
1992	.75	.76	.58
1993	.77	.75	.58
1994	.76	.75	.59
1995	.75	.75	.59

[1]Earnings measure is median weekly earnings among full-time wage and salary workers.
[2]Civilian labor force as a portion of the civilian noninstitutional population.

Source:
U.S. Department of Labor, *Employment and Earnings*, (1983-1996).

Chapter 3

PAY AND PRODUCTIVITY DIFFERENCES BETWEEN MEN AND WOMEN: EVIDENCE FROM VETERINARIANS

Differences in earnings between men and women can be attributed to three factors: differences in personal characteristics, variations in employment, and a residual element that, if observed, may be referred to as wage discrimination. In this chapter, I utilize a unique new data set on veterinarians to study gender differences in pay and productivity. The advantage of using these data is that they examine a relatively homogenous group of professionals, minimizing the personal and employment differences that exist between men and women. By controlling for these factors, a smaller residual, or unexplained portion of the earnings gap, may be obtained.

There is a strand of literature that uses human capital theory to explain observed earnings differences between men and women. It is theorized that women obtain less human capital in the labor market than men, and these differences in human capital, often unobserved, may account for a significant portion of the gender gap in earnings. Goldin and Polachek (1987) claim that women anticipate future child-related career interruptions, and thus, invest less in human capital than do men, even early on in their careers. Lazear and Rosen (1990) contend that employers, in consideration of more career interruptions that occur to women, may be reluctant to hire and promote women into jobs that require a great deal of training and acquisition of firm-specific human capital. Thus, in reaction to the imperfect information they face, employers are said to statistically discriminate against women.

Although relevant in studies on the general population, gender differences in human capital should be less important in explaining earnings differences among veterinarians. First, schooling is virtually identical among female and male veterinarians. In order to become a veterinarian, one must graduate from one of the twenty-seven accredited veterinary schools in the United States. Second, the analysis takes place over a self-selected group of females, one that behaves much like the group of males to whom they are being compared. Thus, there should be fewer differences in motivation, skills, and training among this group than among workers in general. In addition, employers should recognize the high opportunity costs of career interruptions faced by female veterinarians, making statistical discrimination a less likely scenario in this labor market.

An additional advantage of this data set is that it includes valuable proxy measures of productivity. Data on individual worker productivity is generally lacking in the empirical work on wage discrimination. Without productivity controls, it may always be contended that unobserved productivity differences cause observed differences in earnings. Thus, the ability to control for productivity differences between men and women significantly strengthens any evidence that is consistent with the presence of wage discrimination.

There are also drawbacks in using these data to study the issue of gender differences in pay and productivity. The clear disadvantage is that one cannot generalize from this population to the entire sample of working men and women. The mechanisms that determine pay and productivity among veterinarians are not likely to be the same as for the general population. Regardless, the results obtained can be suggestive of the role that gender plays in all labor markets. Wood, Corcoran, and Courant (1993) studied pay differences between male and female lawyers in an approach similar to this study.

In this chapter, my study is focused on veterinarians in the wage-salary sector. Other chapters analyze gender pay differentials among the self-employed. First, I offer a brief description on the market for veterinarians. In Section II, I discuss the data utilized, and in Section III, I offer the empirical framework in which pay and productivity differences will be analyzed. Results and discussion of estimations are presented in Section IV. Finally, I explore possible explanations for the differences in earnings that remain, even after controlling for various productivity-related characteristics.

I. The Market for Veterinarians

Training for a veterinarian entails a minimum of six years, including at least two years of study in a preveterinary program and four years in a college of veterinary medicine. After obtaining a Doctor of Veterinary Medicine (D.V.M.) degree and passing a national board examination, most states allow individuals to apply for licensure without further training (U.S. Department of Labor, 1995a). In 1993, according to the American Veterinary Medical Association (1994), 81% of veterinarians were employed in the private clinical sector, and 19% in the public and corporate sector. Of those in the private clinical sector, 69% were employed in small animal practices, 19% in large animal practices, and the remainder in "mixed" (small and large) practices. Most veterinarians begin their careers as wage-salary workers, and some time later, become partners or owners.[1]

[1] The data utilized in this chapter report that among veterinarians with less than 3 years of experience, 84 percent are located in the wage-salary sector. Among veterinarians with greater than 10 years of experience, only 8 percent are found in the wage-salary sector.

II. Data

The data are obtained from annual wage surveys conducted in 1994 and 1995 by Medical Economics Research Group, at the direction of Veterinary Economics. Veterinary Economics is a monthly publication sent free to all private practice veterinarians who request it. Their circulation is approximately 40,000, representing more than two-thirds of all private practice veterinarians in the United States. A stratified random sample[2] of 4,319 veterinarians in 1994, and 4,322 in 1995, were mailed surveys, with a total of 3,187 usable surveys returned (37% usable return rate).[3] The sample is limited to full-time, private practice veterinarians who have at least one year of experience. Appendix A provides evidence that the sample is representative of the general population of veterinarians, utilizing comparisons with 1990 census data on veterinarians.

Table 1 reports summary statistics from the data. Note that I partition the sample into three sectors: the self-employed, partners, and wage-salary workers.[4] Each sector is treated separately, since I expect the mechanisms that determine earnings will differ between these groups.[5] In addition, what is meant by "earnings"[6] may differ between sectors. In this chapter, I focus on earnings differences among

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[2] Some smaller veterinarian specialties were over-sampled. Summary statistics are weighted by specialty to reflect the "true population" of veterinarians, which is Veterinary Economics' subscriber list.

[3] A total of 145 observations were dropped from the 1994 data, which appeared as probable duplicates in the 1995 data. In addition, I deleted 4 observations that appeared subject to coding errors. The remaining n = 3,038.

[4] The self-employed are defined as those who are the sole owners of their firms, incorporated or unincorporated. Partners share ownership with at least one other individual, and wage-salary workers have no ownership stake in their firm.

[5] When estimating separate earnings regressions for the self-employed, partners, and wage-salary workers, a Chow (1960) test confirmed that the coefficients from the separate regressions are different at the 1% level.

[6] All are asked the same survey question: "Which of the following best represents your personal 1993 (or 1994) compensation from the practice before taxes were withheld?" However, the interpretation of this question is expected to vary across sectors, especially for the self-employed.

wage-salary workers, while in Chapters 5 and 6, I examine pay differences among the self-employed.

Note from this table that male veterinarians, on average, earn considerably more than female veterinarians within each sector, while differences in hours worked per week are relatively small. However, the sample of male veterinarians has almost twice the amount of experience as the sample of female veterinarians (an overall average of 17.8 years compared with 9.0 years). Also reported in Table 1 is a measure of patients seen per hour. Survey respondents report total client visits per week. Using this measure, along with hours worked per week, I construct the patients per hour variable, which will serve to control for productivity differences between veterinarians.

Respondents also report annual revenue produced, which represents the total dollar amount of goods and services billed out by each individual veterinarian for their practice. Most veterinarians keep track of this measure, since it typically figures into their compensation scheme (McCafferty, 1992a).[7] This measure of revenue generation will serve as an alternative proxy measure of productivity.[8] Table 1 also reports a variable called average fee. This represents a measure of the average charge per each client visit. Veterinarians typically also keep track of this measure, since it is thought to be a general indicator of clinic productivity (Bowman, 1996).[9]

Survey respondents also report some firm-level data. Table 1 reports firm size, measured as the total number of veterinarians at each clinic. The sample mean of this variable is 3.2, so the firms examined in this chapter are relatively small. Also available

[7] For example, a veterinarian in the wage-salary sector may be paid a base salary plus a percentage of their annual revenue produced.

[8] Note the distinction between the two measures of productivity. Patients per hour is a measure of average product, and annual revenue produced is a measure of total revenue (total product multiplied by price) per veterinarian.

[9] In the veterinary literature, this is referred to as the ACT (Average Client Transaction charge). Clinics with higher ACTs are generally thought to be more profitable, since each client is spending, on average, more money on each visit to the veterinarian.

are indicators of the clinic specialty where the veterinarian is employed. Last, Table 1 reports that 55 percent of male veterinarians are self-employed, compared to 36 percent of females; and while 23 percent of males are in partnerships, only 10 percent of females are found here; also, while only 13 percent of males are found in the wage-salary sector, 54 percent of females are located here.[10]

III. Empirical Framework

A. Earnings and Productivity Equations

In this chapter, the analysis is focused upon pay and productivity differences between male and female veterinarians in the wage-salary sector. Within my sample of wage-salary sector veterinarians, females earn, on average, 15 percent less than male veterinarians. The U.S. Department of Labor (1995b) reports that in 1994, among all full-time wage-salary workers, females earned 24 percent less than males. By limiting attention to a specific occupation, the gender gap in earnings is narrower, as expected. In addition, the 15 percent gender gap in earnings for veterinarians could be explained, to a significant extent, by differences in characteristics summarized in Table 1.

To explore this issue, I utilize a standard earnings decomposition, due to Oaxaca (1973). First, using OLS, separate earnings regressions are estimated for females and males:

$$\ln \hat{E}_f = \sum B_f \cdot X_f \text{ and } \ln \bar{\hat{E}}_f = \ln \bar{E}_f = \sum B_f \cdot \bar{X}_f \tag{1}$$

$$\ln \hat{E}_m = \sum B_m \cdot X_m \text{ and } \ln \bar{\hat{E}}_m = \ln \bar{E}_m = \sum B_m \cdot \bar{X}_m \tag{2}$$

The first term of each equation denotes the predicted value of ln earnings, the mean of which, $\ln \bar{\hat{E}}$, is equal to the overall mean, $\ln \bar{E}$. The X variables include controls for

[10] In Chapter 5, I show that differences in sector location are primarily explained by differences in age and experience.

experience, hours worked per week, clinic specialty and size, along with region, metropolitan statistical area, and year of survey dummies.

If $\sum B_m \cdot \overline{X}_f$ is added to both equations (1) and (2), and then equation (2) is subtracted from equation (1), the following decomposition is obtained:

$$\ln \overline{E}_m - \ln \overline{E}_f = \sum B_m(\overline{X}_m - \overline{X}_f) + \sum \overline{X}_f(B_m - B_f) \qquad (3)$$

The first term on the right-hand side of equation (3) evaluates the difference in mean values of the X's using male prices, or coefficients. This is generally referred to as the "explained portion" of the earnings gap. The second term on the right-hand side is the conventional measure of wage discrimination, with $\beta_m > \beta_f$ indicating a higher price received by a male worker relative to female worker for the same characteristic. Since there will always exist unobserved differences that cannot be controlled for, it is preferable to refer to this term as the "unexplained portion" of the earnings gap, rather than a direct measure of wage discrimination.

An alternative representation of the difference in ln wages may be expressed as follows:

$$\ln \overline{E}_m - \ln \overline{E}_f = \sum B_f(\overline{X}_m - \overline{X}_f) + \sum \overline{X}_m(B_m - B_f) \qquad (4)$$

This utilizes female coefficients to evaluate gender differences in mean characteristics. Equation (3) implies that in the absence of discrimination, the male earnings structure would prevail, while equation (4) implies that the female earnings structure would exist in a nondiscriminatory environment. The two assumptions do not yield the same result, and thus, I will report estimates of both equations (3) and (4).

Unique to the data set is a measure of annual revenue produced, which permits study of the determinants of productivity, along with any gender differences in productivity that may exist. In order to do this, I estimate the following: [11]

$$\ln(R) = \beta_0 + \beta_1 F + \beta_{j+1} X + e; \quad j = 1.....p. \tag{5}$$

where ln(R) = Ln annual revenue produced
F = Dummy variable for female
X = p controls, including experience, hours worked per week, clinic specialty and size, along with region, metropolitan statistical area, and year of survey dummies.

This will allow me to compare differences in productivity, or generated revenue, with any unexplained earnings differences found in the estimations of equations (3) and (4). A negative and statistically significant coefficient on β_1 would indicate that females generate less revenue than males, even after controlling for various productivity-related characteristics. This would imply that there are unobserved differences, related to productivity, that are not controlled for in the earnings decompositions, which would contribute to any estimate of unexplained differences in earnings. Conversely, if the coefficient on β_1 is estimated as not statistically different from zero, and unexplained differences in earnings are estimated as positive, such a finding would be consistent with the existence of wage discrimination. In other words, among veterinarians who are alike in observable characteristics, finding women on par with men in the ability to generate revenue, but not in earnings, would be evidence consistent with the presence of wage discrimination.

[11] In contrast to the earnings equations, where separate regressions were estimated for males and females, the sample is pooled in the estimation of equation (5). A Chow (1960) test confirms that pooling is permissible when ln annual revenue is the dependent variable.

B. Econometric Issues

Prior to a discussion of results, two econometric notes should be made. First, I do not control for sample selection bias in the estimates. It is possible that veterinarians who select into the wage-salary sector may differ in unobservable ways from veterinarians in the self-employment and partnership sectors. For example, those who choose the wage-salary sector, from the population of veterinarians, may be those who would have the highest earnings in the wage-salary sector. Since my analysis is focused on earnings differences within the wage-salary sector, selection may only pose a problem if there are gender differences in selection behavior (e.g., females negatively selecting into the wage-salary sector, with males positively selecting into the sector). In Appendix B, I provide tests for sample selection bias, and I do not find evidence of selection behavior, either on the part of male or female veterinarians.

Second, survey respondents report annual earnings, and annual revenue produced, as categorical variables. Instead of utilizing an ordered probit model in earnings and revenue estimations, I implement OLS by using the midpoint of the reported range as the dependent variable. If the underlying earnings distributions differ by gender, this could cause a bias in the estimation of unexplained earnings differences between males and females. Appendix C, utilizing tests with 1990 Census data, provides evidence against this concern. However, Appendix C does show that by reducing the amount of variation in the dependent variable, the OLS model is able to estimate a better fit for the data. Although coefficient estimates should be relatively unbiased, estimates of standard errors will be biased downwards. Thus, when utilizing bracket midpoints as the dependent variable, statistical inferences should be made more conservatively.

IV. Result of Estimation

The gender difference in mean ln earnings in the sample of wage-salary veterinarians is [.163] representing an unadjusted wage gap of 15 percent. Table 2 reports a decomposition of this earnings difference. Female and male coefficients, β_f and β_m, are reported from the estimation of equations (1) and (2). The last two columns of Table 2 report the estimation of the "explained portion" of the earnings gap from equations (3) and (4), respectively.

The coefficients on the experience variables are reported positive and jointly statistically significant for both females and males. The set of coefficients for both sexes indicates an upward sloping age-earnings profile. As expected, the difference in average experience explains a considerable portion of the gender gap in earnings. Measured with male coefficients, the set of experience variables explains [.040], or 25 percent, of the difference in mean ln earnings. Evaluation with female coefficients accounts for [.025], or 15 percent, of the earnings difference.

Both the female and male set of coefficients on the hours per week variables are jointly statistically significant. However, the female point estimates are greater at each level than the male point estimates, and some of the male coefficients are not statistically different from zero. Since this sample includes only full-time veterinarians, gender differences in hours worked per week are not great (males work an average of 3.5 more hours per week than females). Differences in this characteristic explain [.011] of the earnings gap when evaluated with male coefficients, and [.024] of the earnings gap when evaluated with female coefficients.

Most of the coefficients on the set of specialty variables are not statistically significant. Differences in clinic specialty explain only [.001] of the earnings difference when evaluated with male coefficients, and actually widen the unexplained earnings gap by [.017] when evaluated with female coefficients. Both equations indicate an earnings increase of 1 percent for each additional veterinarian in the firm, and gender differences in firm size explain a small portion of the earnings gap. Differences in location, and a control for survey year, explain a small portion of the earnings gap when evaluated with male coefficients, but serve to widen the earnings gap by [.050] when evaluated with female coefficients.

Added together, differences in observed characteristics explain [.058], or 36 percent, of the gap in ln earnings when evaluated with male coefficients. When evaluated with female coefficients, differences in observed characteristics serve to widen the earnings gap by [.017]. This leaves an unexplained earnings difference of [.105] or [.179], depending on the specification of the earnings decomposition. Thus, the earnings gap adjusted for differences in observable characteristics is 10 or 16 percent, depending on the specification.

In an effort to control for productivity differences between men and women, the variable patients per hour is added in the next earnings decomposition, reported in Table 3. The female coefficient on this variable is .09, and is statistically significant, indicating a nine percent increase in earnings for seeing one additional patient per hour. The male coefficient is .03, but statistically insignificant. As reported in Table 1, female wage-salary veterinarians see more patients per hour, on average, than male veterinarians in this sector. Thus, adding this variable to the earnings decompositions increases the unexplained portion of the earnings gap. The other coefficients remain relatively unchanged from Table 2. Table 3 reports a total explained portion of the difference in ln earnings of [.056] when evaluated with male coefficients, and an increase in the gap of [.023], when evaluated with female coefficients.

In Table 4, instead of using patients per hour as a control for productivity, I use ln annual revenue produced. A priori, it is not clear that I would want to add this variable to the decomposition. In testing for evidence of wage discrimination, I should not hold constant variables that may be determined in the process of discrimination. For example, it may be as a result of crowding into less productive clinics that women earn less than men. Consequently, females would produce less annual revenue, on average, than males. Unexplained differences in earnings may fall to zero, masking the discrimination that takes place through crowding.

Despite the danger of "over-controlling", Table 4 reports a persistent unexplained earnings differential. The coefficient on ln annual revenue produced is positive and highly statistically significant, reported as .31 for females and .28 for males. For a 10 percent increase in revenue produced, earnings would be expected to rise by 2.8 or 3.1 percent, holding other factors constant. Gender differences in revenue produced explain less than 3 percent of gender differences in earnings. Perhaps unexpected is the fact that most of the other coefficients retain their explanatory power, and remain qualitatively unchanged from previous decompositions. Table 4 reports a total explained portion of the gap in ln earnings of [.068] when measured with male coefficients, and [.002] when measured with female coefficients. Across each decomposition, using male coefficients to evaluate differences in observed characteristics provides the most conservative estimate of the adjusted earnings gap. In each of the three decompositions, the gender gap in earnings, after controlling for observable characteristics, is estimated at approximately 10 percent.

To further explore the issue of productivity, and the determinants thereof, Table 5 reports estimation of equation (5), with ln annual revenue produced as the dependent variable. The first specification uses the same set of controls used in the first earnings decomposition, along with a dummy for female. The coefficient on the female dummy is statistically insignificant. Thus, I find female veterinarians in parity with males in productivity, holding constant the other independent variables. This is consistent with the result reported in Table 4: productivity differences do not explain earnings differences.

The set of experience coefficients is reported positive and jointly statistically significant. Note that the coefficients suggest an upward sloping experience-productivity profile. This supports human capital explanations to account for the upward sloping age-earnings profile found in the earnings decompositions.[12]

The second specification in Table 5 adds the variable patients per hour. As expected, this variable is positively correlated with revenue production, and is highly statistically significant. By adding this variable, the explanatory power of the equation is significantly strengthened, as the adjusted R^2 increases from .13 to .19. The coefficient on female remains statistically insignificant. An additional factor that should be expected to impact a measure of revenue is price. For the subset of veterinarians who report it, the third specification adds the variable ln average fee to the set of regressors. Other factors held constant, an increase in average fees of 10 percent is correlated with an increase in personal revenue produced of 2.0 percent. Once again, the coefficient on female is not statistically different from zero.

V. Unexplained Differences in Earnings

The finding that female veterinarians are found in parity with male veterinarians in productivity, but not in earnings, is significant, because it provides evidence against some theories commonly used to account for unexplained earnings differences. For example, I am unable to control for unobserved ability, and differences in unobserved

[12] This concurs with the findings of Maranto and Rodgers (1984), along with Brown (1989).

ability could be claimed as an explanation for gender differences in unexplained earnings. However, any differences in unobserved ability would be expected to reflect themselves in differences in revenue generation. Since this is not observed, it sheds doubt on the unobserved ability explanation. Additionally, it could be claimed that female veterinarians charge lower prices, or see fewer patients, as a result of customer discrimination.[13] Once again, if this were the case, it should be reflected in gender differences in annual revenue produced. Also, the fact that I am unable to control for weeks worked per year does not appear of consequence, for any gender differences in this variable would be reflected in the revenue variable.[14]

An additional explanation used to account for lower earnings on the part of females, relative to males, depends on gender differences in labor force attachment. On average, women are more likely to have more frequent and longer interruptions in their lifetime pattern of labor force participation. A consequence of a career interruption is a decline in human capital, both general and specific. It is claimed that this loss of human capital leads to lower earnings upon reentry into the labor force. Other researchers, utilizing detailed work histories, have found this to be an important factor in accounting for earnings differences between men and women (see Mincer and Polachek, 1974; Wood, Corcoran, and Courant, 1993). The lack of detailed work histories in the current sample does not appear to be problematic,[15] since once again, this is an omitted variable that should impact annual revenue produced.

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[13] Similarly, it could be claimed that females price discriminate in a manner that negatively impacts their earnings, relative to males.

[14] 1990 Census data report an average of 51.4 weeks worked per year for male veterinarians, and 50.7 weeks worked per year for female veterinarians.

[15] The average experience of females in this sample is only 6.1 years, and gender difference in work histories are more likely to appear later in the life-cycle.

An assumption of the above discussion is that annual revenue produced is a reliable measure of productivity. However, though it measures direct revenue production, it does not measure any indirect revenue production that may take place. For example, it could be the males are more involved in the management of the firm, since they have more average experience. Thus, they may be involved in generating revenue in indirect ways, not measured by the annual revenue produced variable. In order to examine the issue of job duties in the wage-salary sector, I estimate the following equation:

$$\ln(P) = \beta_0 + \beta_1 F + \beta_{j+1} X + e\,; \quad j = 1.....p. \qquad (6)$$

where ln(P) = Ln patients per hour
F = Dummy variable for female
X = p controls, including experience, clinic specialty and size, along with state, metropolitan statistical area, and year of survey dummies

Table 6 reports the results of this estimation. The female dummy is positive and statistically significant, indicating that females see 11 percent more patients per hour than males, other factors held constant. Of interest is the set of coefficients on the experience variables. They indicate that wage-salary veterinarians see more patients per hour as they gain experience (at least through their first 30 years), instead of seeing fewer. In column (2), I add ln average fee as an additional regressor. The coefficient on this variable is reported negative and statistically significant, which should be expected: if a veterinarian charges a higher average fee, it may indicate that he or she is selling more services to each client, and thus, spending more time with each customer. In the second specification, many of the coefficients are not statistically different from zero, likely due to a smaller sample size. However, the coefficient on female remains positive and statistically significant.

