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Two applications of measurement error correction in the economics of human resources

Shih-Neng Chen
Iowa State University

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Shih-Neng Chen

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UMI Number: 9540883

UMI
300 North Zeeb Road
Ann Arbor, MI 48103

DEDICATION

To the Lord, Who has blessed me with salvation and the grace of Jesus Christ through the Cross, as well as with the gift of an inquiring mind and the chance to serve others.

and

In memory of my father, Andrew Chen, who had returned to the heavenly Father's eternal home in February 1994. To my mother, Grace Chen, who has provided for me and continually supported me both spiritually and financially throughout my life.

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GENERAL INTRODUCTION

Dissertation Organization

The main body of this dissertation is comprised of two applications of measurement error correction in the economics of human resources. The presence of measurement error will bias the estimates of the parameters of interest and result in misleading policy implications. Various measurement error corrections are explored in two studies of the economics of human resources: health and comparable worth pay analysis. Each chapter contained in this dissertation is a paper to be submitted to a professional journal for publication. Following the second paper is a general review of conclusions.

Overview

The first chapter introduces nutrition, blood pressure, and prices from a household production approach. Epidemiological studies of the associations between nutrients and health may yield misleading conclusions if relative prices are not taken into account. This paper applies a household production approach to assess impacts of nutrients and other health inputs on one important health indicator, blood pressure. Choice of health inputs in the health production technology are assumed to respond to nutrient prices. Moreover, potential measurement error associated with the health inputs biases the estimates of the health production parameters. Thus, prices, along with wages and other exogenous variables, orthogonal to the error term, serve as instruments in the demand for health inputs and the resulting reduced-form health equations to correct the problems of endogeneity and measurement error of the health inputs in the health production function. Empirical findings using U.S. NHANES II data suggest that food prices are important determinants of health. Hence, policy implications concerning food price interventions to improve health are discussed. Moreover, household production and benchmark epidemiological estimates of the impacts of health inputs upon blood pressure are compared to examine the existence of endogeneity and measurement error associated with the health inputs.

The second chapter reevaluates the impact of measurement error on regression coefficients used in the State of Iowa's comparable worth system. A comparable worth pay analysis for the State of Iowa Merit Employment Pay System was conducted in 1984 by Arthur Young Consulting Company of Milwaukee. Greig (1987) suspected that Arthur Young's recommended pay plans were biased due to possible measurement error in the job evaluation. The presence of measurement error associated with the job evaluation factors will not only bias the estimates of the factor weights but also affect the estimates of other variables used in the pay analysis although the other variables were measured without error. Hence Greig explored the sensitivity analysis of pay recommendations to various measurement error corrections. His estimates were confounded by multicollinearity among several of Arthur Young's originally recommended thirteen job evaluation factors. This paper aims to obtain unbiased estimates for the job factor weights in comparable worth pay analysis by correcting both the problems of measurement error and multicollinearity in the job evaluation factors simultaneously. Potential measurement error correlations between pairwise job evaluation factors are explored to analyze the sensitivity and statistical robustness of the estimates for the job evaluation factor weights to various measurement error correlation specifications.

CHAPTER 1. NUTRITION, BLOOD PRESSURE, AND PRICES: A HOUSEHOLD PRODUCTION APPROACH

A paper prepared to be submitted to the Journal of Human Resources

Shih-Neng Chen

ABSTRACT

Epidemiological studies of the associations between nutrients and health may yield misleading conclusions if relative prices are not taken into account due to the presence of endogeneity and measurement error associated with the nutrients. This paper applies a household production approach to assess impacts of nutrients and other health inputs on one important health indicator, blood pressure. Choice of health inputs in the health production technology are assumed to respond to nutrient prices. Moreover, potential measurement error associated with the health inputs biases the estimates of the health production parameters. Thus, prices, along with wages and other exogenous variables, orthogonal to the error term, serve as instruments in the demand for health inputs and the resulting reduced-form health equations to correct the problems of endogeneity and measurement error of the health inputs in the health production function. Empirical findings using U.S. NHANES II data suggest that food prices are important determinants of health. Hence, policy implications concerning food price interventions to improve health are discussed. Moreover, household production and benchmark epidemiological estimates of the impacts of health inputs upon blood pressure are compared to examine the existence of endogeneity and measurement error

associated with the health inputs.

SECTION I. INTRODUCTION

Increased attention to health policy decisions has focused on assessing nutritional effects on health. In this respect, epidemiological studies emphasize evaluating the relationships between nutrients and health but generally have not addressed the role of prices. The gap between epidemiological aspects of health and economic aspects of health has usually not been considered. Does health status affect nutrient demand? Do variations in prices affect nutrient consumption when exogenous health endowments are present? Do the impacts of nutrients upon health change when prices are taken into account? If the answers are yes, then the conclusions of nutritional effects on health based on epidemiological studies which have not taken prices into consideration have been misleading. This implies that prices can be served as policy instruments to influence health.

The household production framework is particularly applicable in the field of health. According to the theory of household production, a household uses market purchased inputs to produce commodities which are the elements in the household's utility function. The reduced-form input demands depend on input prices, wages, and income, along with other exogenous factors. Economists have applied this approach to study the effects of nutrients, or health inputs in general, on health to the inclusion of prices. For instance, using the household production approach, Pitt and Rosenzweig (1984, 1985) recognized the importance of food prices in determining health by weighing price-induced nutrient changes according to their nutrient effects on health. Thus, price effects on health can be traced from: (a) the effects of price changes on nutrient demands; and (b) the effects of nutrients on the production of health.

This paper explores how health, as measured by blood pressure, is affected by nutrients, exercise, medication, and prices. Using the household production approach, one must first identify the endogeneity (self-selection) of health inputs in the health production function by deriving demand equations for health inputs which depend on prices, wages, and exogenous health endowment in the first stage. Then, the predicted health inputs are used to explain blood pressure in the second stage. Measurement error in the health inputs is another reason to employ a two-stage procedure in the health production function. The empirical data are taken from the second cycle of the U.S. National Health and Nutrition Examination Survey (NHANES II) which contained an individual's blood pressure and health inputs including nutrients, exercise, and medication. Prices of nutrients are derived from food prices using the nutrient equation. Due to the measurement error problem in the nutrient equation, nutrient shadow prices are also measured with error. Therefore, food prices and nutrient shadow prices are used to identify the demand for health inputs and to test the sensitivity of health production estimates to both price specifications.