The results in Table 6 could be consistent with the theory that male veterinarians spend more time in management, and thus, generate revenue in less direct ways. To test this more directly, I utilize supplementary data from the 1995 survey. Survey respondents were asked to report the percentage of time they devote to both medicine and management duties. The following equation is estimated for wage-salary veterinarians:

$$M = \beta_0 + \beta_1 F + \beta_{j+1} X + e\,; \quad j = 1.....p. \tag{7}$$

where M = Percentage of time spent in management
F = Dummy variable for female
X = p controls, including experience, clinic specialty and size, along with a region dummy

Table 7 reports the results of the estimation. Most significantly, the coefficient on female is positive and marginally significant. The point estimate indicates that females spend 3% *more* time in management tasks than males, other factors held constant.[16] This sheds doubt on the suggestion that males are generating revenue in ways that are not reflected in the variable annual revenue produced.

Beyond wage discrimination, two other possibilities are offered for explaining a portion of the earnings gap between men and women. First, it may be that providing benefits to women is more costly than provision to men, and thus total compensation received by women is more on par with men.[17] Second, it may be that female veterinarians perform duties that have higher marginal costs, relative to males. If this were the case, men could be producing more profits for their clinics, relative to females, and thus their higher earnings could follow from this.[18]

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[16] It should be noted that the average percentage time devoted to management among wage-salary veterinarians is only 8.6 hours.

[17] Similarly, females may work in clinics that provide greater compensating differentials, relative to males.

[18] If true, this does not preclude the possibility that such occupational segregation is the result of discrimination (see Reskin and Roos, 1990).

VI. Conclusion

This chapter examines pay differences between men and women utilizing data on wage-salary workers within a narrowly defined occupational group. The gender gap in average earnings is 15 percent. I utilize the standard earnings decomposition due to Oaxaca (1973) to study this difference. Controlling for various observed characteristics, including measures of productivity, the gender gap is narrowed to 10 percent, using the most conservative estimates.

In an effort study the determinants of productivity, I estimate an equation with annual revenue produced as the dependent variable, which represents the annual dollar amount of goods and services billed out by each individual veterinarian. I do not find gender differences in annual revenue produced, other factors held constant. Finding women in parity with men in productivity, but not in earnings, is evidence consistent with the presence of wage discrimination. This also provides evidence against human capital explanations for differences in earnings, for if gender differences in human capital exist, they would be expected to be reflected in productivity differences.

I explore the possibility that male veterinarians may be involved in activities that generate more indirect revenue, in management-related tasks, relative to female veterinarians. Results indicate females spend more time in management duties than men, other factors held constant. In addition, I find that females see more patients per hour, on average, than male veterinarians, holding other factors constant.

Overall, the results suggest that studying pay differences within narrowly defined occupational groups may make an important contribution to the discrimination literature. By limiting attention to one occupation, potential human capital explanations for earnings differences are limited. The study undertaken in this chapter also gives insight into the type of wage discrimination that may be at work. Finding gender differences in earnings, but not productivity, is evidence consistent with direct employer discrimination. However, the evidence is not conclusive, and research on other occupations is desired.

Table 1: Summary Statistics

	Males			Females		
	Self-Employed	**Partners**	**Wage-Salary**	**Self-Employed**	**Partners**	**Wage-Salary**
Annual Earnings[1]	72,441	82,035	46,350	43,874	45,911	38,897
Experience[1]	20.1	18.7	8.8	12.6	11.7	6.1
Age[1]	46.3	44.2	35.2	39.3	38.2	32.4
Hours worked/wk[1]	53.2	52.7	52.8	54.5	49.8	49.3
Patients per hour	1.51	1.37	1.37	1.24	1.32	1.51
Annual Revenue Produced[1]	180,653	195,444	166,579	136,214	153,096	165,501
Average Fee	65.54	70.68	65.71	64.92	60.51	66.79
Firm Size	2.0	4.3	4.9	1.8	3.7	4.3
Clinic Specialty: Small Animal	.60	.45	.62	.76	.62	.82
Mixed	.26	.37	.27	.16	.29	.14
Equine	.04	.02	.02	.05	.05	.02
Dairy	.03	.09	.05	.01	.02	.01
Beef	.04	.04	.02	.01	.02	.01
Swine	.02	.04	.02	.01	.01	.001
Sample Size[2]	1328	782	346	221	66	257
Fraction of gender in sector	.55	.23	.13	.36	.10	.54

Table is weighted to correct for over-sample of some specialties. [1]Data are reported as categorical variables. Means are obtained by using the midpoint of the reported range. [2]Smaller samples for some variables.

Source:
Veterinary Economics, *Continuing Wage Surveys*, Veterinary Medicine Publishing Company, (1994-95).

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Table 2: Earnings Decomposition

Dependent Variable: Ln Annual Earnings

Variable	β_f		β_m		$\beta_m(\bar{X}_m-\bar{X}_f)$	$\beta_f(\bar{X}_m-\bar{X}_f)$
Experience[1]					[.040]	[.025]
3 to 5 years	.11	(1.99)	.12	(2.61)	-.010	-.010
6 to 10 years	.19	(2.94)	.20	(4.02)	-.006	-.005
11 to 20 years	.19	(2.23)	.39	(7.58)	.028	.014
21 to 30 years	.61	(2.85)	.46	(6.32)	.021	.027
31 to 40 years	[5]		.54	(4.45)	.008	.000
over 40 years	[5]		.07	(.28)	.000	.000
Hours per week[2]					[.011]	[.024]
under 25 hours	[5]		-.74	(3.75)	-.004	.000
41 - 50 hours	.14	(2.12)	-.03	(.49)	.004	-.016
51 - 60 hours	.24	(3.36)	.06	(.87)	.002	.007
61 - 70 hours	.18	(2.04)	.06	(.89)	.007	.022
71 - 80 hours	.45	(3.20)	.07	(.78)	.002	.010
over 80 hours	-.16	(1.04)	-.14	(1.06)	.001	.001
Clinic Specialty[3]					[.001]	[-.017]
Mixed	-.06	(.92)	-.07	(1.66)	-.006	-.004
Equine	-.04	(.65)	-.05	(.88)	.002	.001
Dairy	-.17	(1.86)	.00	(.01)	.000	-.021
Beef	.20	(1.35)	-.10	(1.30)	-.003	.006
Swine	[5]		.15	(1.85)	.008	.000
# Vets in Clinic	.01	(1.29)	.01	(2.95)	.005	.002
Constant	10.09	(73.54)	10.43	(96.54)	-	-
Location and Year[4]	yes		yes		[.002]	[-.050]
Sample Size	224		316			
Adjusted R^2	.30		.36			
Total explained					[.058]	[-.017]
Total unexplained					[.105]	[.179]

t-statistics are in parentheses. Numbers in brackets refer to the portion of the ln earnings gap explained by groups of variables. [1]Excluded category is 1 to 2 years. [2]Excluded category is 31-40 hours (no respondents reported 25 - 30 hours). [3]Excluded category is Small Animal. [4]Controls for msa status, region, and the survey year. [5]No data.

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Table 3: Earnings Decomposition with Productivity Control

Dependent Variable: Ln Annual Earnings

Variable	β_f		β_m		$\beta_m(\bar{X}_m-\bar{X}_f)$	$\beta_f(\bar{X}_m-\bar{X}_f)$
Experience[1]					[.039]	[.025]
3 to 5 years	.11	(1.91)	.12	(2.56)	-.011	-.010
6 to 10 years	.19	(2.95)	.19	(3.82)	-.006	-.005
11 to 20 years	..19	(2.22)	.39	(7.40)	.028	.014
21 to 30 years	.60	(2.85)	.43	(5.33)	.019	.026
31 to 40 years	[5]		.53	(4.31)	.008	.000
over 40 years	[5]		.08	(.31)	.000	.000
Hours per week[2]					[.011]	[.028]
under 25 hours	[5]		-.78	(3.89)	-.005	.000
41 - 50 hours	.18	(2.63)	-.04	(.65)	.005	-.020
51 - 60 hours	.28	(3.93)	.05	(.76)	.002	.009
61 - 70 hours	.23	(2.63)	.06	(.77)	.007	.028
71 - 80 hours	.50	(3.58)	.07	(.76)	.002	.011
over 80 hours	-.05	(.33)	-.13	(.92)	.001	.000
Clinic Specialty[3]					[.004]	[-.011]
Mixed	-.05	(.86)	-.07	(1.38)	-.005	-.004
Equine	.02	(.23)	-.03	(.53)	.001	.000
Dairy	-.12	(1.39)	.01	(.28)	.002	-.016
Beef	.26	(1.72)	-.09	(1.10)	-.003	.008
Swine	[5]		.16	(2.01)	.009	.000
# Vets in Clinic	.01	(1.67)	.01	(2.89)	.005	.003
Patients per hour	.09	(3.43)	.02	(1.07)	-.005	-.019
Constant	9.90	(68.92)	10.41	(91.50)	-	-
Location and Year[4]	yes		yes		[.002]	[-.048]
Sample Size	216		309			
Adjusted R^2	.34		.35			
Total explained					[.056]	[-.023]
Total unexplained					[.106]	[.184]

t-statistics are in parentheses. Numbers in brackets refer to the portion of the ln earnings gap explained by groups of variables. [1]Excluded category is 1 to 2 years. [2]Excluded category is 31-40 hours (no respondents reported 25 - 30 hours). [3]Excluded category is Small Animal. [4]Controls for msa status, region, and the survey year. [5]No data.

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Table 4: Earnings Decomposition with Revenue Control

Dependent Variable: Ln Annual Earnings

Variable	β_f		β_m		$\beta_m(\bar{X}_m-\bar{X}_f)$	$\beta_f(\bar{X}_m-\bar{X}_f)$
Experience[1]					[.037]	[.022]
3 to 5 years	.04	(.64)	.08	(1.86)	-.007	-.003
6 to 10 years	.13	(2.02)	.18	(3.82)	-.005	-.004
11 to 20 years	.14	(1.68)	.34	(6.61)	.024	.010
21 to 30 years	.44	(2.31)	.40	(5.76)	.018	.020
31 to 40 years	[6]		.50	(4.04)	.007	.000
over 40 years	[6]		.04	(.15)	.000	.000
Hours per week[2]					[.003]	[.024]
under 25 hours	[6]		-.67	(3.76)	-.004	.000
41 - 50 hours	.13	(1.95)	-.06	(1.01)	.007	-.014
51 - 60 hours	.20	(2.83)	.00	(.08)	.000	.006
61 - 70 hours	.17	(1.97)	-.01	(.11)	-.001	.019
71 - 80 hours	.41	(2.94)	.01	(.13)	.000	.009
over 80 hours	-.50	(3.06)	-.12	(.93)	.001	.003
Clinic Specialty[3]					[.014]	[-.011]
Mixed	-.04	(.62)	-.01	(.28)	-.001	-.003
Equine	-.03	(.50)	.03	(.62)	-.001	.001
Dairy	-.12	(1.45)	.06	(1.39)	.008	-.015
Beef	.19	(1.36)	-.05	(.65)	-.002	.006
Swine	[6]		.17	(2.29)	.009	.000
# Vets in Clinic	.01	(1.10)	.01	(3.25)	.005	.002
Ln Revenue Produced[4]	.31	(7.55)	.28	(8.22)	.004	.005
Constant	6.51	(13.12)	7.20	(17.78)	-	-
Location and Year[5]	yes		yes		[.005]	[-.039]
Sample Size	187		288			
Adjusted R^2	.49		.49			
Total explained					[.068]	[.002]
Total unexplained					[.106]	[.172]

t-statistics are in parentheses. Numbers in brackets refer to the portion of the ln earnings gap explained by groups of variables. [1]Excluded category is 1 to 2 years. [2]Excluded category is 31-40 hours (no respondents reported 25 - 30 hours). [3]Excluded category is Small Animal. [4]Data are reported as categorical variables. The midpoint of the reported range is used as the independent variable. [5]Controls for msa status, region, and the survey year. [6]No data.

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Table 5: Revenue Equation

Dependent Variable: Ln Annual Revenue Produced

Variable	(1)		(2)		(3)	
Female	-.03	(.57)	-.02	(.43)	-.04	(.66)
Experience[1]						
3 to 5 years	.16	(2.69)	.13	(2.17)	.15	(1.78)
6 to 10 years	.10	(1.38)	.07	(.98)	.12	(1.35)
11 to 20 years	.22	(2.74)	.20	(2.65)	.25	(2.19)
21 to 30 years	.28	(2.31)	.13	(1.05)	.05	(.21)
31 to 40 years	.42	(1.77)	.31	(1.36)	.20	(.75)
over 40 years	.45	(.97)	.36	(.81)	.27	(.62)
Hours per week[2]						
under 25 hours	-.22	(.66)	-.42	(1.30)	-1.25	(2.81)
41 - 50 hours	.11	(1.38)	.16	(2.00)	.13	(1.38)
51 - 60 hours	.13	(1.49)	.19	(2.32)	.14	(1.35)
61 - 70 hours	.20	(2.17)	.27	(2.97)	.24	(2.06)
71 - 80 hours	.09	(.70)	.17	(1.33)	.18	(.93)
over 80 hours	.43	(2.32)	.53	(3.02)	.49	(1.86)
Clinic Specialty[3]						
Mixed	-.18	(2.62)	-.15	(2.30)	-.06	(.68)
Equine	-.15	(2.06)	-.07	(.92)	-.10	(.99)
Dairy	-.21	(2.86)	-.12	(1.65)	-.12	(1.16)
Beef	-.16	(1.30)	-.10	(.84)	-.09	(.55)
Swine	.06	(.44)	.16	(1.21)	.11	(.56)
# Vets in Clinic	.00	(.02)	.00	(.15)	.01	(1.39)
Patients per hour			.16	(5.37)	.15	(3.39)
Ln Average Fee					.20	(3.09)
Constant	11.60	(76.07)	11.37	(75.05)	10.39	(31.69)
Location and Year[4]	yes		yes		yes	
Sample Size	479		465		233	
Adjusted R^2	.13		.19		.20	

t-statistics are in parentheses. [1]Excluded category is 1 to 2 years. [2]Excluded category is 31-40 hours (no respondents reported 25 - 30 hours). [3]Excluded category is Small Animal. [4]Controls for msa status, region, and the survey year.

Table 6: Patients per Hour Equation

Dependent Variable: Ln Patients per hour

Variable	(1)		(2)	
Female	.11	(2.05)	.16	(2.35)
Experience[1]				
3 to 5 years	.08	(1.13)	.07	(.68)
6 to 10 years	.18	(2.10)	.13	(1.14)
11 to 20 years	.21	(2.23)	.21	(1.55)
21 to 30 years	.58	(3.75)	.29	(1.22)
31 to 40 years	.50	(1.88)	.62	(1.90)
over 40 years	.19	(.31)	.59	(1.00)
Clinic Specialty[2]				
Mixed	-.34	(4.35)	-.18	(1.68)
Equine	-.69	(8.24)	-.71	(6.25)
Dairy	-.73	(8.15)	-.67	(5.72)
Beef	-.52	(3.24)	-.37	(1.87)
Swine	-1.17	(6.95)	-.70	(2.44)
# Vets in Clinic	-.02	(2.62)	-.01	(.65)
Ln Average Fee			-.28	(3.96)
Constant	-.37	(.63)	1.05	(1.87)
Location and Year[3]	yes		yes	
Sample Size	556		263	
Adjusted R^2	.32		.44	

t-statistics are in parentheses. [1]Excluded category is 1 to 2 years. [2]Excluded category is Small Animal. [3]Controls for msa status, state, and the survey year.

Table 7: Management Equation

Dependent Variable: Percentage of time spent in management

Variable		
Female	3.0	(1.99)
Experience[1]		
3 to 5 years	1.7	(.81)
6 to 10 years	-1.5	(.62)
11 to 20 years	-1.6	(.66)
21 to 30 years	5.6	(1.50)
31 to 40 years	8.5	(1.01)
over 40 years	[4]	
Clinic Specialty[2]		
Mixed	.9	(.50)
Equine	2.6	(1.12)
Dairy	3.0	(1.36)
Beef	1.2	(.32)
Swine	30.2	(7.5)
# Vets in Clinic	.3	(1.52)
Constant	7.0	(1.59)
Location[3]	yes	
Sample Size	288	
Adjusted R^2	.25	

t-statistics are in parentheses. [1]Excluded category is 1 to 2 years. [2]Excluded category is Small Animal. [3]Control for region. [4]No data.

APPENDICES

APPENDIX A

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APPENDIX A

1990 Census Data Comparison

A comparison with census data provides evidence on whether the data set utilized is representative of all veterinarians. Table A1 reports variable means from observations extracted from the 5% sample of the 1990 census, alongside variable means from Veterinary Economics' data. Since the Veterinary Economics' data set covers only full-time, private sector veterinarians, the reported census data is limited to coverage of this group.[1]

The summary statistics reported in Table A1 support the claim that the data utilized is representative of the true population of veterinarians. Even though the data sets have been collected in different years, the reported means for each variable are not statistically different from each other at the 5% level. Thus, veterinarians in the Veterinary Economics' survey appear to be representative of all veterinarians, in terms of age, experience, earnings, hours worked per week, and gender.

[1] In addition, the census appears to classify other employees in veterinary medicine as veterinarians. To correct for this, it was necessary to exclude individuals whose highest level of educational attainment was reported as a bachelor's degree, or less, from the reported data.

Table A1: Census Data Comparison

Summary Statistics

Variable	1990 Census Data	Veterinary Economics Data
Age	41.5	41.9
Experience	15.5	15.7
Earnings[1]	66,908	64,356
Hours worked per week	52.3	52.5
Ratio female	.22	.24
Observations	1802	3036

Veterinary Economics' data are weighted to correct for over-sample of some specialties. [1]All earnings figures are deflated by the Consumer Price Index and expressed in 1994 dollars. Census data report 1989 earnings, while Veterinary Economics data report 1993 and 1994 earnings.

Sources:
Veterinary Economics, *Continuing Wage Surveys*, Veterinary Medicine Publishing Company, (1994-95).
U.S. Department of Commerce, Bureau of the Census, *Decennial Census Public Use Microdata 5% Sample*, (1990).

APPENDIX B

APPENDIX B

Tests for Sample Selection Bias

Sample selection bias occurs when individuals who select into one group are not representative, on average, of the underlying population. In the current context, the concern is that veterinarians in the wage-salary sector may differ from the general population of veterinarians. For example, those who choose the wage-salary sector may be among those who would have the highest earnings in the wage-salary sector among the population of veterinarians. If this was true, the coefficients on OLS equations may be biased. Note, however, that since the analysis in this chapter is focused on earnings differences *within* the wage-salary sector, selection may only pose a problem if there are gender differences in selection behavior.

In order to test for evidence of selection bias, a standard Heckman (1979) correction for sample-selection bias is implemented. First, a reduced-form probit for wage-salary sector employment is estimated separately for both males and females:

$$S_i^* = \alpha_0 + \alpha_j T_i + e_i; \quad j = 1.....p. \tag{1}$$

where S_i^* is not observed directly; $S_i = 1$ if $S_i^* \geq 0$ and $S_i = 0$ if $S_i^* \leq 0$
T_i = p controls, including experience, age, location and year dummies

A selection correction term, λ_i, is obtained from this equation and added to a standard earnings equation:

$$\ln(Y_i) = \beta_0 + \beta_1\lambda_i + \beta_{j+1}X_i + e_i; \quad j = 1.....p. \tag{2}$$

where $\ln(Y_i)$ = ln annual earnings
X_i = p controls, including experience, location and year dummies[1]

[1]Note that I do not include certain variables that were contained in the earnings equations estimated in the main body of the chapter. Hours worked per week, clinic specialty, and firm size are potentially endogenous along with sector choice.

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If the coefficient on the selection correction term, β_1, is estimated as positive and statistically significant, there is evidence of positive selection. Or, if β_1 is estimated as negative and statistically significant, there exists evidence of negative selection.

For identification purposes, it is necessary that there be a variable in reduced-form probit that is not in the earnings equation. Such a variable should affect one's taste for self-employment without directly affecting earnings. Survey respondents report both their age and experience. As expected, experience is positively correlated with earnings; however, there is no reason to expect age to have an impact on earnings, independent of experience.[2] Age has been shown, though, to be negatively correlated with employment in the wage-salary sector (see Fuchs, 1982; Evans and Leighton, 1989). It is theorized that individuals may switch into self-employment later in life as they desire more flexibility.

Table B1 reports estimates of the selection corrected earnings equations. The first column reports the estimates for females. The coefficients on the age variables in the probit equation are negative and statistically significant. However, there is little evidence of selection, as the coefficient on λ in the earnings equation is statistically insignificant. For males, the coefficients on the age variables are all negative, though statistically insignificant. The coefficient on λ is also statistically insignificant. Thus, there is little evidence of selection in the wage-salary sector for either male or female veterinarians.[3] This concurs with the findings of Faucher (1996) in his study of young physicians, who reports little evidence of selection, either on the part of males or females, into the wage-salary or self-employment sectors.

[2]When the age variables are included in an OLS estimation of equation (2) without the correction term, an F-test reports their joint significance as not statistically different from zero.
[3]Estimates for the self-employment and partnership sectors report qualitatively similar results.