The empirical results suggest that ignoring prices and the problems of endogeneity, and the measurement error of the health inputs misspecifies the relationship between health inputs and blood pressure. For example, sodium appears to have no significant impact on blood pressure according to a comparative epidemiological estimate, whereas it has significant effect of lowering blood pressure in the health production estimate. Other health inputs have similar patterns. The specification error of ignoring prices, and endogeneity and measurement error of the health inputs will cause biased estimates of health production parameters and misleading policy implications. Hence, health policy decisions based on epidemiological studies should include prices as useful indicators when examining health input effects on health.

The remainder of this paper is organized as follows. Section II develops the analytical foundation of the health production model by incorporating prices in the analysis. Section III describes the data and estimation procedures. Empirical results using food prices and nutrient shadow prices, respectively, are presented in section IV to estimate the blood pressure production parameters. The last section concludes the paper and gives policy implications.

SECTION II. ANALYTICAL FOUNDATION

A conventional one-person one-period static utility maximization model may be developed emphasizing the technological-biological health production "sector". Assume an individual's preference ordering is characterized by the following utility function. The individual's utility function has the usual properties:

(1) $$U = U(H, Z, L) \qquad U_i > 0, \;\; U_{ii} < 0, \qquad i = H, Z, L$$

where U is the utility function, H is a proxy index for individual health status, Z is a composite non-food good, and L is leisure time consumed. The subscripts i and ii denote the first and second order partial differentiation of U with respect to i, with a positive marginal utility with respect to H, Z, and L that is twice differentiable. Positive marginal utility of health indicates good health is desirable in itself as well as non-food goods and leisure.

The individual maximizes (Eq. 1) subject to technology and budget constraints on his/her choices. The main emphasis of this behavioral model is the biological health production technology constraint in which the individual consumes nutrients and other health-related inputs to produce health. This is the essence of the household production technology. This individual health production function is

$$(2) \qquad H = H(N_1, N_2, \ldots, N_k, E, M\,;\, \Phi, \mu)$$

where N_i is the amount of nutrient i consumption, E is exercise, M is medication, Φ is a vector of other exogenous health-relevant personal characteristics including age, gender, and education, and μ represents exogenous genetic health endowment. This genetic health endowment is known to the individuals but cannot be influenced by them (e.g., genetic traits or family medical history) and, therefore, is treated as exogenous in the production of health.

The signs of the marginal products of nutrients in Eq. (2) can either be positive or negative. A positive marginal product of nutrient i indicates that an increase in the consumption of nutrient i enhances health, while a negative marginal product implies that an increase in the consumption of nutrient i decrease health. For instance, saturated fatty acid is usually considered as deleterious to health, while calcium is beneficial to health. Hence, the marginal product of saturated fatty acid is negative, whereas the marginal product of calcium is positive. Using the same argument, the marginal product of exercise is positive. From the traditional theory of household production (Becker, 1965; Lancaster 1966a, 1966b, 1971; Pollak & Wachter, 1975, 1977), it is the produced commodity, H, rather than the market purchased goods or inputs N_i's, in Eq. (2) that enters directly into the utility function of Eq. (1). Nutrients and medication themselves do not yield utility directly but are treated as inputs into the health production function (Eq. 2) to produce health. The source of nutrients comes from the consumption of a variety of foods. This relationship can be represented by

$$(3) \qquad N_i = a_{i1} F_1 + a_{i2} F_2 + \dots + a_{iq} F_q + \varepsilon_i \qquad i = 1, 2, \dots, k$$

where F_j is consumption of food j, each unit of food j yields a_{ij} units of nutrient i, and ε_i is the error term associated with the i^{th} nutrient equation. Hereafter a_{ij} is referred to as the nutrient coefficient. This nutrient equation specification has been used in the literature (Devaney & Fraker, 1989; Devaney & Moffitt, 1991). Note that the error component ε_i is the measurement error associated with the nutrient Eq. (3). The presence of a measurement error component in the nutrient equation indicates that the measure of nutrient intakes is subject to error. Therefore, any derivation based on this nutrient equation is also subject to error.

According to the theory of household production, the health inputs are market purchased goods. Hence, each health input has an associated market price. The food vector $F = [F_1, F_2, \dots, F_q]'$ has a price vector $P_F = [P_{F1}, P_{F2}, \dots, P_{Fq}]'$ associated with it. Using Eq. (3) one computes the shadow price for each nutrient i, P_i. The specific derivation for P_i is presented in the next section. This nutrient shadow price, P_i, reflects the implicit price an individual has to pay to consume N_i amounts of nutrient i. The nutrient shadow price P_i is unobserved directly but only implied by Eq. (3). Due to the measurement error of the nutrient Eq. (3), nutrient shadow prices are also subject to measurement error. Hence, an individual is assumed to face the nutrient shadow prices P_i's as well as the food prices' P_{Fi}'s to examine the sensitivity of health production parameters to different price specifications. Using this view of nutrient shadow prices, the full-income constraint confronted by the individual with market wage work is

$$(4) \qquad V + WT_w = P_1 N_1 + P_2 N_2 + \dots + P_k N_k + P_z Z + P_M M$$

where V is nonlabor income; W is market wage; T_w is hours of wage work which equals total time endowment T minus exercise E, and leisure time L; $P_1, P_2, \dots, P_k$ are nutrient shadow prices; P_z is price of composite nonfood Z; and P_M is price of medical care. Note that market wage W represents the opportunity cost of time. The opportunity cost of exercise and leisure is the forgone market wage. Hence, market wage is the implicit price of exercise and leisure.

Maximization of the utility function (Eq. 1) subject to health production technology (Eq. 2) and full income constraint (Eq. 4) yields the following Lagrangian maximization problem:

$$(5) \qquad \mathcal{L} = U[\, H(N_1, N_2, \ldots, N_k, E, M\,;\, \Phi, \mu), Z, L\,]$$

$$+ \lambda\,[\, V + WT - (P_1 N_1 + P_2 N_2 + \ldots + P_k N_k + P_z Z + P_M M + WE + WL)\,]$$

where $\mathcal{L}$ represents the Lagrangian multiplier and λ is the marginal utility of one more unit of full income V+WT or the shadow price of the constraint. First order conditions for an interior solution of this problem with respect to each choice variable are:

$$(5a) \qquad N_i : (U_H)(MP_{Ni}) = \lambda P_i \qquad i = 1, 2, \ldots, k$$

$$(5b) \qquad E : (U_H)(MP_E) = \lambda W$$

$$(5c) \qquad M : (U_H)(MP_M) = \lambda P_M$$

$$(5d) \qquad Z : (U_Z) = \lambda P_z$$

$$(5e) \qquad L : (U_L) = \lambda W$$

where MP_j represents the marginal product of input j in the production of health. Equation (5a) shows that the marginal utility of nutrient i is the product of the marginal utility of health and the marginal product of nutrient i on health. Similarly, Eq. (5b) shows that the marginal utility of exercise is the product of the marginal utility of health and the marginal product of exercise on health. Equation (5c) signifies the marginal utility of medical care is the product of the marginal utility of health and the marginal product of medical care on health. Hence, the marginal utility of health input consists of two parts. One is the direct effect of health inputs on health (MP_j, $j = N_i$, E, and M), and the other is the indirect effect of health on utility (U_H). The first-order conditions, with respect to composite non-food and leisure, are interpreted the same as in the standard utility maximization theory.

The solutions for the consumption demands are as follows:

(6a) $$N_i^* = N_i^*(P_1, P_2, \dots, P_k, P_z, P_M, W, V, T, \Phi, \mu) \qquad i = 1, 2, \dots, k$$

(6b) $$E^* = E^*(P_1, P_2, \dots, P_k, P_z, P_M, W, V, T, \Phi, \mu)$$

(6c) $$M^* = M^*(P_1, P_2, \dots, P_k, P_z, P_M, W, V, T, \Phi, \mu)$$

(6d) $$Z^* = Z^*(P_1, P_2, \dots, P_k, P_z, P_M, W, V, T, \Phi, \mu)$$

(6e) $$L^* = L^*(P_1, P_2, \dots, P_k, P_z, P_M, W, V, T, \Phi, \mu)$$

where the asterisk "*" denotes the optimal choice of that variable. These solutions are the utility maximizing consumption demands for the k nutrients, exercise, medical care, composite non-food, and leisure. Equations (6a)-(6c) show that nutrient consumption, exercise, and medication are functions of all prices ($P_1, P_2, \dots, P_k, P_z, P_M$, W) and personal characteristics (Φ, μ). Information on market wage W is as important as information on prices for understanding the determinants of health inputs. Moreover, exogenous health endowment μ, known to the individual but not influenced by him/her, also conditions the demand for nutrients, exercise, and medication.

Substituting the optimum choices of nutrients, exercise, and medication from Eqs. (6a)-(6c) into the health production function (Eq. 2) yields the reduced-form health equation:

$$(7) \qquad H^{*} = H^{*}(P_1, P_2, \dots, P_k, P_z, P_M, W, V, T, \Phi, \mu)$$

Analogous to the health input demand Eqs. (6a)-(6c), the reduced-form health equation (7) shows an individual's health is also directly related to all prices ($P_1, P_2, \dots, P_k, P_z, P_M, W$) and personal characteristics (Φ, μ). The models of the reduced-form utility maximizing demand Eqs. (6a)-(6e) and/or the reduced-form health Eq. (7) have been extensively used in household (health) production literature (Behrman & Deolalikar, 1987, 1990; Pitt & Rosenzweig, 1984, 1985; Rosenzweig & Schultz, 1982, 1983).

An examination of the health input demand Eqs. (6a)-(6c) and the reduced-form health Eq. (7) indicates that comprehensive price information is important for understanding the determinants of nutrient consumption, exercise, medication, and health (Pitt & Rosenzweig, 1985). One objective of this study is to assess price effects on health. Knowledge of health input demand Eqs. (6a)-(6c) and the reduced-form health Eq. (7) along with health production technology (Eq. 2) is important to derive price effects on health. The price effect on health is derived as follows. Consider the effects of a change in the price of nutrient 1, nutrient shadow price P_1, on health:

$$\text{(8)} \qquad dH/dP_l = \sum_{i=1}^{k} MP_{Ni}(dN_i/dP_l) + MP_E(dE/dP_l) + MP_M(dM/dP_l)$$

where dN_i/dP_l denotes price (P_l) effect on nutrient (N_i). The effect of P_l on health thus depends on the relative magnitudes of the marginal products of the health inputs in the health production function (Eq. 2) and the magnitudes and signs of the own- and cross-price effects in the demand for health inputs (Eqs. 6a-6c). Hence, the price effects on health depend on both the properties of health production technology (Eq. 2) and the underlying preference ordering of the demand for health inputs (Eqs. 6a-6c) (Pitt & Rosenzweig, 1985).

To correctly capture the price effects on health, consistent estimates of the marginal productivities of the health inputs in the production function are equally important as consistent estimates of the price effects on the demand for health inputs. Thus, according to Eq. (8), marginal productivities of health inputs serve as weights to the price-induced changes in demand for health inputs to estimate the price effects on health. The empirical estimation of the price effects on health focuses on the reduced-form health Eq. (7) or on both health production technology (Eq. 2) and the demand for health inputs (Eqs. 6a-6c). One estimates the price effects on health using the reduced-form health Eq. (7) and estimates the consistent health production parameters using Eq. (2) and Eqs. (6a)-(6c) to derive policy implications from this empirical analysis.