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Table B1: Tests for Sample Selection Bias in the Wage-Salary Sector

Dependent Variable: Ln Annual Earnings

Variable	Females		Males	
Experience[1]				
3 to 5 years	.11	(2.02)	.11	(2.07)
6 to 10 years	.22	(3.00)	.19	(2.17)
11 to 20 years	.16	(1.49)	.35	(3.16)
21 to 30 years	.38	(1.60)	.49	(3.49)
31 to 40 years	[4]		.46	(2.57)
over 40 years	[4]		-.02	(.07)
λ	.001	(.02)	.004	(.07)
Constant	10.16	(147.93)	10.42	(209.90)
Location and Year[2]	yes		yes	
Probit:				
Age[3]				
35 - 44 years	-.59	(3.64)	-.21	(1.61)
45 - 54 years	-1.17	(3.37)	-.35	(1.67)
55 - 65 years	[4]		-.42	(1.21)
over 65 years	[4]		-.69	(1.17)
Experience[1]				
3 to 5 years	-.08	(.38)	-.79	(3.99)
6 to 10 years	-.95	(4.38)	-1.76	(8.58)
11 to 20 years	-1.29	(5.02)	-2.20	(9.68)
21 to 30 years	-.97	(1.91)	-2.44	(8.50)
31 to 40 years	[4]		-2.52	(6.01)
over 40 years	[4]		-2.36	(3.54)
Constant	.48	(2.27)	.79	(4.14)
Location and Year[2]	yes		yes	
Sample size	542		2423	

t-statistics are in parentheses. [1]Excluded category is 1 to 2 years. [2]Controls for msa status and the survey year. [3]Excluded category is 25 to 34 years. [4]No data.

APPENDIX C

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APPENDIX C

Econometrics of Using Bracket Midpoints as Dependent Variables

Earnings in the Veterinary Economics' survey are reported as categorical variables. For models with discrete, ordered dependent variables, the appropriate estimation technique is ordered probit. Unfortunately, it is unclear how the coefficients in an ordered probit model should be interpreted. Thus, instead of utilizing the ordered probit model, I implement OLS by using the midpoint of the reported range of earnings as the dependent variable. By using the midpoint of the reported range[1], I am not making a distributional adjustment to the data. However, if earnings distributions differ by gender, estimates of unexplained differences in earnings, or "discrimination," may be biased. The direction of such a bias would depend on the manner in which the earnings distributions differed.

Assuming Veterinary Economics' data is representative of the underlying population of veterinarians (see Appendix A), I utilize Census data to provide evidence on whether such a bias may exist. Earnings in the Census are reported as continuous variables. The first column in Table C1 reports a standard earnings regression among wage-salary sector veterinarians.[2] The set of explanatory variables is limited, but the reported coefficients are consistent with the results reported utilizing Veterinary Economics' data.[3] To test whether bias occurs when using bracket midpoints as the

[1]Top-coding is not a problem, for exact earnings are reported when they fall in the highest range.

[2]Survey respondents report both wage-salary and self-employment earnings. I classify individuals as wage-salary workers if their wage-salary earnings are greater than their self-employment earnings. Unfortunately, the census classifies earnings from ownership of a corporation as wage-salary income. Thus, the incorporated self-employed are improperly classified as wage-salary workers.

[3]The coefficient on female, reported as -.33, is greater than the unexplained earnings differences reported in the main body of the chapter. This is most likely a result of the incorporated self-employed being classified as wage-salary workers (see Footnote 2), for unexplained gender differences in earnings are greater among self-employed veterinarians (see Chapter 6).

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dependent variable, I impose a categorical structure upon the earnings variable. First, I recode the earnings data into categorical variables, utilizing the categories from the Veterinary Economics' survey. I then recode the data a second time, using the midpoints of the category ranges. This is then utilized as the dependent variable and estimated by OLS. By doing this, I am able to answer the following hypothetical: If Census earnings data were reported as categorical variables, would an earnings regression underestimate or overestimate the "true" unexplained gender difference in earnings (reported in column 1)?

Column (2) in Table C1 reports the estimation with bracket midpoints as the dependent variable. The key coefficient of comparison is that on the female dummy, and the point estimate falls from -.33 to -.32. The two coefficients are not statistically different from each other; thus, if Census earnings data were reported as categorical variables, it would not have a significant impact on the estimate of unexplained gender differences in earnings. And, assuming that the data from Veterinary Economics is a representative sample, OLS estimates utilizing bracket midpoints as the dependent variable appear a fair representation of "true" unexplained differences in earnings.

A noted difference between columns (1) and (2) is the increase in the adjusted R^2 (from .11 to .20). By reducing the amount of variation in the dependent variable, the OLS model is able to estimate a better fit for the data. Thus, although coefficient estimates should be relatively unbiased, estimates of standard errors will be biased downwards. This is of consequence, since it impacts the ability to make statistical inferences from the data. With the census data, estimates of standard errors in column (2) are 44% less than estimates of standard errors in column (1). Thus, when utilizing bracket midpoints as the dependent variable, statistical inferences should be made with greater caution. [4]

[4]An underestimate of standard errors by 44% would suggest using a t-statistic of 3.5, instead of 2.0, to indicate statistical significance.

Table C1: Earnings Equations with Census Data

Dependent Variable: Ln Annual Earnings

Variable	**(1)**		**(2)**	
Female	-.33	(3.80)	-.32	(6.61)
Experience	.02	(4.54)	.01	(7.06)
Hours per week	.01	(2.78)	.01	(4.51)
Weeks per year	.04	(2.30)	.03	(3.13)
Constant	8.93	(7.97)	9.46	(15.11)
State dummy	yes		yes	
Sample Size	1078		1078	
Adjusted R^2	.11		.20	

t-statistics are in parentheses. Column (1) reports earnings as a continuous variable (as reported in the 1990 Census). Column (2) recodes reported earnings into brackets, then utilizes the midpoint of the bracket as the dependent variable.

Source:
U.S. Department of Commerce, Bureau of the Census, *Decennial Census Public Use Microdata 5% Sample*, (1990).

Chapter 4

EXISTING EVIDENCE ON GENDER DIFFERENCES IN SELF-EMPLOYMENT LABOR MARKET OUTCOMES

Simply defined, the self-employed are individuals, incorporated or unincorporated, whose primary source of income is derived from working for themselves. After a period of decline following World War II, the population of self-employed in the United States has steadily increased. Particularly notable is a recent trend, with the percentage of self-employed among all workers increasing from 6.7 percent in 1970 to 8.8 percent in 1988 (Aronson, 1991). The increase in nonfarm self-employment during this period was led primarily by women, with increases in female self-employment rates exceeding increases in female labor force participation rates. Devine (1994) reports that the nonfarm female self-employment rate increased from 4 percent in 1975 to 6.6 percent in 1990,[1] which represents almost one-eighth of the total increase in female nonfarm employment during this period.

Even after these gains, female self-employment rates lag well behind male self-employment rates, a relationship that has held true ever since the US government has kept statistics on the self-employed (Blau, 1987). This gap exists even within specific occupations, and on average, self employment rates among men are approximately twice those of women. Not only do women enter self-employment less frequently than men, they also earn less. Available data sources report that self-employed females earn significantly less than self-employed males, as well as considerably less than

[1] Lombard (1996) reports corresponding numbers for men as 11.4 and 13.0 percent.

males and females in the wage-salary sector.

Self-employment, as a labor market phenomenon, is not a topic that has received much attention in the economic literature. Recently, there has been some work, referenced above, exploring the recent rise in self-employment rates. In addition, there is a subset of literature that studies gender differences in self-employment labor market outcomes. The purpose of this chapter is to review this literature, both theoretical and empirical, that attempts to explain the lower earnings and lower rates of self-employment among females. In addition, I will review one model of self-employment choice constructed to explain racial differences in self-employment, and apply this model to the issue of gender differences in self-employment.

I. Models of Self-Employment Choice

I divide the existing literature into two categories: discrimination models and other models of self-employment choice.

A. Discrimination Models

1. Employer Discrimination.

Moore (1983) offers a model of employer discrimination, following Becker (1971), in the context of self-employment. Moore's model states that a subset of employers prefer males to females of equal ability. This requires women to accept lower wages in order to obtain employment in the wage-salary sector. That is,

$$E_m^{ws} = E_f^{ws}(1+d) \qquad (1)$$

where E_m^{ws} = Earnings of males in wage-salary sector

E_f^{ws} = Earnings of females in wage-salary sector

d = Discrimination coefficient (positive for some employers)

The model assumes that individuals will choose the sector that offers them the highest earnings. There are no barriers to entry into the self-employment sector, and in addition, customer discrimination is assumed to be nonexistent. Two testable predictions follow from this simple model: First, women should be more likely to enter self-employment than men due to employer discrimination they face in the wage-salary sector. Second, since female earnings in the self-employment sector are not reduced by a discrimination coefficient, the female-male earnings ratio among self-employed workers should be higher than the corresponding ratio in the wage-salary sector. That is, $\frac{E_f^{se}}{E_m^{se}} > \frac{E_f^{ws}}{E_m^{ws}}$. Noting that the first prediction fails since women are underrepresented in self-employment relative to men, Moore focuses on testing the second prediction.

Using 1978 CPS data, Moore estimates predicted earnings equations, controlling for variables such as schooling, age, region, and marital status. After constructing adjusted female-male earnings ratios from these equations, he reports a female-male earnings ratio that is significantly lower in the self-employment sector compared to the wage-salary sector (.50 versus .61), which contradicts the prediction of his model. Hence, Moore concludes that this model of discrimination does not explain the facts of self-employment: lower representation and earnings for females in the self-employment sector.

Moore overlooks an important factor in his model. A key feature of the labor market is that individuals are paid on the basis of their marginal revenue product, which is a function of their ability. While males will enter the self-employment sector if $E_m^{ws}(a_{ws}) < E_m^{se}(a_{se})$ (where *a* represents ability and is allowed to vary by sector), females will enter self-employment if the following holds:

$$E_f^{ws}(a_{ws})(1-d) < E_f^{se}(a_{se}) \tag{2}$$

Because of discrimination in the wage-salary sector, the opportunity cost of entering self-employment is lowered for females, a direct result from discrimination in the wa

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wage-salary sector. In the context of Moore's model, men and women of equal ability in the self-employment sector will have equal earnings; however, on *average*, women in the self-employment sector will have lower ability, and therefore, lower earnings than men.[2] Further intuition for this point is gained by considering two individuals, one female and one male, who have low ability in self-employment, but high ability in wage-salary employment. In the absence of discrimination, both individuals would choose employment in the wage-salary sector. However, with discrimination against females in the wage-salary sector, the female agent's optimizing choice may differ. Specifically, if the discrimination coefficient is great enough so that relationship in equation (2) holds, she will enter the self-employment sector. In the aggregate, this behavior leads to lower female ability, on average, in the self-employment sector. Assuming Moore is unable to completely capture differences in ability in his adjusted earnings estimations, the female-male earnings ratio in the self-employment sector will be reduced, relative to the wage-salary sector. Thus, it is not clear in which sector one would expect to find greater female-male adjusted earnings ratios.

2. Employer Discrimination with Spillovers.

Even if it included considerations of ability, the basic employer discrimination model still fails to predict that females enter self-employment at a lower rate than males. Coate and Tennyson (1992) construct a model of employer discrimination that offers this prediction. Their model incorporates the considerations of ability offered above, predicting that women in the self-employment sector will be, on average, of lower ability than men, resulting from discrimination in the wage-salary sector. Central to their model is that there is a secondary market necessary for self-employment. The example they use is the credit market. A key assumption of their model is that the

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[2] Females and males are assumed to have the same distributions of ability in the population.

credit market is not able to observe self-employment ability. However, lenders are aware that females who enter the self-employment sector are, on average, of lower ability than men. Since the probability of success, and also of loan repayment, is a function of ability, lenders will charge females higher interest rates to compensate for their higher risk.[3]

Since women face a higher interest rate in the self-employment sector, their returns to self-employment are lower, relative to men. Under these assumptions, men and women of equal ability in the self-employment sector will not have equal earnings. In other words, for any given $\bar{a}$, $E_m^{se}(\bar{a}, i(m)) > E_f^{se}(\bar{a}, i(f))$, since $i(m) < i(f)$, where i reflects the interest rate as a function of the gender of the borrower. Up to this point, the Coate and Tennyson model assumes that ability is exogenous and males and females have the same distributions of ability. With these assumptions, Coate and Tennyson show that females will still have a stronger propensity to enter self-employment relative to males, even in the face of lower expected earnings.

Coate and Tennyson modify their model, allowing ability to be endogenous and partially determined by human capital investments. These investments are thought to be made prior to choosing a sector. Since women are discriminated against in the wage-salary sector, facing lower expected earnings than men with identical ability, they may be less likely to invest in human capital. In turn, the credit market rationally expects that females have invested less in human capital, and females are charged even higher interest rates due to their perceived lower average ability. This higher interest rate further reduces women's incentive to invest in human capital. Hence, the

[3] Coate and Tennyson point out that this statistical discrimination on the part of the credit market is a "derived discrimination." In other words, it would not exist in the absence of employer discrimination. They refer to this as a "spillover effect" of employer discrimination.

difference between male and female average abilities may be exacerbated due to their differing incentives to invest in human capital. Coate and Tennyson show that under these conditions females may have less incentive to enter self-employment than males. Therefore, by extending the basic employer discrimination model, allowing spillover effects into the credit and human capital markets, the authors are able to obtain predictions consistent with the behavior of females in the United States.

The authors admit that their analysis embodies a number of restrictive assumptions. There are two characteristics of their analysis that appear particularly questionable. First, given statistical discrimination from the credit market, an important aspect of their model is that female business owners are charged higher interest rates than their male counterparts. However, they offer no evidence and cite no references where such discrimination has been found to exist.[4] In addition, the entire model is driven by employer discrimination in the wage-salary sector. If discriminatory wage differentials exist, one might question if these differentials are large enough to generate the size of the spillovers necessary to obtain their predictions. A discussion of the extent of discrimination in the wage-salary sector necessary to generate their predictions would give more evidence as to the plausibility of their theory.

3. Customer Discrimination.

Borjas and Bronars (1989) offer a model of customer discrimination in an attempt to explain differences that exist between blacks and whites in the self-employment labor market. Females and blacks exhibit similar outcomes in the self-employment labor market, relative to their respective majority groups: lower rates of entry and average incomes. Hence, it appears straightforward to apply their model to

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[4] The authors contend that any market "relevant to self-employment" that statistically discriminates against women can generate their predictions. They offer as an alternative the scenario where customers statistically discriminate against self-employed females on the basis of perceived lower average ability.

the issue of gender differences in self-employment. Thus, applying their model to the issue of gender, it is theorized that male customers suffer disutility in purchasing goods or services from self-employed females. Females customers are assumed indifferent regarding from whom they make their purchases.

A key assumption of the model is that there is incomplete information about a self-employed seller's prices, and there is a search cost, for both buyer and seller, involved in obtaining this information. If female sellers wish to sell to male customers, they must charge $P_f^* = (1-d)P_m^*$, where P_m^* is the price that male sellers charge to all customers. Female sellers may charge $P_f^* = P_m^*$, but then they will sell only to female customers, and they will incur a search cost in turning away potential male customers. Therefore, a female seller has two choices: she can sell to all customers, but charge a lower price, $(1-d)P_m^*$; or she can charge a higher price, P_m^*, but she will have fewer customers. It follows from this that self-employed male sellers will have greater mean incomes than female sellers, since they can charge P_m^* and retain all customers, while this is not true for female sellers. Since customer discrimination is assumed to be absent in the wage-salary sector, females will have less incentive to enter the self-employment sector, relative to males.

Borjas and Bronars' model contains important implications regarding the composition of sellers in the self-employed sector. Since males and females have the same returns to ability in the wage-salary sector, but females have a lower return to their ability in the self-employment sector, females will be less likely than males to select into self-employment. In other words, a female with high self-employment ability has less incentive to enter self-employment, compared to a male of the same self-employment ability.[5] I will discuss the issue of selection at greater length later in this chapter.

In analyzing race differences in self-employment outcomes, Borjas and Bronars test the key predictions of their model using 1980 census data. Their empirical results support their theoretical model: blacks have less incentive to become self-employed (due to their lower average earnings in self-employment) and blacks are less likely to positively select into self-employment relative to whites. The most able blacks remain in the wage-salary sector, and the least able blacks select into the self-employment sector. Since their model is based on the premise that customer contact is essential for the presence of customer discrimination, they expect selection differences to be greater in professional occupations, assuming greater customer contact on the part of professionals. When they stratify their sample to test this hypothesis, however, they do not find greater degrees of selection among professionals. Overall, however, their results are consistent in supporting their model.

Care should be taken in applying the customer discrimination model to the issue of gender differences in self-employment. As Borjas and Bronars point out, their predictions are sensitive to the assumption that blacks are a small minority of the population. Females are not a small minority of the population, and this fact may alter the model's predictions when applied to the issue of gender differences in self-employment outcomes.[6] In addition, there exists a theoretical problem with models of

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[5] This prediction is augmented as the authors show that under the assumptions of their model, females experience less income variance, relative to males, in the self-employment sector. This relationship does not hold true in the wage-salary sector. Therefore, females in the upper tail of the wage-salary income distribution have little incentive to switch into the relatively compressed self-employment income distribution. However, females in the lower tail of the wage-salary distribution have a greater incentive to switch sectors (negative selection).

[6] In particular, the prediction regarding relative variances of the income distributions, mentioned in Footnote 5, becomes undetermined. The model would still generate the same predictions, however, if the model was altered to assume that all customers, both male and female, discriminate against female sellers.

customer discrimination. The models assume that customer discrimination only affects women in the self-employment sector, but this discrimination should also impact wage-salary women, particularly in industries characterized by high levels of direct customer contact. Profit-maximizing firms would be expected to resist employing women if customer discrimination had a negative impact on revenues. However, Aronson reports that in industries with high levels of direct customer contact, women are employed in *greater* proportions when compared to all industries, and they also receive relatively high earnings.

B. Self-Selection Bias

The issue of potential self-selection bias, along with the predictions offered on it by the discrimination models covered, warrants further attention. Self-selection bias arises when individuals who select into one sector are not representative, on average, of the underlying population. In the context of measuring predicted earnings, positive selection refers to the situation where the individuals who choose self-employment are those who would have the highest earnings in self-employment out of the population of workers. Negative selection reflects the situation where individuals who select into self-employment are those who would have the lowest earnings in self-employment out of the population of workers. Since Moore's model of employer discrimination does not incorporate considerations of ability, it does not offer a prediction regarding selection. While not explicitly discussed, Coate and Tennyson's model of employer discrimination does offer a prediction regarding selection. The model predicts that women of lower average ability, relative to males, will enter the self-employment sector. Thus the model predicts selection that is less positive (or more negative) for females relative to males. As previously discussed, Borjas and Bronars' model of customer discrimination also predicts that females will be less likely than males to positively select into the self-employment sector.

The literature discussed offers no empirical evidence on selection into self-employment, and there is very limited evidence on this issue. Devine, using CPS data from 1975-87, estimates an earnings equation for females in the wage-salary sector. Employing the coefficients obtained from this regression, she then predicts potential wage-salary earnings for all females in the sample. These are used to estimate each female's relative position in the wage-salary earnings distribution, and this position is interpreted as a measure of the female's relative skill level. Her results suggest that the average self-employed female is more skilled than the average wage-salary female, evidence consistent with positive selection on the part of self-employed females. However, the statistical or economic significance of this difference is not offered, and evidence is still lacking on gender differences in selection behavior. Lombard (1996), analyzing CPS Data from 1980-91, reports little evidence of selection bias on the part of married females, either in the self-employment or wage-salary sector. Faucher (1996), using a 1987 data set on young physicians, tests for evidence of selection bias among physicians. He concludes that for both male and female physicians, there is little evidence of selection bias in either the wage-salary or self-employment sectors.[7]

I summarize the predictions of the three different models of discrimination in Table 1. Faucher, using young physicians as his population, extensively tests the predictions and assumptions of discrimination models presented in this chapter (along with variants), in his dissertation. Overall, his results do not show support for either employer discrimination model, or the customer discrimination model.

[7] Faucher implements a selection correction procedure similar to Heckman (1979). In Faucher's estimates of selection-corrected earnings equations the coefficient on the selection variable is not significantly different from zero.

The models discussed thus far suffer from one of two problems. Either they do not explain observed self-employment outcomes, as in the employer discrimination model, or they rest on restrictive and perhaps unrealistic assumptions, as in the employer discrimination with spillovers and the customer discrimination models. Also, each of the models presented thus far assume that women simply choose the sector that offers them the highest earnings. The predictions regarding different self-employment rates, therefore, are driven by earnings differences across sectors. The rapid rise in female self-employment in the face of a constant, or even slightly falling, relative earnings position, however, suggests that nonmonetary influences may carry significant weight in female self-employment choices. I now consider models of self-employment choice that incorporate such influences.

C. Other Models of Self-Employment Choice

1. Compensating Differentials.

It is possible that women who enter the self-employment sector accept lower earnings in return for a compensating differential. As an example, the self-employment sector may provide greater flexibility than the wage-salary sector. The following model is due to Lombard (1996). Individuals facing a choice between sectors will choose the self-employment sector if $U(E^{se}, F^{se}) > U(E^{ws}, F^{ws})$, where F represents flexibility. Flexibility is assumed to be more "costly" in the wage-salary sector, or for any given level of F, $\left|\frac{dE^{ws}}{dF}\right| > \left|\frac{dE^{se}}{dF}\right|$. Further, it is assumed that there is a subset of women who are more concerned about flexibility than the remainder of the population. These women choose the self-employment sector, selecting lower relative earnings and higher flexibility.[8] Therefore, this simple model predicts what is observed in the labor market: females in the self-employment sector earning less than both females in the wage-salary sector and males in either sector. However, the model also predicts that females should enter self-employment at rates greater than those of males, contrary to the known facts of self-employment.

There is mixed evidence on the role of a compensating differential, such as flexibility, in the context of self-employment choice. Data from the CPS does report that the self-employed have greater variability in hours worked than wage-salary workers, implying a more flexible work schedule for the self-employed.[9] Lombard develops a model of demand for flexibility, and provides evidence that married females are more likely to become self-employed the greater their demand for non-standard work schedules. Demand for flexibility is shown to be highly correlated with the presence of young children, indicating that family responsibilities may play a significant role in self-employment choice. Faucher offers contrary evidence with his data on young physicians. In a probit specification to determine the likelihood of self-employment, Faucher includes a dummy variable for women with children, along with a dummy variable for women. His results, though marginally significant, suggest that female physicians with children are slightly *less* likely to be self-employed when compared to female physicians without children. In this same specification, the coefficient on the dummy variable for female (with or without children) is still negative and highly significant, suggesting that other factors play an important role in self-employment

[8] Note that the self-employment sector offers a tradeoff between flexibility and earnings. While females who enter the sector are thought to choose low earnings and high flexibility, males are thought to choose high earnings and low flexibility.

[9] Lombard reports that in a given week, married self-employed women work an average of 7.5 hours above or below what they report as their usual hours worked, while this statistic is 4 hours for married wage-salary women.

choice among females.

Attempting to ascertain behavioral reasons for self-employment may be an exercise in futility, as measuring preferences and attitudes is difficult. In addition, although the desire for flexibility may play an important in self-employment choice, no evidence has been offered to indicate that a compensating differential must be paid for flexibility. In other words, greater flexibility in self-employment has not been shown to be correlated with lower earnings. In addition, the simple compensating differentials model fails on one of its keys implications, predicting that females are more likely to enter self-employment than males.

2. Capital Investment Model.

Faucher offers a model of self-employment choice with variable hours worked and capital required to enter self-employment. In Faucher's model, a capital investment is required to enter the self-employment sector, so earnings in this sector are reduced by fixed capital costs. Earnings in self-employment are $E^{se} = (w^{se} \cdot h) - k$, where w^{se} represents hourly earnings, h hours worked, and k the capital investment. Earnings in the wage-salary sector are simply $E^{ws} = (w^{ws} \cdot h)$. Utility is a function of income and the number of hours of leisure, and an individual chooses the sector that offers the highest utility. If $U(E^{se}, L^{se}) > U(E^{ws}, L^{ws})$, where L represents leisure[10], the individual will enter the self-employment sector.

Given that hours of work and leisure are choice variables and that there is a fixed cost of entering self-employment, an individual who prefers more hours of leisure (and therefore fewer hours of work) may be reluctant to enter self-employment because of the fixed costs. This may hold true even if hourly earnings are higher in the

[10] Note that L=T-h, where T is total hours, so leisure includes all non-market activity.

self-employment sector, since fewer hours are available to spread out fixed costs. It is theorized that women have stronger preferences, on average, for nonmarket activity than males, and this may help explain the lower self-employment rate of females. In addition, the model predicts that in the self-employment sector, reported hourly earnings are an increasing function of hours worked as fixed costs are spread among a greater number of hours. Such a relationship in the wage-salary sector, where there are no fixed costs, should not hold.

Faucher's empirical tests support his theoretical model. Specifically, when estimating a reduced form probit for self-employment, Faucher reports that female physicians are 11% less likely to enter self-employment than males when controlling for variables such as experience, age, and specialty. However, when estimating a structural form probit for self-employment, adding controls for differences in hours and earnings between the two sectors, females are found no less likely than males to enter self-employment. Also, when estimating regressions in the self-employed sector with hourly earnings as the dependent variable, Faucher reports that hours worked has a positive and statistically significant impact on hourly earnings, while the impact of hours worked is zero in the wage-salary sector regressions. In addition, in the self-employment sector, female hourly earnings were reported as 15% less than males with the same observable characteristics, without controlling for differences in hours worked. However, after adding a control for differences in hours worked, the coefficient on the female dummy falls to zero.

Faucher is careful not to generalize his results to other markets of self-employment. His results are based on a specific occupational class that differs in many ways from other occupations. Perhaps most notable, start-up capital costs among physicians are very high: as Faucher points out, they can reach over $100,000.

Therefore, the costs of capital investment may have a strong influence on the self-employment decision among physicians, though this may not hold true in other occupations. Faucher offers an important model, however, as his study in the first to incorporate the hours worked decision and capital investments into a model of self-employment choice.

II. Conclusion

A relevant model of self-employment choice applied to the US economy must be able to explain gender differences in both sector entry rates and earnings. In this chapter I reviewed three discrimination models that make this attempt. Each model is hindered from either unrealistic assumptions or lack of empirical support. A model of compensating differentials was also considered, but even though a desire for nonmonetary benefits may play an important role in self-employment choice, existing empirical evidence is lacking in its ability to explain gender differences in self-employment entry rates or earnings. I have also examined a new model from Faucher that incorporates the hours worked decision, along with capital costs, in self-employment. The empirical evidence on this model was promising, but the predictions of this model must be tested on other occupations.

There exist other unexplored avenues. Longstreth, Stafford, and Mauldin (1987) report that female-operated firms tend to be smaller and have lower receipts than male-operated firms. Also, Evans and Leighton (1989) report that individuals with greater assets have a greater probability of entering self-employment. Thus, gender differences in firm size and capital accumulation may play important roles in the self-employment labor market.

At this point, the available evidence only offers clues as to the mechanisms involved in generating gender differences in self-employment labor market outcomes.

In Chapter 5, I test the models of self-employment choice covered in this chapter on a data set of veterinarians. Results will show the models generally lacking in their ability to explain gender differences in self-employment among veterinarians. In Chapter 6, I explore other factors that play a role in self-employment labor markets. Primarily, I examine the role that firm size and levels of resource utilization have on explaining gender differences in earnings among the self-employed.

Table 1: Predictions of Discrimination Models

Prediction	Employer Discrimination	Employer Discrimination with Spillovers	Customer Discrimination
Entry rate into self-employment	females > males	females < males	females < males
Mean Earnings, Self-Employment sector	$E_f^{se} = E_m^{se}$	$E_f^{se} < E_m^{se}$	$E_f^{se} < E_m^{se}$
Mean Earnings, Wage-Salary sector	$E_f^{ws} < E_m^{ws}$	$E_f^{ws} < E_m^{ws}$	$E_f^{ws} \le E_m^{ws}$
Positive Selection, Self-Employment sector		females < males	females < males

Sources:

Moore, R., "Employer Discrimination: Evidence from Self-Employed Workers," *Review of Economics and Statistics*, (1983). [Employer Discrimination]

Coate, S. and S. Tennyson, "Labor Market Discrimination, Imperfect Information and Self-Employment," *Oxford Economic Papers*, (1992). [Employer Discrimination with Spillovers]

Borjas, G. and S. Bronars, "Consumer Discrimination and Self-Employment," *Journal of Political Economy*, (1989). [Customer Discrimination]

Chapter 5

TESTING THE PREDICTIONS AND IMPLICATIONS OF MODELS OF SELF-EMPLOYMENT CHOICE

The self-employed account for a growing portion of the US labor force, evidenced by an increase in the self-employment rate from 6.7 percent in 1970 to 8.8 percent in 1988 (see Aronson, 1991 and Blau, 1987). Women play a significant role in this trend, with increases in female self-employment rates exceeding increases in female labor force participation rates. Devine (1994) reports that the female nonfarm self-employment rate increased from 4 percent in 1975 to 6.6 percent in 1990, which represents almost one-eighth of the total increase in female nonfarm employment during this period. However, even after these gains, female self-employment rates are, on average, one-half those of males. In addition, available data sources suggest that the earnings of self-employed females trail behind the earnings self-employed males, as well as behind the earnings of both males and females in the wage-salary sector.

In Chapter 4, I presented five models of self-employment choice that attempt to explain gender differences in self-employment labor market outcomes. In this chapter, I test the implications and predictions of these theories on a new data set of veterinarians. Using veterinarians to study the issue of self-employment has three advantages. First, veterinarians are a relatively homogenous group, with virtually identical education and training. Therefore, differences in earnings and self-employment behavior are not likely to be derived from differences in human capital or occupation. As Aronson points out, most of the literature on self-employment relies on data that lack controls for occupation, which may explain a great deal of the gender differences observed in self-employment.[1] Second, veterinarians have relatively high rates of self-employment, giving a large number of observations to utilize. Approximately fifty percent of the sample studied here are self-employed. Last, the data used here contains valuable proxy measures of productivity, in addition to detailed firm-level data. Such measures allow for a careful analysis of the mechanisms that generate the gender differences in self-employment that are observed.

There are also drawbacks in using these data to examine the issue of gender differences in self-employment. The obvious disadvantage is that one cannot readily generalize from this sub-group to the population of working men and women. The mechanisms that determine earnings and self-employment choice among veterinarians may not be the same as for the general population. Nevertheless, the results obtained from this specific labor market can be suggestive of the role that gender plays in other labor markets.

In section I, I summarize the five models of self-employment choice, presenting the testable implications of each model. In section II, I describe the data set, as well as offer some background on the market for veterinarians. The empirical framework for testing the predictions of each model is presented in section III, with results reported in section IV.

I. Models of Self-Employment Choice

A. Employer Discrimination

There are five models in the relatively small literature of self-employment choice, three of which are discrimination models. A model of employer discrimination in the

[1] In studying self-employment at the aggregate level, a data problem exists: The Census Bureau and Bureau of Labor Statistics report the self-employed who are incorporated as wage-salary workers, which is not ideal from a theoretical standpoint.

context of self-employment is offered by Moore (1983). In this model, discrimination occurs in the wage-salary sector, where females must accept lower wages in order to obtain employment. That is,

$$E_m^{ws} = E_f^{ws}(1+d)$$

where E_m^{ws} = Earnings of males in wage-salary sector

E_f^{ws} = Earnings of females in wage-salary sector

d = Discrimination coefficient (positive for some employers)

Assuming no discrimination or barriers to entry in the self-employment sector, two testable predictions follow from this simple model. First, earnings will be lower for females than males in the wage-salary sector, a direct result of employer discrimination. Thus, the gender gap in earnings should greater in the wage-salary sector than any gender gap in earnings that may exist in the self-employment sector.[2] Second, females will be more likely than males to enter self-employment, since their opportunity cost of self-employment is reduced by discrimination in the wage-salary sector.

B. Employer Discrimination with Spillovers

Coate and Tennyson (1992) construct a more complex model of employer discrimination, where discrimination in the wage-salary sector produces spillovers into other markets. As in Moore's model, females face a lower opportunity cost of self-employment due to discrimination in the wage-salary sector. Assuming individuals choose the sector that offers higher earnings, males will enter self-employment if $E_m^{ws}(a_{ws}) < E_m^{se}(a_{se})$, while females will enter this sector if $E_f^{ws}(a_{ws})(1-d) < E_f^{se}(a_{se})$, where *E* represents earnings as a function of *a*, ability, and *d* represents a

[2] Analyzing gender gaps in earnings *within sectors* allows for the possibility that what constitutes earnings may differ between sectors. For example, earnings in the self-employment sector may include a return on capital investment. In addition, comparing the *relative size* of gender gaps between sectors allows for the possibility that other factors, not considered, may contribute to the gender gap in earnings.

discrimination coefficient, assumed positive for at least some employers. As a result of optimizing choices made by economic agents, women will, on average, have lower ability in the self-employment sector relative to men. Therefore, while men and women of equal ability in the self-employment sector will have equal earnings, women, *on average*, will have lower earnings than men due to their lower average ability.

Key to the authors' model is that there exists a secondary market necessary for entry into the self-employment sector. The example they use is the credit market, used to secure necessary capital. Although it is assumed that lenders are unable to observe ability in self-employment, they are aware that females who enter the self-employment sector have, on average, lower ability than self-employed males. Since the probability of success, and also loan repayment, is a function of ability, lenders will charge females higher interest rates to compensate for their higher risk.[3] Under these assumptions, women and men of equal ability in the self-employment sector no longer have equal earnings. That is, for any given $\bar{a}$, $E_m^{se}(\bar{a}, i(m)) > E_f^{se}(\bar{a}, i(f))$, since $i(m) < i(f)$, where *i* represents the interest rate as a function of the gender of the borrower.

In order to generate a prediction of lower self-employment rates among females, Coate and Tennyson further modify their model, allowing ability to be endogenous and partially determined by human capital investments. Since women face discrimination not only in the wage-salary sector, but also in the credit market, they may be less likely than males to invest in human capital. Gender differences in human capital investments generate gender differences in ability, which in turn leads the credit market to charge females even higher interest rates. Although resting on restrictive

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[3] Coate and Tennyson point out that this statistical discrimination on the part of the credit market is a "derived discrimination." In other words, it would not exist in the absence of employer discrimination. They refer to this as a "spillover effect" of employer discrimination.

assumptions, Coate and Tennyson show that under certain conditions, females will have less of an incentive to enter self-employment than males, a prediction that I will later test.

C. Customer Discrimination

Borjas and Bronars (1989) offer a model of customer discrimination in an attempt to explain differences between blacks and whites in self-employment. Females and blacks exhibit similar outcomes in self-employment labor markets relative to their respective majority groups: lower rates of entry and average earnings. Thus, it appears straightforward to apply their model to the issue of gender differences in self-employment. The basic assumption of their model is that whites suffer disutility from purchasing goods and services from self-employed blacks. Therefore, in applying this model to the issue of gender, it is assumed that male customers suffer disutility in making purchases from self-employed females, while female customers are indifferent as from whom they make their purchases.

A key assumption of the model is that there is incomplete information about a self-employed seller's prices, and there exists a search cost, for both buyer and seller, involved in obtaining this information. Females sellers charge $P_f^* = (1-d)P_m^*$, where P_m^* is the price that male sellers charge to all customers. Female sellers may charge $P_f^* = P_m^*$, but then they will only sell to female customers, and they will incur a search cost in turning away potential male customers. Therefore, a female seller has two choices: she can sell to all customers, but charge a lower price, $(1-d)P_m^*$; or she can charge a higher price, P_m^*, but sell to fewer customers.

Three testable predictions follow from the customer discrimination model. First, the gender earnings gap should be greater in self-employment relative to the wage-salary sector, a direct result of customer discrimination. Second, females should be less likely than males to enter self-employment. Third, females should be found to charge, on average, lower prices than males in the self-employment sector.

Each of the discrimination models offers one additional testable implication. A key assumption of all three models is that economic agents choose the sector that offers the highest earnings. Differences in earnings between sectors are caused by discrimination, which leads to gender differences in sector choice. It is assumed that no other factors impact the decision to become self-employed. Therefore, if differences in earnings between sectors are accounted for, gender should be shown to have no impact on self-employment choice. Considered next are models of self-employment choice that incorporate other, nonmonetary influences in the decision to become self-employed.

D. Compensating Differentials

Lombard (1996) provides a model of compensating differentials in the context of self-employment. She theorizes that there is a subset of women who have strong preferences for flexibility, and choose to be self-employed since the opportunity cost for flexibility is lower in the self-employment sector.[4] Thus, a female will choose self-employment if $U(E^{se}, F^{se}) > U(E^{ws}, F^{ws})$, where F represents flexibility. Note that the self-employment sector offers a tradeoff between flexibility and earnings. In order to explain gender differences in earnings, females who enter self-employment must

[4] For any given level of F, $\left|\frac{dE^{ws}}{dF}\right| > \left|\frac{dE^{se}}{dF}\right|$.

choose low earnings and high flexibility, while males choose high earnings and low flexibility.

The compensating differentials model offers three testable predictions. First, the gender gap in earnings should be greater in self-employment, since measures of earnings do not incorporate the compensating differentials that females receive in self-employment. Second, females will enter self-employment at rates greater than those of males, even after controlling for differences in earnings between sectors. Finally, flexibility, or variability in hours worked, should be negatively correlated with earnings.

E. Capital Investment Model

In his dissertation, Faucher (1996) offers a model of self-employment choice that incorporates capital costs. In his model, a capital investment is required to enter the self-employment sector, so earnings in this sector are reduced by fixed capital costs. Earnings in self-employment are $E^{se} = (w^{se} \cdot h) - k$, where w^{se} represents hourly earnings, *h* hours worked, and *k* the capital investment. Earnings in the wage-salary sector are simply $E^{ws} = (w^{ws} \cdot h)$. Utility is a function of income and the number of hours of leisure, and an individual chooses the sector that offers the highest utility. If $U(E^{se}, L^{se}) > U(E^{ws}, L^{ws})$, where L represents leisure, the individual will enter the self-employment sector.

The postulate of Faucher's model is that since hours of work and leisure are choice variables and since there is a fixed cost of entering self-employment, an individual who prefers more hours of leisure, and therefore fewer hours of work, may be reluctant to enter self-employment because of the fixed costs. This may be true even if hourly earnings are higher in the self-employment sector, since fewer hours are available to spread out fixed costs. Faucher theorizes that there is a subset of women who prefer nonmarket activity more than males, and this contributes to the lower self-employment rate of females.

Two testable predictions follow from this model. First, the model assumes that females work fewer hours in self-employment than males due to greater preferences for nonmarket activity. Thus, if differences in earnings and hours are not controlled for, females should be shown to be less likely to enter self-employment than males. Second, as a result of fewer hours for self-employed females to distribute fixed capital costs, the gender gap in earnings should be greater in the self-employment sector relative to the wage-salary sector.

Predictions of the five models of self-employment choice are summarized in Table 1. These predictions will be tested on a data set of veterinarians, a description of which follows in the next section, along with some background on the market for veterinarians.

II. Background and Data

The 1990 census reports the population of veterinarians as 48,258. In 1993, according to the American Veterinary Medical Association (1994), 81% of veterinarians were employed in the private clinical sector, and 19% in the public and corporate sectors. Of those in the private clinical sector, 69% were employed in small animal practices, 19% in large animal practices, and the remainder in "mixed" (small and large) practices. Most veterinarians in private practice begin their careers as wage-salary workers, and some time later, become partners or owners.[5]

The data used in this chapter come from annual wage surveys conducted in 1994 and 1995 by Medical Economics Research Group, at the direction of Veterinary

[5] The data utilized in this chapter report that among veterinarians with less than 3 years of experience, 84 percent are located in the wage-salary sector. Among veterinarians with greater than 10 years of experience, 64 percent are sole owners, and 29 percent are partners.

Economics. Veterinary Economics is a monthly publication sent free to all private practice veterinarians who request it. Their circulation is approximately 40,000, representing more than two-thirds of all private practice veterinarians in the United States. A stratified random sample[6] of 4,319 veterinarians in 1994, and 4,322 in 1995, were mailed surveys, with a total of 3,187 usable surveys returned (37% usable return rate).[7] The sample is limited to full-time, private practice veterinarians who have at least one year of experience. In Appendix A of Chapter 3, I provide evidence that the sample is representative of the general population of veterinarians, utilizing comparisons with 1990 census data.

Table 2 reports summary statistics from the data. Note that I partition the sample into three sectors: the self-employed, partners, and wage-salary workers. The self-employed are defined as those who are sole owners of their firms, incorporated or unincorporated. Partners share ownership with at least one other individual,[8] and wage-salary workers have no ownership in their firm. Each sector is treated separately, since I expect the mechanisms that determine earnings will differ between these groups.[9]

All veterinarians self-report their earnings in answering the following question: "Which of the following best represents your personal 1993 (or 1994) compensation

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[6] Some smaller veterinarian specialties were over-sampled. Summary statistics are weighted by specialty to reflect the "true population" of veterinarians, which is Veterinary Economics' subscriber list.

[7] A total of 145 observations were dropped from the 1994 data, which appeared as probable duplicates in the 1995 data. In addition, I deleted 4 observations that appeared subject to coding errors. The remaining n = 3,038.

[8] It may not be unreasonable to classify partners as "self-employed", since median partnership size in the sample is 2. However, in order to maintain a more theoretically satisfying definition of self-employment, I limit classification of the self-employed to sole owners of firms. An analysis of gender differences within partnerships would prove interesting, but small sample size, especially for females partners (n=66), hinders such a study.

[9] When estimating separate earnings regressions for the self-employed, partners, and wage-salary workers, a Chow (1960) test confirmed that the coefficients from the separate regressions are different at the 1% level.

from the practice before taxes were withheld?" Using responses to this question as a measure of earnings for the self-employed may pose a problem, particularly since there are tax avoidance incentives unique to the self-employment sector, which may lead owners to underreport their earnings. In Appendix A, I develop an alternative measure of earnings for the self-employed, deriving itself from reported firm revenues and expenses. All models are then reestimated using the alternative measure of earnings. Briefly, Appendix A reports no qualitative differences in the main results of this chapter, regardless of which measure of earnings is utilized.

Table 2 reports that male veterinarians, on average, earn considerably more than female veterinarians within each sector, while differences in hours worked per week are relatively small. However, the sample of male veterinarians has almost twice the amount of experience as the sample of female veterinarians (an overall average of 17.8 years compared with 9.0 years). Thus, differences in experience could account for a significant potion of the gender earnings gap. Also reported in Table 2 is a measure of patients seen per hour, a proxy variable for productivity, which will serve to control for productivity differences between veterinarians.

Table 2 also reports a variable called average fee. This represents a measure of the average charge per each client visit. Veterinarians typically keep track of this measure, since it is thought to be a general indicator of clinic productivity (Bowman, 1996).[10] Also reported is some firm-level data. Firm size is measured as the total number of veterinarians at each clinic. The sample mean of this variable is 3.2, so the firms examined in this study are relatively small. Also reported is an indicator of clinic specialty. Last, Table 2 reports that 55 percent of male veterinarians are

[10] In the veterinary literature, this is referred to as the ACT (Average Client Transaction charge). Clinics with higher ACTs are generally thought to be more productive, since each client is spending, on average, more money on each visit to the veterinarian.

self-employed, compared to only 36 percent of females; 23 percent of males are in partnerships, compared to only 10 percent of females; also, only 13 percent of males are found in the wage-salary sector, while 54 percent of females are located here.

III. Empirical Framework

A. Earnings Decompositions

Each model of self-employment choice offers a prediction regarding relative earnings gaps between sectors. However, these gaps should be adjusted to control for differences in observable characteristics, which could account for a significant portion of the unadjusted earnings gap. To do this, I utilize a standard earnings decomposition, due to Oaxaca (1973). First, using OLS, separate earnings regressions for each sector are estimated for females and males:

$$\ln \hat{E}_f = \sum B_f \cdot X_f \text{ and } \ln \bar{\hat{E}}_f = \ln \bar{E}_f = \sum B_f \cdot \bar{X}_f \qquad (1)$$

$$\ln \hat{E}_m = \sum B_m \cdot X_m \text{ and } \ln \bar{\hat{E}}_m = \ln \bar{E}_m = \sum B_m \cdot \bar{X}_m \qquad (2)$$

The first term of each equation denotes the predicted value of ln earnings, the mean of which, $\ln \bar{\hat{E}}$, is equal to the overall mean, $\ln \bar{E}$. The *X* variables include controls for experience, hours worked per week, patients seen per hour, clinic specialty and size, along with region, metropolitan statistical area, and year of survey dummies.