Two important points need to be discussed before considering the empirical analysis. First, Eqs. (6a)-(6c) show that behavioral choices of nutrient consumption, exercise, and medication in health production technology (Eq. 2) depend on the exogenous health endowment μ along with prices. Similarly, Eq. (7) shows that the resulting reduced-form health equation depends on μ as well as prices. An individual's behavioral choices of health inputs in the health production function (Eq. 2) differ due to the difference in exogenous health endowment μ. The difference in μ across a randomly selected population is what Rosenzweig and Schultz (1982, 1983), and Strauss and Thomas (1994) termed "population heterogeneity". However, Rosenzweig and Schultz (1983) argued:

> that . . . the health production inputs are behavioral variables implies that even if only information on the technology of health production were desired, having measures of *all* important behavioral inputs and the health output would not be adequate to describe the health technology. The difficulty arises chiefly from the presence of exogenous health factors that can be known to individuals but that are not observed by the researcher. (p. 727)

Therefore, heterogeneity bias in the context of health studies is most likely to affect the levels of health inputs chosen in the presence of health production technology. In the current study, heterogeneity bias may also affect the estimates of the health production parameters. Individuals choose levels of health inputs according to their health status but this is not directly observed in the survey data. Hence, empirical estimations need to take into account the effects of exogenous health endowment in the health production technology (Eq. 2). Taken together, the simultaneity of both prices and the exogenous health endowment in determining nutrient consumption, exercise, medication, and health is important in analyzing the effects of prices and of health inputs on health.

Second, examining the nutrient Eq. (3) reveals the fact that computation of the nutrients involves measurement error. Nutrient consumption depends on the summation of the product of the nutrient coefficient a_{ij} and the amount of food consumption over all foods. There are three potential sources of measurement error associated with nutrient Eq. (3). First, the nutrient coefficient a_{ij} represents the amount of nutrient i contained in each unit of food j. This coefficient a_{ij} may be subject to measurement error. Second, the amount of food consumption involves measurement errors. Equation (3) is summed across all food consumption. Each food consumption amount has a measurement error, hence, the sum across all foods contains measurement errors. Third, there is an equation error ε_i associated with the i^{th} nutrient equation (Eq. 3) which is the discrepancy between the observed amount of nutrient intake and the true amount of nutrient intake. The difference between the observed and the true amount of nutrient intake, as discussed earlier, is a component of measurement error. Moreover, in the current study, two more health inputs, exercise and medication, are also potentially measured with error. In this empirical analysis, measures of exercise and medication are proxies for the corresponding endogenous choices in the health production function. For example, only three categories (very active, moderately active, and less active) in the sample represent a person's exercise level. In the empirical NHANES II data, medical care is defined as a dummy variable representing whether a person is taking medicine regularly or not. How exactly "regularly" is defined may vary from person to person. Hence, measurement error is an issue for the endogenous choice variables in the household production function for health (Eq. 2).

An estimation method which simultaneously solves both the problems of endogeneity (heterogeneity bias) and the measurement error of the health inputs, including nutrients, exercise, and medication, in health production technology (Eq. 2) is to use the two-stage least squares procedure. In this method, predicted health inputs from exogenous prices along with personal characteristics are replaced in the health production function to estimate consistent health production parameters. A consistent estimator has the property wherein, as the sample size increases, the estimator can be made to lie arbitrarily close to the true value of the parameter with the probability arbitrarily close to one. More briefly, in the limit the estimator is said to converge in probability to the true parameter (Maddala, 1992). By plugging the estimates of the optimum choices of nutrients, exercise, and medical care from the first-stage into the health production function (Eq. 2), consistent second-stage estimates for the underlying health production parameters can be derived. Empirical specification for the two-stage procedure will be discussed in detail in the next section.

SECTION III. DATA AND ESTIMATION PROCEDURES

A. Data

The empirical data used in this study are from the second cycle of the U.S. National Health and Nutrition Examination Survey (NHANES II) which was conducted from February 1976 to February 1980. This national health survey is one of a series of population based surveys designed to determine the health status of the nation. Data were collected through responses to questionnaire items on medical history, food consumption, and health-related behaviors. The data were also collected through direct medical examination. Examinations were performed in mobile examination centers which traveled to 64 different sites across the

United States. The NHANES II was conducted on a nationwide probability sample of approximately 28,000 persons, aged 6 months to 74 years. The NHANES II sample was selected so that certain population groups thought to be at high risk of malnutrition (persons with low income, preschool children, and the elderly) were oversampled.

Due to the absence of food price data in NHANES II, in the present study a subsample was selected from NHANES II based on the availability of food price data from other sources. This was the first application of NHANES II with food price data. The subsample included 1,982 persons from the sampling dates between February 1976 through March 1978. These were taken from eleven standard metropolitan statistical areas: San Jose, Tacoma, Minneapolis-St. Paul, Chicago, New York, Newark, Boston, Pittsburgh, Los Angeles-Long Beach, San Diego, and Honolulu.

NHANES II collected information on individual blood pressure. The blood pressure for each examinee was recorded in three different ways in NHANES II. They were a seated blood pressure early in the examination, a recumbent blood pressure at the end of the examination, and a second seated blood pressure at the end of the examination. In this paper the examinee's recumbent systolic blood pressure (SYS) at the end of the examination was used as an indicator of health.

The other major part of data in the health production function is the consumption of nutrient information. The NHANES II contains the dietary data for individual calories and 17 nutrients. The information was collected during the period of time from midnight to midnight preceding the interview, and it generally reflects intakes reported from Mondays through Fridays, excluding most holidays. To decide which and how many nutrients significantly affect blood pressure, two different sources of nutrient specifications were considered in the health production function of Eq. (2). First, from the study of previous medical literature (Bennett & Cameron, 1984; Bennett & Newport, 1987; Bursztyn, 1987; McCarron et al., 1984), fat, calcium, potassium, sodium, vitamin C, and cholesterol were identified as having significant positive or negative effects upon blood pressure. The second source of information on the relationship between nutrients and blood pressure was taken from previous NHANES II studies. This includes studies done by Pirkle et al. (1985) and Atkinson et al. (1986). Although their studies emphasized estimating the relationship between blood lead concentration and blood pressure, they found that vitamin C, riboflavin, saturated fatty acid, and oleic acid significantly affected blood pressure.