If $\sum B_m \cdot \bar{X}_f$ is added to both equations (1) and (2), and then equation (2) is subtracted from equation (1), the following decomposition is obtained:

$$\ln \bar{E}_m - \ln \bar{E}_f = \sum B_m(\bar{X}_m - \bar{X}_f) + \sum \bar{X}_f(B_m - B_f) \qquad (3)$$

The first term on the right-hand side of equation (3) evaluates the difference in mean values of the X's using male prices, or coefficients. This is generally referred to as the "explained portion" of the earnings gap. The second term on the right-hand side is the conventional measure of wage discrimination, with $\beta_m > \beta_f$ indicating a higher price received by a male worker relative to female worker for the same characteristic. Since there will always exist unobserved differences that cannot be controlled for, it is preferable to refer to this term as the "unexplained portion" of the earnings gap, rather than a direct measure of wage discrimination.

An alternative representation of the difference in ln earnings may be expressed as follows:

$$\ln \overline{E}_m - \ln \overline{E}_f = \sum B_f(\overline{X}_m - \overline{X}_f) + \sum \overline{X}_m(B_m - B_f) \tag{4}$$

This utilizes female coefficients to evaluate gender differences in mean characteristics. Equation (3) implies that in the absence of discrimination, the male earnings structure would prevail, while equation (4) implies that the female earnings structure would exist in a nondiscriminatory environment. The two assumptions do not yield the same result, and thus, I will report estimates of both equations (3) and (4). In addition, as a matter of notation, I will refer to the unexplained portion of the earnings gap as D^R. Thus, $D^R = \sum \overline{X}_m(B_m - B_f)$ or $\sum \overline{X}_f(B_m - B_f)$, depending on the specification of the earnings decomposition.

B. Econometric Issues

With regard to estimation of the earnings decompositions, two econometric notes should be made. First, I do not control for sample selection bias in the estimates. It is possible that veterinarians who select into a specific sector may differ in unobservable ways from the general population of veterinarians. For example, those who choose self-employment, from the population of veterinarians, may be those who would have the highest earnings in the self-employment sector. Since my primarily analysis is focused on earnings differences within sectors, selection may only pose a problem if there are gender differences in selection behavior (e.g., females negatively selecting into the self-employment sector, with males positively selecting into the same sector). In Appendix B, I provide tests for sample selection bias, and I do not find evidence of selection behavior, either on the part of male or female veterinarians, in either sector.

Second, survey respondents report annual earnings as a categorical variable. Instead of utilizing an ordered probit model in estimations, I implement OLS by using the midpoint of the reported range as the dependent variable. If the underlying earnings distributions differ by gender, this could cause a bias in the estimation of D^R. In Appendix C of Chapter 3, I test for this with census data, and I provide evidence against this concern. However, my analysis does show that by reducing the amount of variation in the dependent variable, the OLS model is able to estimate a better fit for the data. Although coefficient estimates should be relatively unbiased, estimates of standard errors will be biased downwards. Thus, when utilizing bracket midpoints as the dependent variable, statistical inferences should be made more conservatively.

C. Probit for Self-employment

Each model of self-employment choice offers predictions regarding the likelihood of females choosing self-employment, relative to males. To test these predictions, the following probit model is estimated:

$$S_i^* = \alpha_0 + \alpha_1 F_i + \alpha_{j+1} X_i + e_i \quad ; \qquad j = 1.....p. \qquad (5)$$

where S_i^* is not observed directly; $S_i = 1$ if $S_i^* \geq 0$ and $S_i = 0$ if $S_i^* \leq 0$.
F_i = Dummy variable for female
X_i = p controls, including experience, age, clinic specialty, along with region, msa, and year of survey dummies

Of primary interest is estimation of α_1, the coefficient on the female dummy variable.

As noted earlier, a central assumption of all three discrimination models of self-employment is that individuals choose the sector that offers them the highest earnings. In order to test this assumption, I impose some structure on the probit model. First, I estimate the following equation for the self-employment sector, separately for both males and females:

$$\ln(E^{se}) = \beta_0^{se} + \beta_j^{se} X + e; \qquad j = 1.....p. \tag{6}$$

where $\ln(E_i)$ = log annual earnings
X_i = p controls, including experience, clinic specialty, hours worked per week, patients per hour, along with region, msa, and year of survey dummies

Similarly, the following is estimated for the wage-salary sector, separately for both males and females:

$$\ln(E^{ws}) = \beta_0^{ws} + \beta_j^{ws} X + e; \qquad j = 1.....p. \tag{7}$$

After these equations are estimated, predicted log annual earnings are computed for each individual, based on individual characteristics and the estimated coefficients from equations (6) and (7). The difference between predicted self-employment earnings and predicted wage-salary earnings is then computed for each individual ($\hat{E}_i^{se} - \hat{E}_i^{ws}$).

For identification, it is necessary that there be at least one variable in my probit equation that is not in my earnings equations. Such a variable should affect one's preferences for self-employment without directly affecting earnings. The age variables serve this purpose here, since theoretically, age should not affect earnings apart from experience.[11] In addition, identification also requires that there be at least one variable in the earnings equations that does not appear in the probit equation. The variables

[11] When the age variables are included in the estimations of (6) and (7), an F-test confirms their joint significance as not statistically different from zero.

used here are proxies for productivity: hours worked per week and patients per hour. It is assumed that one's productivity does not affect one's preferences for self-employment, independently of its affect on earnings.

C. Test for Specific Models

Estimations of the above equations will offer implications for all five models of self-employment choice. In addition, I offer two tests that are specific to the predictions of the customer discrimination and compensating differentials models.

A key prediction of the customer discrimination model is that female sellers will charge, on average, lower prices than male sellers. In order to test this, I estimate the following for the self-employed, separately for each specialty:

$$\ln(P^{se}) = \beta_0^{se} + \beta_1^{se} F + \beta_{j+1}^{se} X + e \; ; \quad j = 1.....p. \tag{8}$$

where ln(P) = log average fee
F = Dummy variable for female
X = p controls including experience, patients per hour, along with region, msa, and year of survey dummies

β_1 estimated as less than zero would be evidence offered in support of the customer discrimination model.

The compensating differentials model predicts that flexibility should be negatively correlated with earnings. I test for this by adding a dummy variable, V, as a control variable to the earnings decompositions (equations 3 and 4). V = 1 if individuals work a nonstandard work week, classified as less than 41 hours or greater than 60 hours.[12] It is important to test whether variability in hours worked has an impact on earnings *independent* of the number of hours worked. To accomplish this, I will use

[12] The data set includes only veterinarians who report themselves as "full-time." The mean numbers of hours worked is 52.5 hours per week; 58 percent of all veterinarians work between 41-60 hours per week, 10 percent less than 41 hours per week, and 32 percent greater than 60 hours per week.

hourly earnings, instead of annual earnings, as the dependent variable, which effectively controls for the number of hours worked.[13]

IV. Results of Estimation

A. Earnings Decompositions

The gender difference in mean ln annual earnings in the sample of wage-salary veterinarians is [.163], representing an unadjusted wage gap of 15 percent. Table 3 reports a decomposition of this earnings difference. Female and male coefficients, β_f and β_m, are reported from the estimation of equations (1) and (2). The last two columns of Table 2 report estimations of the "explained portion" of the earnings gap from equations (3) and (4), respectively.

The coefficients on the experience variables are reported positive and jointly statistically significant for both females and males. As expected, the difference in average experience explains a significant portion of the gender gap in earnings. Measured with male coefficients, the set of experience variables explains [.039], or 25 percent, of the difference in mean ln earnings. Evaluation with female coefficients accounts for [.025], or 15 percent, of the earnings difference.

For both females and males, coefficients on the hours per week variables are jointly statistically significant. However, the female point estimates are greater at each level than the male point estimates, and some of the male coefficients are not statistically different from zero. Since this sample includes only full-time veterinarians, gender differences in hours worked per week are not great (in the wage-salary sector, males work an average of 3.5 more hours per week than females). Differences in this characteristic explain [.011] of the earnings gap when evaluated with male coefficients, and [.028] of the earnings gap when evaluated with female coefficients.

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[13] Hourly earnings = annual earnings/(52 x hours worked per week).

Most of the coefficients on the set of specialty variables are not statistically significant. Differences in clinic specialty explain only [.004] of the earnings difference when evaluated with male coefficients, and actually widen the unexplained earnings gap by [.011] when evaluated with female coefficients. Both equations indicate an earnings increase of 1 percent for each additional veterinarian in the firm, and gender differences in this variable explain a small portion of the earnings gap.

The female coefficient on the proxy variable for productivity, patients per hour, is .09 and statistically significant, indicating a nine percent increase in earnings for seeing one additional patient per hour. The male coefficient is .03, but statistically insignificant. Since female wage-salary veterinarians see more patients per hour, on average, than male veterinarians in the wage-salary sector, accounting for this characteristic increases the unexplained portion of the earnings gap. Differences in location, and a control for survey year, explain a small portion of the earnings gap when evaluated with male coefficients, but serve to widen the earnings gap by [.048] when evaluated with female coefficients.

Added together, differences in observed characteristics explain [.056], or 34 percent, of the gap in ln earnings when evaluated with male coefficients. When evaluated with female coefficients, differences in observed characteristics serve to widen the earnings gap by [.023]. This leaves an unexplained earnings difference of [.106] or [.184], depending on the specification of the earnings decomposition. Thus, D_{WS}^{R}, the earnings gap in the wage-salary sector adjusted for differences in observable characteristics, is 10 or 17 percent, depending on the specification.

Table 4 reports the earnings decomposition for the self-employment sector. The gender difference in mean ln annual earnings in the sample of self-employed veterinarians is [.573], representing an unadjusted earnings gap of 44 percent. The coefficients on the experience variables are reported positive and jointly statistically significant for both females and males, and once again, gender differences in experience play a significant role in accounting for the earnings gap. Measured with male coefficients, the set of experience variables explains [.073], or 13 percent, of the difference in mean ln earnings. Evaluation with female coefficients accounts for [.152], or 27 percent, of the earnings difference.

For both females and males, coefficients on the hours per week variables are positive and jointly statistically significant. Differences in hours worked explain [.022] of the earnings gap when evaluated with male coefficients, and [.016] of the earnings gap when evaluated with female coefficients. The coefficients on the patient per hour variables are positive and statistically significant, once again indicating a positive relationship between the proxy measure of productivity and earnings. Since self-employed females see fewer patients per hour, on average, than males, differences in this characteristic account for [.039] or [.035] of the earnings gap when evaluated with male and female coefficients respectively, accounting for approximately 6 percent of the total earnings gap.

Added together, differences in observed characteristics explain [.100], or 17 percent, of the gap in earnings when evaluated with male coefficients. When evaluated with female coefficients, differences in observed characteristics explain [.189], or 33 percent of the earnings gap. This leaves an unexplained earnings difference of [.474] or [.381], depending on the specification of the earnings decomposition. Therefore, D_{SE}^{R}, the earnings gap in the self-employment sector adjusted for differences in observable characteristics, is 38 or 32 percent, depending on the specification.

For purposes of the current study, the key result from Tables 3 and 4 is that the unexplained portion of the earnings gap is smaller in the wage-salary sector than the self-employment sector. That is, $D^R_{WS} < D^R_{SE}$, and this holds true regardless of the specification of the earnings decomposition.[14] This result has implications for the models of self-employment choice summarized earlier. From Table 1, note that the simple employer discrimination model fails on its prediction of a larger adjusted earnings gap in the wage-salary sector, or $D^R_{WS} > D^R_{SE}$. However, the customer discrimination, compensating differentials, and capital investment models all predict what is observed among veterinarians: an adjusted earnings gap that is larger in the self-employment sector relative to the wage-salary sector.

To further establish the relative earnings position of self-employed females, a comparison of female earnings between sectors is made. Table 2 reports that females in the self-employment sector earn 9 percent more than their wage-salary counterparts. However, self-employed females have, on average, more than twice the experience of wage-salary females, and thus it is important to account for this.

In an earnings decomposition context, I construct the following adjusted earnings ratio: $\sum B_f^{ws} \cdot \overline{X}_f^{se} / \overline{E}_f^{se}$, where B_f^{ws} represents the coefficients from the earnings regression for females in the wage-salary sector; $\overline{X}_f^{se}$ represents the female averages of the control variables in the self-employment sector; and $\overline{E}_f^{se}$ are average female earnings in the self-employment sector. Conceptually, the model predicts what women in the self-employment sector would earn if they were in the wage-salary sector. I estimate the adjusted earnings ratio as 1.15, suggesting the females in the

[14]In separate estimations, I test whether this result is simply an artifact of differences in average experience between sectors. Stratifying the sample by experience and sector, I find that D^R does not vary much by experience *within sectors*.

self-employment would earn *15 percent more* than they currently earn if they switched to the wage salary sector.[15] Therefore, the low relative earnings position of self-employed female veterinarians corresponds to the outcome observed in the general population: self-employed females earning less than self-employed males, and less than both males and females in the wage-salary sector.

B. Probit for Self-employment

Table 5 reports estimates of the probit model in equation (5).[16,17] The first specification does not control for experience or age, and the coefficient on the female dummy is negative and statistically significant. In the second and third specifications, I add controls for age and experience. Coefficients on age and experience variables are all positive and highly statistically significant. The reported positive relationship between age and self-employment is consistent with the findings of Evans and Leighton (1989) who, utilizing CPS and NLSY data, reported self-employment rates positively correlated with age. Note, however that the coefficient on the female dummy in both specifications is not statistically different from zero. This is an interesting result that conflicts with other evidence on female self-employment rates. This may indicate that much of the difference that exists between male and female self-employment rates can be explained by differences in industry and occupation. In other words, women may be located in fields where there is relatively little self-employment. As Aronson

[15] An alternative explanation for this outcome has to do with unobserved heterogeneity. The adjusted wage gaps suggest that unobserved heterogeneity may be greater in the self-employment sector relative to the wage-sector. If unobservables are correlated with observed characteristics, estimates on coefficients in the self-employment sector may be more biased, relative to coefficients in the wage-salary sector. Thus, inferences from the model should be made with caution.

[16] Results reported are partial derivatives, evaluated at means of the independent variables, and for discrete changes of dummy variables from 0 to 1.

[17] Accounting for the partnership sector, a multinomial logit model was estimated with results qualitatively similar to those in Table 5.

points out, much of the existing work on self-employment lacks controls for occupational differences.

This finding has implications for all five models of self-employment choice. Note from Table 1 that each model offers a prediction regarding the likelihood of finding women in the self-employment sector: the employer discrimination model predicts that women should be more likely to enter self-employment, while the other models predict that females should be less likely to enter self-employment. My results suggest that among veterinarians, controlling for age and experience, females are neither more nor less likely to enter self-employment than males.

The fourth specification adds as a control the difference in predicted earnings between sectors, $\hat{E}_i^{se} - \hat{E}_i^{ws}$. The coefficient on this variable is reported positive and statistically significant at the 6% level. The point estimate suggests that if earnings are 10% higher in self-employment compared to the wage-salary sector, a veterinarian's likelihood of entering self-employment increases by 1%. This supports the assumption of each model, that earnings are an important determinant of sector choice.

The coefficient on the female dummy in the fourth specification remains statistically insignificant. This contradicts a key implication of compensating differentials model, which predicts that females are more likely to choose self-employment, after controlling for differences in earnings. Also of note from the fourth specification is that the coefficients on the experience variables remain positive and jointly statistically significant. This suggests that experience plays a role in self-employment choice, independent of $\hat{E}_i^{se} - \hat{E}_i^{ws}$. Experience may be necessary to accumulate the capital required to enter self-employment. This explanation would be consistent with the findings of Evans and Leighton, who report that individuals with greater assets are more likely to switch into self-employment.

C. Tests for Specific Models

Testing for evidence of gender differences in fees charged, Table 6 reports the estimation of equation (8). Results are reported separately for each specialty. Note that I include as an independent variable patients per hour, which effectively controls for differences in time spent with each client. Within each specialty, the coefficient on female is not statistically different from zero, which contradicts the key prediction of the customer discrimination model.[18,19]

The customer discrimination model offers as a possible outcome that female sellers charge the same prices as male sellers, but as a result, have fewer customers. Manifested in this manner, customer discrimination would reflect itself in fewer patients per hour for female veterinarians. Table 4 reports that gender differences in this variable explains 6-7 percent of the earnings gap among the self-employed. This suggests that customer discrimination may exist among self-employed veterinarians, although if present, it explains a relatively small portion of the gender gap in earnings.

Table 7 reports a test of the compensating differentials model, by adding a dummy for "variable hours" to the earnings decompositions for veterinarians in the self-employment sector. In order to test the impact of a nonstandard work schedule on earnings *independent* of number of hours worked, a measure of hourly earnings is utilized as the dependent variable. Although the coefficient estimates are statistically insignificant, the point estimates indicate a negative correlation between variability in

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[18] In addition to reporting average fee, survey respondents report fees across an array of medical services. The large majority of the averages of these fees do not differ significantly by gender.

[19] A separate regression pooling all specialties, and including a dummy variable for each specialty, was estimated with the same main result.

hours worked and hourly earnings, for both females and males. This finding concurs with the prediction of the compensating differentials model. However, for a compensating differential such as flexibility to explain a substantial portion of the gender gap in earnings, significant gender differences in this characteristic would have to be present. Among self-employed veterinarians, this does not appear to be true, as including this variable in the earnings decomposition explains less than 2% of the gender gap in earnings.

V. Conclusion

In this chapter, I test five models of self-employment choice on a data set of veterinarians. The predictions of each model are summarized in Table 1, and each model fails at least one test. The employer discrimination model fails on its key prediction that the gender gap in earnings, adjusted for differences in observable characteristics, should be greater in the wage-salary sector than the self-employment sector. All five models fail on the prediction that there should exist gender differences in the likelihood of choosing self-employment, among males and females who are alike in observable characteristics. Results reported in Table 6 show no evidence of gender differences in fees charged, contrary to the prediction of the customer discrimination model. In addition, although results reported in Table 7 suggest that a nonstandard work schedule may be negatively correlated with earnings, the sample does not indicate significant gender differences in demand for this characteristic. Finally, although I do not offer a specific test for the capital investment model, in order for this model to explain earnings differences in the self-employment sector, females must work on average, fewer hours per week than males. However, within the sample of self-employed veterinarians, females work, on average, more hours per week than males.

Summarizing my main results, probit estimations reported in Table 5 suggest that gender does not have a significant impact on self-employment choice, among veterinarians similar in age and experience. This suggests that existing differences in self-employment rates in the general population may be explained, to a large extent, by differences in occupation. Females may choose occupations where self-employment rates are relatively low.

After controlling for differences in observed characteristics, I report an unexplained earnings gap of 10-17 percent in the wage-salary sector, and 32-38 percent in the self-employment sector, from Tables 3 and 4 respectively. Results presented offer little explanation for the low relative earnings position of self-employed female veterinarians.

In Chapter 6, I focus on an examination of firm-level data, and the potential contribution that firm characteristics can make in accounting for the relatively large gap in earnings between self-employed males and females. This analysis will take into explicit consideration the self-employed as owners of firms, who employ factors of production, a full consideration of which is lacking from existing models of self-employment choice.

Table 1: Predictions of Self-Employment Choice Models

Prediction	Employer Discrimination	Employer Discrimination with spillovers	Customer Discrimination	Compensating Differentials	Capital Investment
Adjusted Earnings Gap	$D^R_{WS} > D^R_{SE}$ [1]	$D^R_{WS} \geq or \leq D^R_{SE}$	$D^R_{WS} < D^R_{SE}$	$D^R_{WS} < D^R_{SE}$	$D^R_{WS} < D^R_{SE}$
Probit for SE	F[2] > 0	F < 0	F < 0	F > 0	F < 0
Probit for SE, control for $(E_{se}-E_{ws})$[3]	F = 0	F = 0	F = 0	F > 0	F $\leq$ 0
Fees			F < 0		
Impact of hours variability on earnings				V[4] < 0	

[1] $D^R = \sum \overline{X}_m(B_m - B_f) or \sum \overline{X}_f(B_m - B_f)$.
[2] F = Coefficient on dummy variable for female.
[3] $(E_{se}-E_{ws})$ = difference in earnings between the self-employed and wage-salary sectors.
[4] V = Coefficient on dummy variable for hours variability.

Sources:
Moore, R., "Employer Discrimination: Evidence from Self-Employed Workers," *Review of Economics and Statistics*, (1983). [Employer Discrimination]
Coate, S. and S. Tennyson, "Labor Market Discrimination, Imperfect Information and Self-Employment," *Oxford Economic Papers*, (1992). [Employer Discrimination with Spillovers]
Borjas, G. and S. Bronars, "Consumer Discrimination and Self-Employment," *Journal of Political Economy*, (1989). [Customer Discrimination]
Lombard, K., "Female Self-Employment and the Demand for Flexible, Non-standard Work Schedules," Mimeograph, University of Miami, (1996). [Compensating Differentials]
Faucher, A., "Essays on Physician Self-Employment," Dissertation, University of Pennsylvania, (1996). [Capital Investment]

Table 2: Summary Statistics

	Males			Females		
	Self-Employed	Partners	Wage-Salary	Self-Employed	Partners	Wage-Salary
Annual Earnings[1]	72,441	82,035	46,350	43,874	45,911	38,897
Experience[1]	20.1	18.7	8.8	12.6	11.7	6.1
Age[1]	46.3	44.2	35.2	39.3	38.2	32.4
Hours worked/wk[1]	53.2	52.7	52.8	54.5	49.8	49.3
Patients per hour	1.51	1.37	1.37	1.24	1.32	1.51
Average Fee	65.54	70.68	65.71	64.92	60.51	66.79
Firm Size	2.0	4.3	4.9	1.8	3.7	4.3
Clinic Specialty: Small Animal	.60	.45	.62	.76	.62	.82
Mixed	.26	.37	.27	.16	.29	.14
Equine	.04	.02	.02	.05	.05	.02
Dairy	.03	.09	.05	.01	.02	.01
Beef	.04	.04	.02	.01	.02	.01
Swine	.02	.04	.02	.01	.01	.001
Sample Size[2]	1328	782	346	221	66	257
Fraction of gender in sector	.55	.23	.13	.36	.10	.54

Table is weighted to correct for over-sample of some specialties. [1]Data are reported as categorical variables. Means are obtained by using the midpoint of the reported range. [2]Smaller samples for some variables.