The current study, the empirical estimations examined how these two different nutrient sets affect health status. The union of these two sets included nine nutrients considered in this study: fat (FAT), calcium (CALC), potassium (POTA), sodium (SODI), vitamin C (VITC), cholesterol (CHOL), riboflavin (RIBO), saturated fatty acid (FAAC), and oleic acid (OLAC). Two other endogenous covariates affecting blood pressure in this study were exercise (REEXER) and medication (MEDICINE). The NHANES II data contained subjective self-judgement of recreational exercise levels which included physically "very active" (3), "moderately active" (2), and "very inactive" (1). A dummy variable representing whether a person is taking medicine regularly or not was used as proxy for medication in the health production function.

Other exogenous health-relevant personal characteristics affecting blood pressure included age (AGE), gender (GENDER, 1 = male), years of education (ED), and health endowment (μ). The initial health endowment was known to the individuals but was unobserved by the researcher. This problem has been investigated by Rosenzweig and Schultz (1983). Hence, the effects of health endowment on the input demand equations (6) and the reduced-form health equation (7) were contained in the error terms in the corresponding reduced-form estimating equations. This will be discussed in detail in the next section. Other exogenous variables included in the reduced-form health input and health estimating equations were natural logarithm of hourly wage (LNHRWAGE), natural logarithm of income levels (LNINCOME), and total number of persons in the household (NUMPERS). The household compositions may affect an individual's consumption for nutrients and other choices of health inputs. Thus, this household composition factor was incorporated as a regressor in the reduced-form equations.

The food price data were obtained from the Estimated retail food prices by city (U.S. Bureau of Labor Statistics [BLS], 1976-1978). The retail food prices were reported monthly over the NHANES II sample period from January 1976 through May 1978. Because individuals were surveyed at different times throughout the sample period, all retail food prices were deflated to January 1976 dollars. Nineteen reported BLS food prices corresponded closely to the reported NHANES II food consumption frequencies. A correlation matrix of the original nineteen food prices and wages is reported in the Appendix (Table A.5). Due to multicollinearity among the nineteen food prices, the dimensionality of the food prices were condensed to be ten. The ten food prices used in this empirical estimation were: price of whole milk (PWHMILK), price of eggs (PE), price of sugar (PSUGAR), price of coffee (PCOFFEE), price of cola (PCOLA), price of all meat (PMEATS), price of poultry (PPOULTRY), price of fruits and vegetables (PFUVG), price of cereals (PCEREALS), and price of fats and oils (PFAOL).

The nutrient shadow prices discussed in the previous section were derived from the nineteen retail food prices. For each city, there was a nutrient shadow price for each nutrient. Hence, there were nine nutrient shadow prices in total in each city. All nutrient consumption levels were converted to milligrams to compute nutrient shadow prices. Because the food consumption in NHANES II was recorded in frequencies per week or per day, the food frequencies were converted into the same weekly basis in the present study. The nutrient coefficients a_{ij} in Eq. (3) represent milligrams of nutrient i obtained per unit frequency of food j consumption. Let $\overline{F}_{mj}$ represent the sample mean of food m consumption frequencies per week for city j, and m = 1, 2, ... , q.

The following average ith nutrient consumption is derived for city j as:

$$(9) \qquad \overline{N}_{ij} = a_{i1j}\overline{F}_{1j} + a_{i2j}\overline{F}_{2j} + \ldots + a_{iqj}\overline{F}_{qj} + \overline{\varepsilon}_{ij} \qquad i = 1, 2, \ldots, k$$

Dividing both sides by $\overline{N}_{ij}$ yields:

$$(9a) \qquad 1 = (1 / \overline{N}_{ij})(a_{i1j}\overline{F}_{1j} + a_{i2j}\overline{F}_{2j} + \ldots + a_{iqj}\overline{F}_{qj} + \overline{\varepsilon}_{ij})$$

The term $(a_{imj} / \overline{N}_{ij})$ represents food m share of nutrient i in city j. Then the i[th] nutrient's shadow price can be derived as:

$$(10) \qquad P_{ij} = \sum_{m=1}^{q} (a_{imj} \overline{F}_{mj} / \overline{N}_{ij}) \gamma_{im} P_{mj} + \text{error} \qquad i = 1, 2, \ldots, k$$

where P_{ij} and P_{mj} are the shadow price for nutrient i and food price for food m in city j, respectively, γ_{im} is a transformation coefficient of converting unit of food m to units of nutrient i. The unit for this transformation coefficient is the reciprocal of milligrams of nutrient i contained in a unit of food. Equation (10) transforms food prices into nutrient i's shadow price in city j for all the k nutrients. The empirical data for the nutrient shadow prices include price of fat (PFAT), price of calcium (PCALC), price of sodium (PSODI), price of potassium (PPOTA), price of riboflavin (PRIBO), price of vitamin C (PVITC), price of saturated fatty acid (PFAAC), price of oleic acid (POLAC), and price of cholesterol (PCHOL).

Due to the error term associated with nutrient Eq. (3), there is an error component associated with the nutrient shadow price in Eq. (10). As discussed earlier, the nutrient coefficient a_{imj}, food consumption $\overline{F}_{mj}$, and the transformation coefficient γ_{im} in (10) are also potentially measured with error. Hence, the nutrient shadow prices are measured with error. Measurement error associated with the nutrient shadow prices makes them stochastic regressors in the present empirical estimations. Food prices are correlated with nutrient shadow prices and are uncorrelated with the error term in estimation. Therefore, the food prices serve as alternative instrumental variables of the nutrient shadow prices in the empirical settings.

The NHANES II does not report hourly market wage rates. Therefore, wage equations were generated separately for males and females using the 1978 Current Population Survey (CPS) data using regressors common to the CPS and NHANES II data sets. The predicted wages for NHANES II individuals were generated using the coefficients derived from the CPS data corrected for sample selection bias.

The wage generating procedure was conducted by first considering a wage work participation equation from the CPS data:

$$Y_i = \boldsymbol{X}_{pi}\beta + u_{pi} \tag{11}$$

where Y_i is a zero-one dummy of wage work participation for individual i, $\boldsymbol{X}_{pi}$ is a vector of factors affecting labor supply decision, β is a vector of parameters, and u_i is an error term with zero mean and constant variance σ_{ii}. Factors affecting labor supply decision include standard metropolitan statistical area (SMSA), number of persons in the household (NUMPERS), number of kids (KIDS), marital status (MARSTAT), race (RACE), age (AGE), years of education (ED), other income (OTHINC), and region (REGION). Since Y_i is a zero-one dependent variable, probit procedure was used in this participation equation

(Eq. 11).