Source:
Veterinary Economics, *Continuing Wage Surveys*, Veterinary Medicine Publishing Company, (1994-95).

Table 3: Earnings Decomposition: Wage-Salary Sector

Dependent Variable: Ln Annual Earnings

Variable	β_f		β_m		$\beta_m(\bar{X}_m-\bar{X}_f)$	$\beta_f(\bar{X}_m-\bar{X}_f)$
Experience[1]					[.039]	[.025]
3 to 5 years	.11	(1.91)	.12	(2.56)	-.011	-.010
6 to 10 years	.19	(2.95)	.19	(3.82)	-.006	-.005
11 to 20 years	..19	(2.22)	.39	(7.40)	.028	.014
21 to 30 years	.60	(2.85)	.43	(5.33)	.019	.026
31 to 40 years	5		.53	(4.31)	.008	.000
over 40 years	5		.08	(.31)	.000	.000
Hours per week[2]					[.011]	[.028]
under 25 hours	5		-.78	(3.89)	-.005	.000
41 - 50 hours	.18	(2.63)	-.04	(.65)	.005	-.020
51 - 60 hours	.28	(3.93)	.05	(.76)	.002	.009
61 - 70 hours	.23	(2.63)	.06	(.77)	.007	.028
71 - 80 hours	.50	(3.58)	.07	(.76)	.002	.011
over 80 hours	-.05	(.33)	-.13	(.92)	.001	.000
Clinic Specialty[3]					[.004]	[-.011]
Mixed	-.05	(.86)	-.07	(1.38)	-.005	-.004
Equine	.02	(.23)	-.03	(.53)	.001	.000
Dairy	-.12	(1.39)	.01	(.28)	.002	-.016
Beef	.26	(1.72)	-.09	(1.10)	-.003	.008
Swine	5		.16	(2.01)	.009	.000
# Vets in Clinic	.01	(1.67)	.01	(2.89)	.005	.003
Patients per hour	.09	(3.43)	.02	(1.07)	-.005	-.019
Constant	9.90	(68.92)	10.41	(91.50)	-	-
Location and Year[4]	yes		yes		[.002]	[-.048]
Sample Size	216		309			
Adjusted R^2	.34		.35			
Total explained					[.056]	[-.023]
Total unexplained					[.106]	[.184]

t-statistics are in parentheses. Numbers in brackets refer to the portion of the ln earnings gap explained by groups of variables. [1]Excluded category is 1 to 2 years. [2]Excluded category is 31-40 hours (no respondents reported 25 - 30 hours). [3]Excluded category is Small Animal. [4]Controls for msa status, region, and the survey year. [5]No data.

Table 4: Earnings Decomposition: Self-Employment Sector

Dependent Variable: Ln Annual Earnings

Variable	β_f		β_m		$\beta_m(\bar{X}_m-\bar{X}_f)$	$\beta_f(\bar{X}_m-\bar{X}_f)$
Experience[1]					[.073]	[.152]
1 to 2 years	-.89	(2.07)	-.04	(.14)	.001	.024
6 to 10 years	.31	(1.73)	.16	(1.68)	-.034	-.064
11 to 20 years	.35	(2.06)	.38	(4.41)	-.023	-.021
21 to 30 years	.42	(1.47)	.40	(4.53)	.086	.091
31 to 40 years	1.10	(2.09)	.36	(3.63)	.039	.121
over 40 years	[5]		.07	(.50)	.002	.000
Hours per week[2]					[.022]	[.016]
under 25 hours	-1.03	(2.99)	-.79	(3.99)	.014	.018
25 - 30 hours	-.47	(.92)	-.30	(2.01)	-.003	-.005
41 - 50 hours	.23	(1.16)	.24	(3.33)	.000	.000
51 - 60 hours	.19	(.92)	.36	(5.09)	.020	.010
61 - 70 hours	.41	(2.03)	.55	(7.21)	-.010	-.008
71 - 80 hours	.11	(.48)	.47	(5.22)	-.001	-.001
over 80 hours	.09	(.28)	.55	(5.38)	.004	.001
Clinic Specialty[3]					[-.004]	[.007]
Mixed	-.28	(1.54)	-.20	(3.40)	-.012	-.016
Equine	-.15	(.97)	-.22	(3.95)	.023	.015
Dairy	.19	(.77)	.02	(.26)	.001	.010
Beef	-.15	(.50)	-.23	(3.07)	-.023	-.016
Swine	.44	(1.11)	.23	(2.48)	.007	.014
# Vets in Clinic	.09	(1.37)	.07	(5.38)	.006	.008
Patients per hour	.14	(2.01)	.16	(8.50)	.039	.035
Constant	9.80	(30.51)	10.22	(62.38)	-	-
Location and Year[4]	yes		yes		[-.037]	[-.028]
Sample Size	176		1040			
Adjusted R^2	.22		.27			
Total explained					[.100]	[.189]
Total unexplained					[.474]	[.381]

t-statistics are in parentheses. Numbers in brackets refer to the portion of the ln earnings gap explained by groups of variables. [1]Excluded category is 3 to 5 years. [2]Excluded category is 31-40 hours. [3]Excluded category is Small Animal. [4]Controls for msa status, region, and the survey year. [5]No data.

Table 5: Probit for Self-Employment

Variable	(1)	(2)	(3)	(4)
Female	-.17	-.02	-.01	.02
	(6.52)	(.53)	(.28)	(.63)
$\hat{E}_{se} - \hat{E}_{ws}$				.10
				(1.89)
Clinic Specialty:[1]				
Mixed	-.08	-.07	-.08	-.06
	(2.55)	(2.25)	(2.50)	(2.01)
Equine	.18	.19	.17	.20
	(6.07)	(6.13)	(5.56)	(6.34)
Dairy	-.14	-.12	-.20	-.13
	(3.81)	(3.25)	(5.64)	(3.41)
Beef	.04	.05	.06	.07
	(.87)	(1.08)	(1.28)	(1.44)
Swine	-.04	-.04	-.11	-.05
	(.79)	(.67)	(2.15)	(.88)
Experience:[2]				
3 to 5 years		.17	.17	.13
		(2.42)	(2.39)	(1.80)
6 to 10 years		.41	.36	.32
		(6.59)	(5.54)	(4.44)
11 to 20 years		.55	.42	.37
		(9.04)	(5.90)	(4.77)
21 to 30 years		.52	.35	.31
		(9.12)	(4.39)	(3.61)
31 to 40 years		.49	.34	.31
		(9.23)	(3.61)	(3.21)
over 40 years		..50	.41	.38
		(8.39)	(3.00)	(2.60)
Age:[3]				
35 - 44 years			.18	.19
			(4.74)	(4.86)
45 - 54 years			.29	.30
			(5.53)	(5.65)
55 - 64 years			.29	.30
			(4.02)	(4.16)
over 65 years			.44	.45
			(4.48)	(4.61)
Sample Size	2915	2914	2913	2913

t-statistics are in parentheses. Results reported are partial derivatives, evaluated at means of the independent variables, and for discrete changes of dummy variables from 0 to 1. Additional Controls: state, msa, and year of survey dummies. [1]Excluded category is Small Animal. [2]Excluded category is 1 to 2 years. [3]Excluded category is 25 to 34 years.

Table 6: Fees in the Self-employment sector

Dependent Variable: Ln Average Fee

Variable	(1) Small Animal	(2) Mixed	(3) Equine	(4) Dairy	(5) Beef	(6) Swine
Female	-.09	-.14	.19	.02	.19	-.29
	(1.61)	(1.10)	(1.55)	(.08)	(.46)	(.19)
Experience:[1]						
1 to 2 years	-.02	-.77	-.20	-.89	-.10	[2]
	(.10)	(1.42)	(.44)	(1.07)	(.11)	
6 to 10 years	-.15	.03	-.28	.20	.54	1.01
	(1.27)	(.14)	(1.30)	(.56)	(1.11)	(.62)
11 to 20 years	-.11	-.10	-.35	.31	.02	1.45
	(.95)	(.62)	(1.64)	(.99)	(.06)	(1.07)
21 to 30 years	-.18	-.26	-.45	-.08	.22	1.37
	(1.52)	(1.43)	(1.95)	(.24)	(.54)	(1.02)
31 to 40 years	-.30	-.26	-.64	-.03	.05	1.20
	(2.14)	(1.28)	(2.02)	(.08)	(.12)	(.91)
over 40 years	-.38	-1.08	-.53	-.31	[2]	.95
	(2.34)	(2.87)	(1.22)	(.63)		(.48)
Patients per hour	-.02	.02	-.06	-.29	.01	-.80
	(.83)	(.34)	(1.21)	(1.35)	(.16)	(1.42)
Constant	4.23	4.31	4.96	4.92	2.78	4.91
	(24.53)	(15.38)	(14.36)	(9.09)	(2.58)	(2.64)
R^2	.23	.16	.18	.35	.10	.33
Sample Size	248	159	148	76	84	25

Regression is OLS. Additional controls include region, msa status, and a year of survey dummy. T-statistics are in parentheses. [1]Excluded category is 3 to 5 years. [2]No Data.

Table 7: Earnings Decomposition: Variable Hours in SE Sector

Dependent Variable: Ln Hourly Earnings

Variable	β_f		β_m		$\beta_m(\bar{X}_m-\bar{X}_f)$	$\beta_f(\bar{X}_m-\bar{X}_f)$
Experience[1]					[.085]	[.167]
1 to 2 years	-1.10	(2.70)	-.09	(.31)	.002	.030
6 to 10 years	.35	(1.99)	.14	(1.46)	-.029	-.073
11 to 20 years	.39	(2.30)	.38	(4.40)	-.023	-.023
21 to 30 years	.59	(2.08)	.41	(4.63)	.089	.127
31 to 40 years	.95	(1.84)	.39	(3.94)	.043	.106
over 40 years	[5]		.10	(.74)	.003	.000
Clinic Specialty[2]					[-.003]	[.004]
Mixed	-.23	(1.30)	-.21	(3.71)	-.012	-.014
Equine	-.05	(.33)	-.28	(5.08)	.028	.005
Dairy	.10	(.43)	-.01	(.10)	.000	.005
Beef	-.04	(.13)	-.25	(3.34)	-.025	-.004
Swine	.38	(.93)	.22	(2.30)	.007	.012
# Vets in Clinic	.09	(1.38)	.07	(5.11)	.006	.008
Patients per hour	.15	(2.08)	.16	(8.51)	.040	.037
Variable hours[3]	-.17	(1.45)	-.06	(1.73)	.004	.009
Constant	2.16	(7.05)	2.65	(17.12)	-	-
Location and Year[4]	yes		yes		[-.038]	[-.026]
Sample Size	176		1040			
Adjusted R^2	.17		.24			
Total explained					[.094]	[.199]
Total unexplained					[.473]	[.367]

t-statistics are in parentheses. Numbers in brackets refer to the portion of the ln earnings gap explained by groups of variables. [1]Excluded category is 3 to 5 years. [2]Excluded category is Small Animal. [3]Dummy variable=1 if hours worked per week is outside the 41-60 range. [4]Controls for msa status, region, and the survey year. [5]No data.

APPENDICES

APPENDIX A

APPENDIX A

Earnings in Self-Employment

For both wage-salary and self-employed veterinarians, earnings are determined by survey responses to the following question: "Which of the following best represents your 1993 (or 1994) compensation from the practice before taxes were withheld?" Using this definition of earnings for the self-employed may pose a problem, since earnings could include a return on capital investment. In addition, there are tax avoidance incentives unique to the self-employment sector, which may lead owners to underreport their earnings.

A more theoretically satisfying measure of earnings for the self-employed may be firm profits, a measure of which may be obtained from the data. Firm owners are asked the following questions: "Which of the following best represents the practice's 1993 (or 1994) total gross revenue?" and "What were your total 1993 (or 1994) practice expenses, excluding all owner compensation?" Utilizing responses to these questions, a measure of "gross profit" may be obtained.[1] Mean gross profit among female sole-owners is $56,984, and the corresponding number for male sole-owners is $90,095. This represents a gap of 37 percent, smaller than the earnings gap of 41 percent reported in Table 2, suggesting that female owners may reinvest more profits into their firms than male owners.

Results in Tables 4, 5, and 7 are reestimated, utilizing gross profit as the measure of self-employed earnings. Overall, the results reported in the following Tables

[1]Earnings are reported as categorical variables. When falling in the lowest range, "Less than $15,000," earnings are coded as $10,000. To maintain consistency, all measures of gross profit estimated less than $10,000 are recoded as $10,000.

A4, A5, and A7, are qualitatively unchanged from those reported in the main text. The adjusted gender gap in earnings, reported in Tables A4 and A7, is 31 to 35 percent, depending on the specification. In addition, results obtained in the structural form probit, reported in Table A5, are similar to those reported in Table 5.

Coefficients across specifications are estimated with less precision, which may be a reflection of the smaller sample from which a measure of gross profit may be obtained. Measurement error may also be a relatively greater problem in these estimates, for the gross profit variable is constructed from two other variables, which themselves are subject to measurement error.[2] In addition, it may be argued that firm owners are better able to accurately report personal earnings than firm revenues and expenses. Also, an incentive to underreport earnings may still reflect itself in a measure of gross profit. Given these concerns, self-reported earnings are utilized in the text as the preferred measure of earnings for sole owners.

[2]An attempt was made to minimize measurement error. Owners who reported total expenses as less than 25 percent of total revenue were assumed as reporting with error, and their responses were not used in the following estimations.

Table A4: Earnings Decomposition: Self-Employment Sector

Dependent Variable: Ln Annual Earnings

Variable	β_f		β_m		$\beta_m(\bar{X}_m-\bar{X}_f)$	$\beta_f(\bar{X}_m-\bar{X}_f)$
Experience[1]					[.031]	[.014]
1 to 2 years	.04	(.08)	-.36	(.68)	.010	-.001
6 to 10 years	.34	(1.34)	.27	(1.59)	-.055	-.070
11 to 20 years	.12	(.51)	.29	(1.93)	-.017	-.007
21 to 30 years	.43	(1.04)	.35	(2.27)	.076	.092
31 to 40 years	[5]		.10	(.60)	.011	.000
over 40 years	[5]		.20	(.80)	.007	.000
Hours per week[2]					[.026]	[.021]
under 25 hours	-.56	(1.14)	-1.00	(3.00)	.017	.010
25 - 30 hours	-.14	(.22)	.09	(.30)	.001	-.001
41 - 50 hours	.44	(1.58)	.12	(.91)	.000	.001
51 - 60 hours	.57	(2.03)	.32	(2.40)	.017	.031
61 - 70 hours	.80	(2.84)	.60	(4.15)	-.010	-.014
71 - 80 hours	.41	(1.26)	.52	(3.16)	-.003	-.003
over 80 hours	-.42	(.76)	.52	(2.81)	.004	-.003
Clinic Specialty[3]					[-.006]	[.041]
Mixed	-.18	(.68)	-.20	(1.91)	-.012	-.011
Equine	.10	(.47)	-.12	(1.16)	.012	-.010
Dairy	.12	(.37)	.11	(.91)	.006	.006
Beef	.27	(.61)	-.17	(1.29)	-.017	.027
Swine	.91	(1.73)	.15	(.93)	.005	.029
# Vets in Clinic	-.05	(.45)	.04	(1.77)	.003	-.004
Patients per hour	.22	(1.58)	.19	(5.81)	.046	.054
Constant	10.21	(23.24)	10.33	(34.77)	-	-
Location and Year[4]	yes		yes		[-.016]	[-.079]
Sample Size	135		801			
Adjusted R^2	.19		.12			
Total explained					[.084]	[.046]
Total unexplained					[.401]	[.436]

t-statistics are in parentheses. Earnings are defined as gross profits. Numbers in brackets refer to the portion of the ln earnings gap explained by groups of variables. [1]Excluded category is 3 to 5 years. [2]Excluded category is 31-40 hours. [3]Excluded category is Small Animal. [4]Controls for msa status, region, and the survey year. [5]No data.

Table A5: Probit for Self-Employment

Variable	(1)	(2)	(3)	(4)
Female	-.17	-.02	-.01	.03
	(6.52)	(.53)	(.28)	(85)
$\hat{E}_{se} - \hat{E}_{ws}$				.14
				(2.94)
Clinic Specialty:[1]				
Mixed	-.08	-.07	-.08	-.06
	(2.55)	(2.25)	(2.50)	(1.87)
Equine	.18	.19	.17	.18
	(6.07)	(6.13)	(5.56)	(5.79)
Dairy	-.14	-.12	-.20	-.15
	(3.81)	(3.25)	(5.64)	(3.83)
Beef	.04	.05	.06	.06
	(.87)	(1.08)	(1.28)	(1.18)
Swine	-.04	-.04	-.11	-.05
	(.79)	(.67)	(2.15)	(.86)
Experience:[2]				
3 to 5 years		.17	.17	.17
		(2.42)	(2.39)	(2.34)
6 to 10 years		.41	.36	.34
		(6.59)	(5.54)	(4.98)
11 to 20 years		.55	.42	.41
		(9.04)	(5.90)	(5.73)
21 to 30 years		.52	.35	.34
		(9.12)	(4.39)	(4.26)
31 to 40 years		.49	.34	.37
		(9.23)	(3.61)	(3.94)
over 40 years		.50	.41	.39
		(8.39)	(3.00)	(2.73)
Age:[3]				
35 - 44 years			.18	.18
			(4.74)	(4.75)
45 - 54 years			.29	.29
			(5.53)	(5.51)
55 - 64 years			.29	.30
			(4.02)	(4.07)
over 65 years			.44	.44
			(4.48)	(4.58)
Sample Size	2915	2914	2913	2913

T-statistics are in parentheses. Earnings are defined as gross profits in the self-employment sector. Results reported are partial derivatives, evaluated at means of the independent variables, and for discrete changes of dummy variables from 0 to 1. Additional Controls: state, msa, and year of survey dummies. [1]Excluded category is Small Animal. [2]Excluded category is 1 to 2 years. [3]Excluded category is 25 to 34 years.

Table A7: Earnings Decomposition: Variable Hours in SE Sector

Dependent Variable: Ln Hourly Earnings

Variable	β_f		β_m		$\beta_m(\bar{X}_m-\bar{X}_f)$	$\beta_f(\bar{X}_m-\bar{X}_f)$
Experience[1]					[.043]	[.037]
1 to 2 years	-.13	(.26)	-.38	(.72)	.010	.003
6 to 10 years	.35	(1.40)	.26	(1.56)	-.054	-.072
11 to 20 years	.21	(.89)	.29	(1.90)	-.017	-.012
21 to 30 years	.55	(1.37)	.37	(2.39)	.080	.118
31 to 40 years	[5]		.15	(.87)	.016	.000
over 40 years	[5]		.24	(.97)	.008	.000
Clinic Specialty[2]					[-.007]	[.037]
Mixed	-.21	(.79)	-.21	(2.04)	-.012	-.012
Equine	.09	(.43)	-.16	(1.61)	.016	-.009
Dairy	.07	(.21)	.08	(.65)	.004	.004
Beef	.28	(.65)	-.19	(1.42)	-.019	.029
Swine	.83	(1.57)	.12	(.74)	.004	.026
# Vets in Clinic	-.01	(.10)	.04	(1.59)	.003	-.001
Patients per hour	.20	(1.83)	.19	(5.74)	.045	.049
Variable hours[3]	-.17	(1.07)	.03	(.51)	-.002	.010
Constant	2.76	(6.47)	2.69	(9.89)	-	-
Location and Year[4]	yes		yes		[-.014]	[-.070]
Sample Size	135		801			
Adjusted R^2	.11		.08			
Total explained					[.068]	[.062]
Total unexplained					[.373]	[.379]

t-statistics are in parentheses. Earnings are defined as gross profits. Numbers in brackets refer to the portion of the ln earnings gap explained by groups of variables. [1]Excluded category is 3 to 5 years. [2]Excluded category is Small Animal. [3]Dummy variable=1 if hours worked per week is outside the 41-60 range. [4]Controls for msa status, region, and the survey year. [5]No data.

APPENDIX B

APPENDIX B

Tests for Sample Selection Bias

Sample selection bias occurs when individuals who select into one group are not representative, on average, of the underlying population. In the current context, the concern is that veterinarians in a specific sector may differ from the general population of veterinarians. For example, those who choose the self-employment sector may be among those who would have the highest earnings in the self-employment sector among the population of veterinarians. If this was true, the coefficients on OLS equations may be biased. Note, however, that since the analysis in this chapter is primarily focused on earnings differences by sex *within* sectors, selection may only pose a problem if there are gender differences in selection behavior.

In order to test for evidence of selection bias, a standard Heckman (1979) correction for sample-selection bias is implemented. First, a reduced-form probit for employment in each sector is estimated, separately for both males and females:

$$S_i^* = \alpha_0 + \alpha_j T_i + e_i; \quad j = 1.....p. \tag{1}$$

where S_i^* is not observed directly; $S_i = 1$ if $S_i^* \geq 0$ and $S_i = 0$ if $S_i^* \leq 0$
T_i = p controls, including experience, age, location and year dummies

A selection correction term, λ_i, is obtained from this equation and added to a standard earnings equation:

$$\ln(Y_i) = \beta_0 + \beta_1\lambda_i + \beta_{j+1}X_i + e_i; \quad j = 1.....p. \tag{2}$$

where $\ln(Y_i)$ = ln annual earnings
X_i = p controls, including experience, location and year dummies[1]

If the coefficient on the selection correction term, β_1, is estimated as positive and statistically significant, there is evidence of positive selection. Conversely, if β_1 is estimated as negative and statistically significant, there exists evidence of negative selection.

For identification purposes, it is necessary that there be a variable in reduced-form probit that is not in the earnings equation. Such a variable should affect one's preference for self-employment without directly affecting earnings. Survey respondents report both their age and experience. As expected, experience is positively correlated with earnings; however, there is no reason to expect age to have an impact on earnings, independent of experience. Age has been shown, though, to be positively correlated with employment in the self-employment sector (see Fuchs, 1982; Evans and Leighton, 1989). It is theorized that individuals may switch into self-employment later in life as they desire more flexibility.

Table B1 reports estimates of the selection corrected earnings equations for the wage-salary sector. Estimates for females are reported in column 1. The coefficients on the age variables in the probit equation are negative and statistically significant. However, there is little evidence of selection bias, as the coefficient on λ in the earnings equation is statistically insignificant. For males, in column 2, the coefficients on the age variables are also all negative, though statistically insignificant. The coefficient on λ is also statistically insignificant.

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[1]Note that I do not include certain variables that were contained in the earnings equations estimated in the main body of the chapter. Hours worked per week, clinic specialty, and firm size are potentially endogenous along with sector choice.

Estimates of the selection corrected earnings equations for the self-employment sector are reported in Table B2. The coefficients on the age variables in the probit equation are positive and statistically significant for both females and males. Once again, there is little evidence of selection, as the coefficient on λ in both earnings equations is statistically insignificant.

Thus, results indicate that selection bias does not appear to be present in the wage-salary or self-employment sector, among male or female veterinarians. This concurs with the findings of Faucher (1996) in his study of young physicians, who finds little evidence of selection, either on the part of males or females, in the wage-salary or self-employment sectors. In addition, Lombard (1996), in a study of married females from the CPS, reports little evidence of selection bias in either sector.

Table B1: Tests for Sample Selection Bias in the Wage-Salary Sector

Dependent Variable: Ln Annual Earnings

Variable	Females		Males	
Experience[1]				
3 to 5 years	.11	(2.02)	.11	(2.07)
6 to 10 years	.22	(3.00)	.19	(2.17)
11 to 20 years	.16	(1.49)	.35	(3.16)
21 to 30 years	.38	(1.60)	.49	(3.49)
31 to 40 years	[4]		.46	(2.57)
over 40 years	[4]		-.02	(.07)
λ	.001	(.02)	.004	(.07)
Constant	10.16	(147.93)	10.42	(209.90)
Location and Year[2]	yes		yes	
Probit:				
Age[3]				
35 - 44 years	-.59	(3.64)	-.21	(1.61)
45 - 54 years	-1.17	(3.37)	-.35	(1.67)
55 - 65 years	[4]		-.42	(1.21)
over 65 years	[4]		-.69	(1.17)
Experience[1]				
3 to 5 years	-.08	(.38)	-.79	(3.99)
6 to 10 years	-.95	(4.38)	-1.76	(8.58)
11 to 20 years	-1.29	(5.02)	-2.20	(9.68)
21 to 30 years	-.97	(1.91)	-2.44	(8.50)
31 to 40 years	[4]		-2.52	(6.01)
over 40 years	[4]		-2.36	(3.54)
Constant	.48	(2.27)	.79	(4.14)
Location and Year[2]	yes		yes	
Sample size	542		2423	

t-statistics are in parentheses. [1]Excluded category is 1 to 2 years. [2]Controls for msa status and the survey year. [3]Excluded category is 25 to 34 years. [4]No data.

Table B2: Tests for Sample Selection Bias in the Self-Employment Sector

Dependent Variable: Ln Annual Earnings

Variable	Females		Males	
Experience[1]				
1 to 2 years	-.50	(1.31)	-.18	(.53)
6 to 10 years	.44	(1.68)	.31	(2.74)
11 to 20 years	.53	(1.82)	.53	(4.76)
21 to 30 years	.69	(1.99)	.53	(4.71)
31 to 40 years	.09	(.21)	.43	(3.49)
over 40 years	[4]		.10	(.58)
λ	-.03	(.10)	.17	(1.65)
Constant	9.80	(21.29)	10.19	(61.12)
Location and Year[2]	yes		yes	
Probit:				
Age[3]				
35 - 44 years	.60	(3.59)	.38	(3.27)
45 - 54 years	1.19	(4.13)	.55	(3.69)
55 - 65 years	[4]		.62	(3.08)
over 65 years	[4]		1.12	(3.68)
Experience[1]				
1 to 2 years	-.54	(1.78)	-.73	(2.75)
6 to 10 years	.69	(4.08)	.37	(3.07)
11 to 20 years	.61	(3.00)	.53	(3.79)
21 to 30 years	.14	(.36)	.36	(2.16)
31 to 40 years	[4]		.33	(1.45)
over 40 years	[4]		.12	(.35)
Constant	-.89	(5.81)	-.91	(9.17)
Location and Year[2]	yes		yes	
Sample size	542		2423	

t-statistics are in parentheses. [1]Excluded category is 3 to 5 years. [2]Controls for msa status and the survey year. [3]Excluded category is 25 to 34 years. [4]No data.

Chapter 6

THE IMPACT OF FIRM SIZE ON THE EARNINGS OF THE SELF-EMPLOYED

Available data sources report that self-employed females earn significantly less than self-employed males, as well as less than both males and females in the wage-salary sector.[1] The low relative earnings position of self-employed females has remained relatively unchanged since the early 1970s. Despite these facts, female self-employment rates are trending upward, for the first time in over a century (Lombard, 1996).

Other researchers have attempted to explain the low relative earnings position of self-employed females.[2] In Chapter 5, I tested five theories on a new data set of veterinarians. Generally, the models were found unable to account for the earnings gap between self-employed male and female veterinarians. In this chapter I study this issue further, utilizing detailed firm-level data that is available in my sample of veterinarians. Specifically, I study the impact of firm scale, or size, on the earnings of the self-employed. Scale is defined in terms of output, or total revenue. Longstreth, Stafford, and Mauldin (1987), report that female-operated firms tend to be smaller and have lower revenues than male-operated firms. If firm size can be shown to be correlated with earnings, a portion of the earnings gap could be explained by gender differences in this characteristic.

In section I, I present a description of the data, along with some background

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[1] For a comprehensive treatment of self-employment, see Aronson (1991).
[2] See Moore (1983), Coate and Tennyson (1992), and Faucher (1996).

information on the market for veterinarians. In section II, I present the empirical framework for analyzing the impact of firm size on earnings; the results are presented in section III. In section IV, I discuss the potential factors that form the underlying basis for gender differences in firm size. Finally, in section V, I offer some concluding remarks.

I. Background and Data

In 1993, according to the American Veterinary Medical Association (1994), 81% of veterinarians were employed in the private clinical sector, and 19% in the public and corporate sectors. Of those in the private clinical sector, 69% were employed in small animal practices, 19% in large animal practices, and the remainder in "mixed" (small and large) practices. Most veterinarians in private practice begin their careers as wage-salary workers, and later in their careers become partners or owners.[3]

The data used in this chapter come from annual wage surveys conducted in 1994 and 1995 by Medical Economics Research Group, at the direction of Veterinary Economics. Veterinary Economics is a monthly publication sent free to all private practice veterinarians who request it. Their circulation is approximately 40,000, representing more than two-thirds of all private practice veterinarians in the United States. A stratified random sample[4] of 4,319 veterinarians in 1994, and 4,322 in 1995, were mailed surveys, with a total of 3,187 usable surveys returned (37% usable return

[3] The data utilized in this chapter report that among veterinarians with less than 3 years of experience, 84 percent are located in the wage-salary sector. Among veterinarians with greater than 10 years of experience, 64 percent are sole owners, and 29 percent are partners.
[4] Some smaller veterinarian specialties were over-sampled. Summary statistics are weighted by specialty to reflect the "true population" of veterinarians, which is Veterinary Economics' subscriber list.

rate).[5] The sample is limited to full-time, private practice veterinarians who have at least one year of experience. In Appendix A of Chapter 3, I provide evidence that the sample is representative of the general population of veterinarians, utilizing comparisons with 1990 census data.

Table 1 reports summary statistics for the sample of self-employed veterinarians.[6] The self-employed are defined as those who are sole owners of their firms, incorporated or unincorporated.[7] All veterinarians self-report their earnings as the answer the following question: "Which of the following best represents your personal 1993 (or 1994) compensation from the practice before taxes were withheld?" Using responses to this question as a measure of earnings for the self-employed may pose a problem, particularly since there are tax avoidance incentives unique to the self-employment sector, which may lead owners to underreport their earnings. In Appendix A of Chapter 5, I develop an alternative measure of earnings for the self-employed, deriving itself from reported statistics of firm revenues and expenses. Briefly, I conclude that using self-reported earnings is the preferred measure of earnings for the self-employed.

Table 1 reports that among self-employed veterinarians, males earn, on average, $72,441 per year, while females earn $43,874 per year. Differences in hours worked per week are not significant, but male self-employed veterinarians have, on average, 7.5 more years of experience than the sample of female veterinarians. Thus, differences in experience could account for a significant potion of the gender earnings

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[5] A total of 145 observations were dropped from the 1994 data, which appeared as probable duplicates in the 1995 data. In addition, I deleted 4 observations that appeared subject to coding errors. The remaining n = 3,038.

[6] For summary statistics on wage-salary and partner veterinarians, see Chapter 5, Table 2.

[7] Note that I do not include partners in the sample of self-employed. It may not be unreasonable to classify partners as "self-employed", since median partnership size in the sample is 2. However, in order to maintain a more theoretically satisfying definition of self-employment, I limit classification of the self-employed to sole owners of firms.

gap. Also reported in Table 1 is a measure of patients seen per hour, a proxy variable for productivity, which will serve to control for productivity differences between veterinarians. Table 1 also reports a variable called average fee. This represents a measure of the average charge per each client visit. Veterinarians typically keep track of this measure, since it is thought to be a general indicator of clinic productivity (Bowman, 1996).[8]

Table 1 also reports various firm-level data. Male sole-owners employ, on average, 1.0 other veterinarians, while the sample mean of this variable for females is .8. Self-employed males employ, on average, 3.5 other nonveterinarian workers, compared to 3.0 workers for self-employed females. In addition, male owners report an average of 2,463 total clients, with a corresponding figure of 1,897 for female owners. Also reported is an indicator of clinic specialty. Most self-employed veterinarians are located in small animal clinics, females more so than males.

Survey respondents also report measures of firm gross revenues and gross expenses,[9] and the means of these variables are also reported in Table 1.[10] Male sole owners report an average of $300,885 per year in gross revenue, approximately $100,000 greater than the corresponding figure reported for female sole-owners. Mean average expenses are also greater for males than females, reported as $219,793 and $150,725, respectively. A measure of "gross profit" is constructed by subtracting gross

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[8] In the veterinary literature, this is referred to as the ACT (Average Client Transaction charge). Clinics with higher ACTs are generally thought to be more productive, since each client is spending, on average, more money on each visit to the veterinarian.

[9] Firm owners are asked the following questions: "Which of the following best represents the practice's 1993 (or 1994) total gross revenue?" and "What were your total 1993 (or 1994) practice expenses, excluding all owner compensation?"

[10] Excluded from the means reported in Table 1 are respondents who did not report *both* revenues and expenses. In addition, owners who reported total expenses as less than 25 percent of total revenue were assumed as reporting with error, and their responses are not included in the reported means.

expenses from gross revenue. Mean gross profits for male-owned firms are $81,901, while the corresponding figure for female-owned firms is $48,337.

The revenue and expense statistics lend support to the theory that gender differences in firm scale may account for a significant portion of the gender gap in earnings. From Table 1, the gender gap in mean earnings is 40 percent, with a corresponding gap in gross revenue of 34 percent. In addition, the gender difference in the measure of mean gross profits is 40 percent. Assuming owners compensate themselves out of gross profits,[11] this coincides well to the gender gap in mean earnings. A measure of (total expenses/total revenues) may also be constructed from Table 1. This figure averages .73 for males and .76 for females. This indicates a mean "gross profit margin" of 27 percent for males, and 24 percent for females.[12]

A subset of sole owners report a breakdown of gross revenues and expenses, and means of these responses are reported in Table 2. Revenues are reported as derived from doctor services, medications, over the counter sales, boarding, grooming, pet food, and other sales. Gender averages are statistically different from each other in the doctor services, medications, and over the counter sales categories. Expenses are reported as compensation for nonveterinarian and veterinarians employees, as well rent,[13] medical supplies, medical equipment/repair, advertising, continuing education, consultants, and other expenses. Gender means are statistically different from each other in the employee compensation categories, as well the medical supplies and other expenses categories.

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[11] Gross profits are calculated before consideration of owner compensation (see Footnote 9).
[12] This statistic is not well correlated with total revenue, suggesting constant returns to scale may apply for the firms covered in the survey.
[13] Survey respondents were asked to report rent, mortgage payments, or 12% of the value of the property.

II. Empirical Framework

In order to analyze the impact of firm scale on earnings in a more rigorous framework, I utilize a standard earnings decomposition, due to Oaxaca (1973). First, using OLS, separate earnings regressions for each sector are estimated for females and males:

$$\ln \hat{E}_f = \sum B_f \cdot X_f \text{ and } \ln \hat{\bar{E}}_f = \ln \bar{E}_f = \sum B_f \cdot \bar{X}_f \tag{1}$$

$$\ln \hat{E}_m = \sum B_m \cdot X_m \text{ and } \ln \hat{\bar{E}}_m = \ln \bar{E}_m = \sum B_m \cdot \bar{X}_m \tag{2}$$

The first term of each equation denotes the predicted value of ln earnings, the mean of which, $\ln \hat{\bar{E}}$, is equal to the overall mean, $\ln \bar{E}$. The *X* variables include controls for experience, hours worked per week, patients seen per hour, clinic specialty, number of veterinarians, along with region, metropolitan statistical area, and year of survey dummies. In addition, I will include a measure of total revenue as an independent variable, representing a control for differences in firm scale.

If $\sum B_m \cdot \bar{X}_f$ is added to both equations (1) and (2), and then equation (2) is subtracted from equation (1), the following decomposition is obtained:

$$\ln \bar{E}_m - \ln \bar{E}_f = \sum B_m(\bar{X}_m - \bar{X}_f) + \sum \bar{X}_f(B_m - B_f) \tag{3}$$

The first term on the right-hand side of equation (3) evaluates the difference in mean values of the X's using male prices, or coefficients. This is generally referred to as the "explained portion" of the earnings gap. The second term on the right-hand side is the conventional measure of wage discrimination, with $\beta_m > \beta_f$ indicating a higher price received by a male worker relative to female worker for the same characteristic. Since there will always exist unobserved differences that cannot be controlled for, it is preferable to refer to this term as the "unexplained portion" of the earnings gap, rather than a direct measure of wage discrimination.

An alternative representation of the difference in ln earnings may be expressed as follows:

$$\ln \overline{E}_m - \ln \overline{E}_f = \sum B_f(\overline{X}_m - \overline{X}_f) + \sum \overline{X}_m(B_m - B_f) \tag{4}$$

This utilizes female coefficients to evaluate gender differences in mean characteristics. Equation (3) implies that in the absence of discrimination, the male earnings structure would prevail, while equation (4) implies that the female earnings structure would exist in a nondiscriminatory environment. The two assumptions do not yield the same result, and thus, I will report estimates of both equations (3) and (4).

With regard to estimation of the earnings decomposition, two econometric notes should be made. First, I do not control for sample selection bias in the estimates. It is possible that veterinarians who select into the self-employment sector may differ in unobservable ways from the general population of veterinarians. For example, those who choose self-employment, from the population of veterinarians, may be those who would have the highest earnings in self-employment. Since my analysis is focused on earnings differences within the self-employment sector, selection may only pose a problem if there are gender differences in selection behavior (e.g., females negatively selecting into the self-employment sector, with males positively selecting into the same sector). In Appendix B of Chapter 5, I provide tests for selection behavior, and I do not find evidence of sample selection bias in the sample of veterinarians.

Second, survey respondents report annual earnings as a categorical variable. Instead of utilizing an ordered probit model in estimations, I implement OLS by using the midpoint of the reported range as the dependent variable. If the underlying earnings distributions differ by gender, this could cause a bias in the estimation of unexplained differences in earnings. In Appendix C of Chapter 3, I test for this utilizing census data, and I provide evidence against this concern. However, my analysis does show that by reducing the amount of variation in the dependent variable, the OLS model is able to estimate a better fit for the data. Although coefficient estimates should be relatively unbiased, estimates of standard errors will be biased downwards. Thus, when utilizing bracket midpoints as the dependent variable, statistical inferences should be made more conservatively.

III. Results

The gender difference in mean ln annual earnings in the sample is [.573]. A decomposition of this earnings difference, prior to controlling for differences in firm scale, is reported in Table 4 of Chapter 5. Summarizing, gender differences in experience are found to play a significant role in accounting for the earnings gap. Measured with male coefficients, the set of experience variables explains [.073], or 13 percent, of the difference in mean ln earnings. Evaluation with female coefficients accounts for [.152], or 27 percent, of the earnings difference. Table 4 reports that added together, differences in observed characteristics explain [.100], or 17 percent, of the gap in ln earnings when evaluated with male coefficients. When evaluated with female coefficients, differences in observed characteristics explain [.189], or 33 percent of the gap in ln earnings. This leaves an unexplained ln earnings difference of [.474] or [.381], representing 38 or 32 percent, depending on the specification of the earnings decomposition.

Results reported in Table 3 of this chapter add a control for firm scale, represented by the measure of ln total revenue. Both male and female coefficients on ln total revenue are positive and highly statistically significant. β_f is.67, suggesting that a 10 percent increase in firm scale would increase earnings by 6.7 percent, other factors held constant. β_m is a similar magnitude of .59. Most of the other coefficients retain their expected sign, although the statistical significance of each coefficient is reduced after adding a control for total revenue. This is not surprising, given the correlation that these variables should be expected to have with a measure of revenue.

Differences in firm scale, proxied by total revenue, account for [.218], or 38 percent of gender earnings gap when evaluated with male coefficients, and [.246], or 43 percent of the gap when evaluated with female coefficients. Including the contributions made by differences in other observed characteristics, a total of [.247] or [.353], representing 43 or 62 percent, of the gender gap in earnings may be accounted for. This leaves an unexplained earnings difference of [.326] or [.220], depending on the specification of the earnings decomposition. Thus, the earnings gap between self-employed male and female veterinarians, adjusted for differences in observable characteristics, is 28 or 20 percent, depending on the specification.

A relatively substantial portion of the earnings gap remains unexplained, even after controlling for differences in firm scale. However, if total revenue is reported with error, the presence measurement error will downward bias the estimation of both male and female coefficients on the total revenue variable. Such a bias would reduce estimations of the explained portion of the earnings gap, $\beta_m(\overline{X}_m - \overline{X}_f)$ *or* $\beta_f(\overline{X}_m - \overline{X}_f)$. It is well known that individuals often report measures of earnings with error. It is reasonable to expect that some of the same factors that cause individuals to misreport earnings could cause owners to misreport measures of total revenue. Thus, if measurement error is present, differences in firm scale could potentially explain a greater portion of the earnings gap than that reported in Table 3.

IV. Potential Determinants of Firm Size

Finding that female-owned firms are, on average, of smaller scale than male-owned firms, motivates the following question: Why are female-owned firms smaller? I will discuss three potential factors that may form the basis for gender differences in firm size. Since the analysis focuses on factors that are not available in the data, specifically preferences and constraints, I can only offer suggestions as to the underlying factors.

A. Preferences

Females may have preferences for smaller firms. On average, women are more likely to have more frequent interruptions in their lifetime pattern of labor force participation than males (Polachek, 1981). Thus, female owners may choose to operate on a smaller scale, anticipating periods when they will not be working full-time. This seems plausible, assuming a smaller firm may be more manageable in a time of part-time employment.

If females demonstrate preferences for smaller firms, they will employ fewer inputs, relative to males. Two significant inputs for veterinary clinics are reported in the data: nonveterinarian labor along with capital, proxied by a measure of rent. In order to test whether there are gender differences in the employment of these resources, I estimate the following two equations:

$$\ln(K) = \beta_0 + \beta_1 F + \beta_{j+1} X + e \;; \qquad j = 1.....p. \tag{5}$$

where ln(K) = log annual rent
F = Dummy variable for female
X = p controls including experience, clinic specialty, number of veterinarians, along with region, msa, and year of survey dummies

$$\ln(L) = \beta_0 + \beta_1 F + \beta_{j+1} X + e \;; \qquad j = 1.....p. \tag{6}$$

where ln(L) = log (Number of nonveterinarian employees)

F = Dummy variable for female
X = p controls including experience, clinic specialty, number of veterinarians, along with region and msa dummies

Table 4 reports results of estimation of equation (5), with log annual rent utilized as the dependent variable. The first specification, excluding controls for experience and the number of veterinarians, reports the coefficient on the dummy variable for females as -.47 and statistically significant. In the second specification, the experience variables are added as regressors, and jointly, they are not statistically different from zero. The coefficient on female is -.42, and retains its statistical significance. The third specification adds the number of veterinarians as an independent variable. The coefficient on the number of veterinarians is positive and statistically significant, indicating an increase in rent paid of 15 percent for each additional veterinarian employed.[14] After adding this control, the coefficient on the female dummy is -.40 and remains statistically significant. Assuming rent a good proxy for capital, this suggests that female owners employ 33 percent less capital than male owners, holding other factors constant.

Table 5 reports estimation of equation (6), with the number of nonveterinarian employees utilized as the dependent variable.[15] The first specification, excluding controls for experience and the number of veterinarians, reports the coefficient on the dummy variable for female as -.24 and statistically significant. The coefficient retains its explanatory power when the experience variables are added in the second specification. In the third specification, the number of veterinarians is added as an independent variable. The coefficient on this variable is .38 and highly

[14] This result implies complementarily between veterinary labor and capital in the production of veterinary services.
[15] Nonveterinarian employees were only reported in the 1995 survey, so the sample size smaller.

statistically significant, indicating a 35 percent increase in nonveterinarian employees for each additional veterinarian employed.[16] The coefficient on the female dummy remains negative and statistically significant, and reported as -.20, suggests that female owners employ 18 percent less nonveterinarian labor than male owners, other factors held constant.

Results reported in Table 5 and Table 6 are consistent with the theory that females prefer smaller scale firms and utilize lower levels of resources in the production of veterinary services. However, the results could also reflect a constraint on the employment of resources. I consider two potential constraints: credit market constraints, and customer discrimination.