From the wage work participation Eq. (11), the predicted value is computed from the standardized regressors:

$$(12) \qquad Z_i = -(\boldsymbol{X}_{pi}\beta)/(\sigma_{ii})^{1/2}$$

The sample selection correction term is computed by

$$(13) \qquad \lambda_i = \phi(Z_i)/[(1 - \Phi(Z_i)]$$

where $\phi(\bullet)$ and $\Phi(\bullet)$ are the standard normal pdf and cdf. The λ_i is the inverse of Mill's ratio. Using the λ_i as a sample selection correction term in the CPS wage equation adjusts for sample selection bias. The versatility of the Mill's ratio method as a correction for specification error has been shown by Heckman (1979). The wages in CPS are measured by dividing total annual salaries by total hours of work during that year. The wage equation is

$$(14) \qquad W_i = \boldsymbol{X}_{wi}\gamma + \delta\lambda_i + u_{wi}$$

where W_i is the wage rate for individual i, $\boldsymbol{X}_{wi}$ is a vector of factors affecting wage rates, γ and δ are parameters to be estimated, and u_{wi} is an error term.

In addition to human capital personal attributes, the wage equation also includes regressors of industrial, occupational, and regional dummies as well as the interaction terms of the dummies. The main industrial dummies are manufacturing (MFG), wholesale and retail trade (WSRTTR), finance, insurance, real estate, business, and repair services (FNBU), personal services, entertainment, recreation services, professional, and related services (PFRS). The occupational classification includes professional, technical, and kindred workers (PROF), managers, administrators, with the exception of farm, sales workers, and clerical and kindred workers (MASACL), craftsman and kindred workers (CRAF), operatives (OPER), and service workers (SERV). The regional dummies include northeast (NE), mid-west (MW), and south (SO). The interaction terms are the products of industrial, occupational, and regional dummies. In this study four industrial dummies, five occupational dummies, and three regional dummies combine to make a total of sixty dummies.

Taking the regression coefficients, $\hat{\gamma}$, from the predicted wage equation in CPS and applied to the NHANES II corresponding variables (dropping the sample selection term λ_i) result in the predicted wage equation in NHANES II. These estimated wages represent, in essence, the expected wage for an individual with given human capital attributes occupying a given occupation/industry/region cell. The participation probit and OLS wage regression results separately for males and females using CPS are attached in the Appendix. Table 1 lists a summary of sample statistics used in this study. The total sample size used was comprised of 1,982 U.S. NHANES II examinees.

Table 1. Summary of sample statistics

Variable	N	Mean	Std Dev	Minimum	Maximum
SYS	1982	129.0181635	22.1599361	72.0000000	248.0000000
FAT	1982	79.7456609	52.6192750	0	598.5700000
CALC	1982	778.5560949	604.4067950	0	5541.0600000
SODI	1982	2766.8400000	1790.8200000	0	18033.9800000
POTA	1982	2556.0700000	1320.4600000	0	12402.2200000
RIBO	1982	1.9053078	1.7654201	0	29.1500000
VITC	1982	110.6349495	110.3256696	0	1415.9200000
FAAC	1982	28.7253986	20.7126290	0	254.6500000
OLAC	1982	29.0857972	20.4604735	0	252.3100000
CHOL	1982	353.5374723	293.0834278	0	2717.6000000
REEXER	1982	1.4702321	0.4992390	1.0000000	2.0000000
MEDICINE	1982	0.3284561	0.4697702	0	1.0000000
AGE	1982	44.7255298	17.8594927	12.0000000	74.0000000
GENDER	1982	0.4788093	0.4996768	0	1.0000000
ED	1982	12.1579213	3.1768956	0	17.0000000
PWHMILK	1982	75.2036529	9.6123275	60.9173012	105.8083938
PE	1982	75.2851515	8.1054503	65.1004304	92.3499203
PSUGAR	1982	107.0751290	9.5114091	94.5634850	126.3000000
PCOFFEE	1982	274.6697390	71.7324646	153.3000000	383.1697834
PCOLA	1982	139.0889304	23.0755297	89.6051001	174.3195704
PMEATS	1982	550.7510509	82.6420111	430.7475736	706.8119152
PPOULTRY	1982	60.0529301	7.7261963	48.3978957	83.2300336
PFUVG	1982	53.5989047	8.2199856	44.1811952	74.6460459
PCEREALS	1982	66.9083966	6.1787107	59.3358066	89.4337923
PFAOL	1982	181.7434721	10.8157517	165.6304250	210.9142908
PFAT	1982	14.3120481	1.5460872	12.0741000	17.8896000
PCALC	1982	0.6849973	0.0702216	0.5694000	0.8038000
PSODI	1982	1.1020764	0.0794963	1.0171000	1.3439000
PPOTA	1982	0.0668439	0.0099425	0.0551000	0.0927000
PRIBO	1982	156.5650043	10.0568746	146.4028000	187.3991000
PVITC	1982	1.7062964	0.1004393	1.5615000	1.9985000
PFAAC	1982	21.7237608	2.5090582	17.8685000	27.4364000
POLAC	1982	51.4042188	5.0736633	42.8926000	59.6823000
PCHOL	1982	0.2443093	0.0153098	0.2250000	0.2825000
LNHRWAGE	1982	1.0150430	0.8851907	0	2.5584908
LNINCOME	1982	9.4892127	0.7799558	6.2146081	10.5320962
NUMPERS	1982	3.0509586	1.7590687	1.0000000	11.0000000
SMSA	1982	1.0000000	0	1.0000000	1.0000000
RACE	1982	0.1644803	0.3708044	0	1.0000000
FULPRT	1235	0.8226721	0.3821007	0	1.0000000
NE	1982	0.3183653	0.4659596	0	1.0000000
MW	1982	0.2891019	0.4534598	0	1.0000000
SO	1982	0	0	0	0
MFG	1982	0.1765893	0.3814170	0	1.0000000
WSRTTR	1982	0.1256307	0.3315163	0	1.0000000
FNBU	1982	0.0686176	0.2528665	0	1.0000000
PFRS	1982	0.2209889	0.4150177	0	1.0000000
PROF	1982	0.1231080	0.3286440	0	1.0000000
MASACL	1982	0.2431887	0.4291164	0	1.0000000
CRAF	1982	0.0746720	0.2629278	0	1.0000000
OPER	1982	0.0953582	0.2937832	0	1.0000000
SERV	1982	0.0923310	0.2895657	0	1.0000000