B. Credit Market Constraints

Female owners may be constrained in their ability to borrow funds and purchase capital, which would be consistent with the result reflected in Table 4: females employing less capital than males, other factors held constant. If true, females would employ fewer complementary resources, such as nonveterinarian labor, which is the result reported in Table 5. Also, the relative magnitudes of the coefficient estimates on the female dummies in Tables 4 and 5 lend some support for this theory. Gender differences in capital employed (33 percent) are greater than gender differences in nonveterinarian labor employed (18 percent), and this difference is statistically significant. A constraint in the ability to acquire capital could induce some substitution towards other factors of production, such as nonveterinarian labor.

[16] This result implies complementarily between veterinary labor and nonveterinarian labor in the production of veterinary services.

C. Customer Discrimination

Customers may discriminate against female veterinarians, constraining the amount of revenue female owners are able to produce. Borjas and Bronars (1989) offer a model of customer discrimination, and when applied to the issue of gender differences in self-employment, the model predicts that female sole owners will charge, on average, lower prices than male sole owners. I test for this, and as reported in Table 6 of Chapter 5, I do not find significant gender differences in fees charged among veterinarians.

However, the customer discrimination can be extended to predict that female sellers charge the same prices as male sellers, but as a result, have fewer customers. Manifested in this manner, customer discrimination would reflect itself in fewer patients per hour for female veterinarians. In order to study this more carefully, I estimate the following equation:

$$\ln(P) = \beta_0 + \beta_1 F + \beta_{j+1} X + e; \quad j = 1.....p. \tag{7}$$

where ln(P) = Ln patients per hour
F = Dummy variable for female
X = p controls including experience, clinic specialty, number of veterinarians, along with region, msa, and year of survey dummies

Table 6 reports the estimation of equation (7). The first specification excludes the experience variables. The female dummy is negative and statistically significant, and reported as -.27, indicates that females have 24 percent fewer patients per hour than males, other factors held constant. The second specification adds the experience variables, and the coefficient on the female dummy remains negative (-.19) and statistically significant. In the third specification, I add ln average fee as an additional regressor. The coefficient on this variable is negative and statistically significant, which should be expected: if a veterinarian charges a higher average fee, it may indicate that he or she is providing more services to each client, and thus, spending more time with each customer. Note however, that the coefficient on female remains negative (-.21) and statistically significant.

Results in Table 6 are contrary to results found in the wage-salary sector. In Chapter 3, when estimating the same equation for wage-salary workers, I found female veterinarians as seeing 17 percent *more* patients per hour than male veterinarians, holding other factors constant (see Table 6 in Chapter 3). Finding the opposite result among the self-employed would be evidence consistent with existence of customer discrimination against females in the self-employment sector.

In Chapter 5, I reported that the gender difference in patients per hour explains 6-7 percent of the earnings gap among the self-employed, depending on the specification of the earnings decomposition (see Table 4 in Chapter 5). This may indicate the direct impact of customer discrimination on the earnings of the self-employed. However, customer discrimination may also have an indirect impact, working primarily through differences in scale, or revenue. For example, customer discrimination may not only impact the number of patients that a female sole-owners sees, but the number of patients for all other employed veterinarians at her clinic. In addition, sales of over the counter merchandise and medications may be negatively impacted.[17] This potential indirect impact of customer discrimination may not be reflected in a reduced form earnings equation.

V. Conclusion

In this chapter, I utilize detailed firm-level data to study earnings differences between male and female self-employed veterinarians. The unadjusted gender

[17] Table 2 reports that the gender means of revenues derived from both medications and over the counter sales are significantly different from each other at the 5% level.

earnings gap is 40 percent. Utilizing an earnings decomposition, I control for differences in firm scale, represented by a measure of firm total revenue. By controlling for firm scale, along with other observable characteristics, I am able to explain 43 to 62 percent of gender gap in earnings, depending on the specification of the earnings decomposition.

Potential determinants of firm scale were discussed. Results in Tables 4 and 5 indicate female self-employed veterinarians employ fewer inputs than male veterinarians, other factors held constant. Lower levels of resource utilization by females may reflect the preferences of self-employed females. Alternatively, female sole-owners may face constraints: they may be constrained in acquiring capital in the credit market, or they may be constrained in revenue production by customer discrimination.

Even after controlling for differences in firm scale, the adjusted gender gap in earnings is reported as 20-28 percent, depending on the specification of the earnings decomposition. Possible explanations for the remaining gender gap include gender differences in profit reinvestment behavior, gender differences in entrepreneurial ability, as well as potential measurement error in the total revenue variable.[18] Regardless, the present analysis indicates that a significant portion of the gender gap in earnings may be explained by differences in firm size. Thus, when studying the self-employed, it is important to regard them as owners of firms, individuals who employ factors of production. Future empirical studies of the self-employed, along with the development of new models of self-employment choice, should incorporate such considerations.

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[18] The data cast some doubt on the first two explanations: Summary statistics from Table 1 suggest that males and females compensate themselves out of gross profits at a similar rate (an average of 89 percent for males, and 91 percent for females); measures of gross profit margins are also similar (an average of 27 percent for males, and 24 percent for females).

Table 1: Summary Statistics: Self-Employed

	Males	Females
Annual Earnings[1]	72,441	43,874
Experience[1]	20.1	12.6
Age[1]	46.3	39.3
Hours worked/wk[1]	53.2	54.5
Patients per hour	1.51	1.24
Average Fee	65.54	64.92
Other vets employed	1.0	.8
Non-vet employees	3.5	3.0
Total clients	2,463	1,897
Clinic Specialty:		
Small Animal	.60	.76
Mixed	.26	.16
Equine	.04	.05
Dairy	.03	.01
Beef	.04	.01
Swine	.02	.01
Gross Revenue	300,885	199,061
Gross Expenses	219,793	150,725
Gross Profit	81,091	48,337
Sample Size[2]	1328	221

Table is weighted to correct for over-sample of some specialties. [1]Data are reported as categorical variables. Means are obtained by using the midpoint of the reported range. [2]Smaller samples for some variables.

Source:
Veterinary Economics, *Continuing Wage Surveys*, Veterinary Medicine Publishing Company, (1994-95).

Table 2: Comparison of Revenues and Expenses

	Males	Females
Gross Revenues:		
Doctor Services*	197,820	128,373
Medications*	54,203	32,127
Counter Sales*	18,401	7,590
Boarding	10,486	8,082
Grooming	6,713	4,936
Pet Food	11,703	10,369
Other	6,352	2,340
Gross Expenses:		
Nonvet Employees*	47,066	34,317
Nonowner Vets*	19,969	9,872
Rent[1]	18,505	15,537
Medical Supplies*	70,095	39,567
Medical Equipment/Repair	6,739	5,192
Advertising	2,598	2,687
Continuing Education	2,707	2,423
Consultants	2,060	2,443
Other*	51,081	39,567
Sample Size	773	114

Table is weighted to correct for over-sample of some specialties. *Gender means are statistically difference from each other at the 5% level. [1]Rent, mortgage payments, or 12% of the value of the property.

Table 3: Earnings Decomposition with Revenue Control

Dependent Variable: Ln Annual Earnings

Variable	β_f		β_m		$\beta_m(\bar{X}_m-\bar{X}_f)$	$\beta_f(\bar{X}_m-\bar{X}_f)$
Experience[1]					[.049]	[.121]
1 to 2 years	-.69	(1.72)	.02	(.10)	-.001	.019
6 to 10 years	.21	(1.37)	.04	(.57)	-.009	-.044
11 to 20 years	.19	(1.27)	.16	(2.18)	-.009	-.011
21 to 30 years	.46	(1.84)	.19	(2.56)	.040	.098
31 to 40 years	.53	(1.16)	.23	(2.84)	.025	.059
over 40 years	[6]		.07	(.64)	.002	.000
Hours per week[2]					[.009]	[.008]
under 25 hours	-.45	(1.49)	-.46	(2.83)	.008	.008
25 - 30 hours	-.16	(.37)	-.12	(1.04)	-.001	-.002
41 - 50 hours	.13	(.72)	.09	(1.48)	.000	.000
51 - 60 hours	.08	(.44)	.11	(1.82)	.006	.004
61 - 70 hours	.09	(.48)	.19	(2.96)	-.003	-002
71 - 80 hours	-.03	(.15)	.08	(1.01)	.000	.000
over 80 hours	-.20	(.66)	.06	(.73)	.000	-.001
Clinic Specialty[3]					[-.010]	[-.016]
Mixed	-.11	(.66)	-.13	(2.83)	-.008	-.006
Equine	.18	(1.29)	-.03	(.55)	.003	-.018
Dairy	.14	(.66)	.15	(2.52)	.008	.007
Beef	.08	(.29)	-.13	(2.23)	-.014	.008
Swine	-.20	(.56)	.05	(.62)	.002	-.006
# Vets in Clinic	-.04	(.49)	-.03	(2.68)	-.003	-.004
Patients per hour	.07	(1.15)	.06	(3.87)	.015	.018
Ln Total Revenue[4]	.67	(6.83)	.59	(23.00)	.218	.246
Constant	2.60	(2.37)	3.66	(11.57)	-	-
Location and Year[5]	yes		yes		[-.031]	[-.020]
Sample Size	169		1015			
Adjusted R^2	.44		.53			
Total explained					[.247]	[.353]
Total unexplained					[.326]	[.220]

t-statistics are in parentheses. Numbers in brackets refer to the portion of the ln earnings gap explained by groups of variables. [1]Excluded category is 3 to 5 years. [2]Excluded category is 31-40 hours. [3]Excluded category is Small Animal. [4]Data are reported as categorical variables. The midpoint of the reported range is used as the independent variable, except when top-coded, where exact revenue is reported. [5]Controls for msa status, region, and the survey year. [6]No data.

Table 4: Capital Equation

Dependent Variable: Ln Annual Rent[1]

Variable	(1)		(2)		(3)	
Female	-.47	(3.22)	-.42	(2.79)	-.40	(2.66)
Clinic Specialty[2]						
Mixed	-.43	(2.84)	-.43	(2.85)	-.36	(2.43)
Equine	-.98	(6.76)	-.99	(6.77)	-.93	(6.42)
Dairy	-1.06	(5.35)	-1.05	(5.25)	-.98	(4.87)
Beef	-1.26	(6.07)	-1.24	(5.93)	-1.16	(5.65)
Swine	-.73	(2.67)	-.74	(2.70)	-.67	(2.53)
Experience[3]						
1 to 2 years			-.72	(1.20)	-.75	(1.29)
6 to 10 years			.23	(.95)	.14	(.59)
11 to 20 years			.29	(1.25)	.26	(1.16)
21 to 30 years			.31	(1.29)	.25	(1.09)
31 to 40 years			.09	(.31)	.03	(.10)
over 40 years			.63	(1.30)	.46	(.98)
# Vets in Clinic					.14	(4.07)
Constant	9.53	(31.58)	9.32	(25.19)	8.99	(4.07)
Location and Year[4]	yes		yes		yes	
Sample Size	769		769		728	
Adjusted R^2	.10		.10		.12	

t-statistics are in parentheses. [1]Rent, mortgage payments, or 12% of the value of the property. [2]Excluded category is Small Animal. [3]Excluded category is 3 to 5 years. [4]Controls for msa status, region, and the survey year.

Table 5: Labor Equation

Dependent Variable: Ln Nonveterinarian Employees

Variable	(1)		(2)		(3)	
Female	-.24	(3.09)	-.23	(2.87)	-.20	(2.80)
Clinic Specialty[1]						
Mixed	-.28	(3.63)	-.31	(4.03)	-.28	(4.23)
Equine	-.91	(11.75)	-.92	(12.03)	-.84	(12.41)
Dairy	-.93	(8.20)	-.94	(8.35)	-.91	(9.02)
Beef	-.64	(5.97)	-.65	(6.02)	-.60	(6.36)
Swine	-.59	(4.21)	-.63	(4.48)	-.54	(4.41)
Experience[2]						
1 to 2 years			-.28	(.88)	-.06	(.21)
6 to 10 years			.06	(.40)	.02	(.13)
11 to 20 years			.28	(2.16)	.20	(1.76)
21 to 30 years			.14	(1.04)	.09	(.74)
31 to 40 years			.04	(.30)	.01	(.05)
over 40 years			-.04	(.19)	.01	(.05)
# Vets in Clinic					.30	(13.56)
Constant	1.10	(6.87)	1.02	(5.15)	.38	(2.10)
Location[3]	yes		yes		yes	
Sample Size	651		651		645	
Adjusted R^2	.26		.27		.44	

t-statistics are in parentheses. [1]Excluded category is Small Animal. [2]Excluded category is 3 to 5 years. [3]Controls for msa status and region.

Table 6: Patients per Hour Equation

Dependent Variable: Ln Patients per hour

Variable	(1)		(2)		(3)	
Female	-.27	(4.84)	-.19	(3.27)	-.21	(2.81)
Clinic Specialty[1]						
Mixed	-.34	(5.72)	-.34	(5.81)	-.13	(1.68)
Equine	-.69	(12.31)	-.65	(12.11)	-.57	(8.02)
Dairy	-1.02	(13.75)	-1.00	(13.61)	-.79	(7.62)
Beef	-.79	(9.99)	-.79	(10.11)	-.59	(5.57)
Swine	-1.06	(10.38)	-1.06	(10.39)	-.67	(4.42)
# Vets in Clinic	.02	(1.50)	.02	(1.42)	.02	(1.19)
Experience[2]						
1 to 2 years			-.08	(.36)	-.26	(1.02)
6 to 10 years			.17	(1.87)	.06	(.50)
11 to 20 years			.26	(3.02)	.19	(1.74)
21 to 30 years			.31	(3.52)	.22	(1.85)
31 to 40 years			.44	(4.37)	.33	(2.42)
over 40 years			.43	(3.14)	.28	(1.41)
Ln Average Fee					-.16	(3.42)
Constant	.34	(2.74)	.09	(.61)	.66	(2.43)
Location and Year[3]	yes		yes		yes	
Sample Size	1368		1368		684	
Adjusted R^2	.21		.22		.25	

t-statistics are in parentheses. [1]Excluded category is Small Animal. [2]Excluded category is 3 to 5 years. [3]Controls for msa status, region, and the survey year.

CONCLUSION

This dissertation studies various issues in the labor market for veterinarians. Results obtained in studying a specific labor market should not be generalized to the entire US labor force. However, reported findings can offer some interest and relevance to more general labor markets. I have analyzed three main issues: human capital investment decisions, pay and productivity differences between men and women in the wage-salary sector, and gender differences in self-employment labor market outcomes.

In Chapter 1, I test for evidence of a cobweb model in the labor market for veterinarians. The key assumption of the cobweb model is that human capital investors behave myopically, arriving at investment decisions based on market conditions years prior to entry into the labor market. A labor market following a cobweb model is characterized by alternating periods of oversupply and undersupply of labor, trends that are identifiable by sizable fluctuations in starting salaries. In the qualitative analysis undertaken in the first portion of Chapter 1, trend data on veterinarians suggests the appropriateness of applying a cobweb model to the labor market for veterinarians. Econometric estimation of supply and demand equations further supports the results that Freeman (1975a, 1975b, 1976a, 1976b) obtained with engineers, lawyers, and physicists, with an important exception: the veterinary labor market appears to be characterized by a *seven-year* lag between the time of occupational choice and entry into the labor market. Such a lag would induce even longer periods of disequilibrium than estimated by Freeman.

The time series in the econometric models are relatively short (ranging from 15 to 20 years), and thus, inferences from such estimates should be made with caution. In addition, fluctuations in supply are dampened by constraints imposed by veterinary colleges. With these qualifications, the estimations provide support for the hypothesis that individuals in highly skilled professions respond to market conditions long before entry into the labor market. This myopic behavior, in turn, can have an important impact on the operation of specific labor markets over time.

Chapter 2 reviews the major theories that attempt to explain the observed differences in earnings between males and females in the US labor force. Three theories first introduced by Becker (1971), which base themselves on a "taste" for discrimination, are surveyed: employer, employee, and customer discrimination. All of the models are somewhat unsatisfactory in that they predict segregation and are unable to explain the existence of discrimination in the long-run. However, the work of follow-up researchers has shown that some of these predictions may be modified, and thus the potential relevance of taste discrimination models should not be disregarded.

The statistical discrimination model by Phelps (1972), based on the market failure of imperfect information, reconciles profit-maximization with labor market discrimination. This model, although somewhat lacking in its ability to predict group discrimination, may be particularly relevant in employer hiring and promotion practices. The occupational crowding hypothesis offers a discrimination-based explanation for occupational segregation by gender, something that is observed in the US labor force. As a result of discrimination, females are segregated into specific occupations and earnings are depressed. Although its claims are debatable, the fact that researchers have found a negative correlation between the percentage female in an occupation and earnings offers support for this theory.

Human capital theorists offer an alternative explanation for occupational segregation. Some researchers contend that females are "crowded" into occupations as a result of their own choices. Taking into account their intermittent lifetime labor force participation, females choose jobs that have training that is general in nature, with relatively low penalties imposed for discontinuous participation. Available evidence appears to suggest that both crowding on the part of firms and voluntary choices made by women contribute to occupational segregation.

Chapter 3 studies pay differences between male and female veterinarians, and by analyzing this issue with a narrowly defined occupational group, gender differences in human capital should be minimized. The gender gap in average earnings among the sample of wage-salary veterinarians is 15 percent. I utilize the standard wage decomposition due to Oaxaca (1973) to analyze this difference. Controlling for various observed characteristics, including proxy measures of productivity, the adjusted gender gap in earnings is 10 percent, based on the most conservative estimates.

In an effort to study the determinants of productivity, I estimate an equation with the dependent variable as annual revenue produced, which represents the total dollar amount of goods and services billed out by each individual veterinarian. I do not find gender differences in annual revenue produced, other factors held constant. Thus, finding women in parity with men productivity, but not in earnings, is evidence consistent with the presence of wage discrimination. This finding also provides evidence against human capital explanations for differences in earnings, for if gender differences in human capital exist, they should be reflected in measures of productivity.

I explore the possibility that male veterinarians may be involved in activities that generate more indirect revenue, in management-related tasks, relative to female veterinarians. Results indicate women spend more time in management duties than men, other factors held constant. In addition, I report that females see more patients per hour, on average, than male veterinarians, holding other factors constant. Overall, the results suggest that studying pay differences within narrowly defined occupational groups may make an important contribution to the discrimination literature, for by limiting attention to one occupation, potential human capital explanations for earnings differences are limited.

Chapters 4, 5, and 6 turn to a study of the role that gender plays in self-employment labor markets. Available data sources indicate that women are less likely to be self-employed than men, and in addition, the earnings of self-employed women trail behind the earnings of self-employed men, as well as behind the earnings of both men and women in the wage-salary sector. In Chapter 4, I review three discrimination models that attempt to explain gender differences in self-employment labor market outcomes: Employer discrimination (Moore, 1983), employer discrimination with spillovers (Coate and Tennyson, 1992), and a customer discrimination model (Borjas and Bronars, 1989). Each model is hindered by either unrealistic assumptions or lack of empirical support. A model of compensating differentials (Lombard, 1996) was also considered, with flexibility serving as the compensating differential. However, even though a desire for flexibility may play an important role in self-employment choice, existing empirical evidence is lacking in its ability to explain gender differences in self-employment entry rates or earnings. I also examine a capital investment model from Faucher (1996) that incorporates the hours worked decision, along with capital costs, in self-employment. This model, tested on a data set of young physicians, yielded promising results, but requires further testing on other occupations.

In Chapter 5, I test each model of self-employment choice on the sample of self-employed veterinarians. The employer discrimination model fails on its key prediction that the gender gap in earnings, adjusted for differences in observable characteristics, should be greater in the wage-salary sector than the self-employment sector. All five models fail on the prediction that there should exist gender differences in self-employment rates, among males and females who are alike in observable characteristics. I also report no evidence of gender differences in fees charged, contrary to the prediction of the customer discrimination model. In addition, although flexibility, represented by a nonstandard work schedule, may be negatively correlated with earnings, the sample does not indicate significant gender differences in demand for this job characteristic. Finally, in order for the capital investment model to explain earnings differences in the self-employment sector, females must work on average, fewer hours per week than males. However, within the sample of self-employed veterinarians, females work, on average, more hours per week than males.

A main result reported in Chapter 5 is that gender does not have a significant impact on self-employment choice, among veterinarians similar in age and experience. This suggests that existing differences in self-employment rates in the general population may be explained, to a large extent, by differences in occupation. In other words, females may choose occupations where self-employment rates are relatively low. As Aronson points out, most of the literature on self-employment relies on data that lack occupational controls.

Generally, all five models tested in Chapter 5 fail to account for the large adjusted gender earnings gap among the self-employed, which is 32 to 38 percent, depending on the earnings decomposition. In Chapter 6, I explore this issue further, utilizing detailed firm-level data available in the sample. The unadjusted earnings gap between male and female self-employed veterinarians is 40 percent. Utilizing an earnings decomposition, I control for differences in firm scale, represented by a measure of total revenue. By controlling for gender differences in firm scale, along with other observable characteristics, I am able to explain approximately 50 percent of gender gap in earnings, varying somewhat with specification of the earnings decomposition.

Potential determinants of firm scale were discussed. Results indicate self-employed female veterinarians employ fewer resources than male veterinarians, other factors held constant. Lower levels of resource utilization may reflect the preferences of self-employed females. Alternatively, female sole-owners may face constraints: they may be constrained in acquiring capital in the credit market, or they may be constrained in revenue production by customer discrimination.

Even after controlling for differences in firm scale, the adjusted gender gap in earnings is 20-28 percent, depending on the specification of the earnings decomposition. Possible explanations for the remaining gender gap include gender differences in profit reinvestment behavior, gender differences in entrepreneurial ability, as well as potential measurement error in the total revenue variable. Regardless, the present analysis indicates that a significant portion of the gender gap in earnings may be explained by differences in firm size. Thus, when studying the self-employed, it is important to regard the self-employed as owners of firms, individuals who employ factors of production. Future empirical studies of the self-employed, along with the development of new models of self-employment choice, should incorporate such considerations.

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