B. Estimation Procedures

The health proxy variable is the U.S. NHANES II examinee's recumbent systolic blood pressure (SYS) since blood pressure is an important indicator of an individual's health status. As addressed by Bursztyn (1987), high blood pressure is one of the major sources of chronic ill-health and premature death in modern society (Swales, 1979). Hypertensive cardiovascular disease remains the principal cause of morbidity and mortality in the U.S. (Levy & Moskwitz, 1982; McCarron et al., 1984). Hence, using blood pressure as an indicator of health status is a useful way to quantify a measure of health. Three possible functional forms of the health production technology (Eq. 2) were preliminarily tested. They are the linear, transcendental logarithmic (translog), and Cobb-Douglas (double logs) health production functions. After experimenting, it was concluded that the Cobb-Douglas functional form best describes the health production technology embodied in equation (2). The sixty-six additional interaction and quadratic terms of the endogenous health inputs embodied in the translog functional specification of health production technology are not jointly statistically significant. The F value computed from the OLS residuals is 1.24, whereas the critical value at the five percent level of significance is 1.32. Hence, Cobb-Douglas (double logs) approximations are applied to the health production function (2).

Traditional epidemiological studies attempt to relate disease incidence and prevalence to variables in the host and environment (Olson, 1979). According to Olson, epidemiology intends to establish associations between an environmental or host variable and occurrence of a disease. Therefore, in the current study a benchmark model relating blood pressure to nutrients, exercise, and medication along with other exogenous variables has been set up for comparison with the health production model in which nutrients, exercise, and medication are treated as endogenous choice variables in the blood pressure production technology embedded in Eq. (2).

A benchmark epidemiological model of systolic blood pressure without prices or other exogenous information is given by

$$(15) \qquad LSYS = \eta_0 + \eta_1 LN_1 + \eta_2 LN_2 + \ldots + \eta_k LN_k + \eta_E E + \eta_M M + \eta_\Phi \Phi + \mu + e_{SYS}$$

where the prefix L denotes the natural logarithm of the respective variable, Φ is a vector of variables affecting blood pressure including age (LAGE), gender (GENDER, male = 1), and education (LED), η_i's are the regression coefficients, and e_{SYS} is the random disturbance term. Note that the η_i's in Eq. (15) capture the observed associations between nutrients, exercise, and medication and systolic blood pressure without taking prices into account. Recall the reduced-form health Eq. (7). The reduced-form health equation relates health directly to exogenous prices, along with wages, income, other exogenous variables, and health endowment.

A comparison of the benchmark epidemiological model of health Eq. (15) and the reduced-form health Eq. (7) indicates that the former captures the observed associations between nutrients, other health inputs, and health while the latter relates prices and other exogenous variables to health. Equation (15) is the structural model of health whereas Eq.

(7) is the reduced-form model of health. Since prices, wages, income, and other exogenous variables are uncorrelated with the exogenous health endowment, the regression estimates using an approximation of the reduced-form health Eq. (7) are unbiased. Therefore, ordinary least squares regression was applied to Eq. (15) to estimate the epidemiological benchmark estimates of the associations between nutrients, exercise, and medication, and systolic blood pressure. Note that μ is unobserved, it is treated as an error component in Eq. (15).

Two potential problems arise from the benchmark epidemiological regression using Eq. (15). First, as shown by Rosenzweig and Schultz (1983), the error term in Eq. (15), containing μ, is likely to be correlated with the regressors of nutrients, exercise, and medication. Examining Eq. (6) reveals that nutrients, exercise, and medical care demand equations, indeed, depend on the exogenous health endowment μ. This implies that nutrients, exercise, and medication are, themselves, choice variables in the blood pressure production function, and, therefore, are not exogenous in the determination of blood pressure production. The endogeneity of the choice variables in the blood pressure production technology is one concern for the problem in estimation using Eq. (15). Moreover, the presence of μ on the right-hand-side of Eq. (15) causes the estimation of the impacts of health inputs on blood pressure to be afflicted with simultaneity bias.

Second, as discussed earlier, the endogenous choice variables are subject to measurement error. The presence of measurement error biases the coefficients of the blood pressure production parameters in the epidemiological benchmark regression. A formal proof of the biases due to the measurement error problem which existed in the regressors in regression analysis will be given in the second chapter of this dissertation. Hence, the epidemiological estimates of the underlying health production parameters, η_i's, used in Eq. (15) are inconsistent. By definition, the inconsistency is that the epidemiological estimates of the associations between health inputs along with other exogenous variables and blood pressure do not converge to the true blood pressure production parameter. Consistent estimation of the underlying health production parameters embodied in Eq. (2) can be obtained using the two-stage least squares estimation approach which is discussed as follows.

The theoretical model discussed in the previous section emphasizes the health production approach in which health inputs are, themselves, choice variables in health production technology. Based on the health production model, the two stage least squares estimation approach is used. The price effects upon blood pressure are decomposed into the two stages. The first stage involves estimating nutrient consumption demand, exercise, and medication equations using health input Eqs. (6a)-(6c). In this stage, an individual chooses the amount of nutrients, the level of exercise, and the amount of medicine conditional on the right-hand-side exogenous variables of Eqs. (6a)-(6c). In the second stage, the amount of nutrients consumed, the level of exercise undertaken, and the amount of medicine taken, will affect the individual's health by health production technology (Eq. 2). Nutrient consumption, exercise, and medication which were estimated and, hence, predicted from the first stage, are used as inputs in the second stage production of blood pressure. Based on the log-linear approximations to Eq. (6a), the first stage nutrient estimation equations are:

$$\text{(16)} \qquad LN_i = \beta_{i0} + \beta_{i1}P_1 + \beta_{i2}P_2 + \ldots + \beta_{ik}P_k + \beta_{iz}P_z + \beta_{iM}P_M$$
$$+ \beta_{i\Omega}\Omega + \beta_{i\Phi}\Phi + \mu + \varepsilon_i \qquad i = 1, 2, \ldots, k$$

where β_{ij}'s are the regression coefficients associated with the i^{th} nutrient demand equation, Ω is a set of other exogenous variables affecting nutrient consumption demand including logarithm of generated hourly wage (LNHRWAGE), logarithm of income level (LNINCOME), number of persons in the family (NUMPERS), Φ and μ as defined in Eq. (2) earlier, and ε_i is the random disturbance term. Note that μ in Eq. (16) is contained in the error component. The regression coefficients β_{ij}'s in Eq. (16) fully capture the nutrient's own and cross shadow price effects on nutrient demand for $j = 1, 2, \ldots, k$. The ordinary least squares (OLS) estimation applied to Eq. (16) yields the first stage nutrient estimation. The nine nutrients considered in this study are: fat, calcium, potassium, sodium, vitamin C, cholesterol, riboflavin, saturated fatty acid, and oleic acid.

In addition to the nine nutrients, the proxies for exercise level (REEXER) and medication (MEDICINE) are also considered in the first stage. As discussed above, in NHANES II the exercise variable is measured as physically "very active" (3), "moderately active" (2), or "very inactive" (1). To obtain the predicted value of this endogenous choice variable in the first stage, the consistent estimation of OLS is used in the first stage exercise equation. This can be expressed as:

$$(17) \qquad E = \delta_0 + \delta_1 P_1 + \delta_2 P_2 + \ldots + \delta_k P_k + \delta_M P_M + \delta_\Omega \Omega + \delta_\Phi \Phi + \mu + \upsilon_E$$

where E represents exercise, δ_i's are the regression coefficients, and υ_E is the random disturbance term associated with this exercise OLS regression equation.

Similarly, medication (MEDICINE) in NHANES II is a dummy variable measuring whether the sample person is taking medicine regularly or not (1 = yes, 0 = no). Hence, the OLS estimating equation for medical care is:

$$(18) \qquad M = \gamma_0 + \gamma_1 P_1 + \gamma_2 P_2 + \ldots + \gamma_k P_k + \gamma_M P_M + \gamma_\Omega \Omega + \gamma_\Phi \Phi + \mu + \nu_M$$

where the γ_i's are the regression coefficients and ν_M is the disturbance term.

Since exercise and medication are limited dependent variables, probit procedure is also applied to Eqs. (17) and (18). The results of these two probit estimations are reported in the Appendix (Tables A.6 and A.7).

Using the predicted values from the first stage estimations of Eqs. (16), (17), and (18) as explanatory variables for nutrients, exercise, and medication, respectively, in the second stage blood pressure equation yields consistent estimation of the blood pressure production parameters since the two potential problems associated with the epidemiological benchmark regression of Eq. (15) are purged away by using the two-stage procedure. The first stage estimation results are reported in the next section.

One issue of employing the first stage estimations that needs to be keep in mind is the following. In the first stage estimation, prices and wages were used as identifying instruments to obtain predicted health inputs. Although the health endowment, μ, is an important factor in the demand equations for health inputs (Eqs. 6a-6c), it is treated as an error component in the first stage estimations. This causes potential problem since the error term in Eqs. (16)-(18), containing μ, is likely to be correlated with other regressors (e.g. age, gender) in the equations. Nonetheless, the main interest in the first stage estimations is to obtain predicted left-hand-side dependent variables (health inputs) by employing prices and wages as instruments. Prices and wages were assumed to be uncorrelated with the health endowment. Therefore, the first stage predictions are useful regressors in the second stage.

Using $L\hat{N}_i$'s, $\hat{E}$, and $\hat{M}$, from Eqs. (16), (17), and (18) as the predicted nutrients, exercise, and medication proxies, respectively, from the first stage OLS estimations, the second stage blood pressure equation are estimated using the OLS procedure. The second stage blood pressure OLS regression equation can be expressed as:

$$(19) \qquad LSYS = \xi_0 + \xi_1 L\hat{N}_1 + \xi_2 L\hat{N}_2 + \ldots + \xi_k L\hat{N}_k + \xi_E \hat{E} + \xi_M \hat{M} + \xi_\Phi \Phi + \mu + u_{SYS}$$

where ξ_i's are the OLS regression coefficients, and u_{SYS} is the disturbance term. The $L\hat{N}_i$'s, $\hat{E}$, and $\hat{M}$, in Eq. (19) are the first stage predicted values of the OLS regression Eqs. (16), (17), and (18), respectively. Since the error term in Eq. (19), which includes μ, is independent of the exogenous variables in the health production technology and the predicted value of the health inputs are linear functions of the exogenous variables, it can be shown that, in the limit, the predicted health inputs and the error term (any unobservables) in Eq. (19) are uncorrelated (Maddala, 1992). Therefore, this satisfies one of the important assumptions in the OLS regression: regressors need to be independent of the error term in the regression of interest. Hence, blood pressure production parameter estimates using the OLS regression in Eq. (19) are consistent. The regression results in terms of sign and statistical significance from the epidemiological benchmark in Eq. (15) and the two-stage consistent health production in Eq. (19) are critically compared to examine the sensitivity of estimates to the inclusion of nutrient shadow prices in the blood pressure production Eq. (2) along with endogeneity and measurement error problems associated with the health inputs.

As discussed earlier, nutrient shadow prices are potentially measured with error. The measurement error problem makes the nutrient shadow prices stochastic regressors in the first stage reduced-form health input estimations in Eqs. (16), (17), and (18). According to the shadow price derivation in Eq. (10), food prices are highly correlated with nutrient shadow prices. Therefore, an alternative is to use food prices as identifying instruments in the reduced-form health input Eqs. (6a)-(6c) and the reduced-form health Eq. (7). Hence, as an alternative, first stage estimations of Eqs. (16), (17), and (18), the use of food prices are employed to analyze the sensitivity of the nutrient demand, exercise, and medication equations to the inclusion of food prices and the resulting second-stage blood pressure production parameter estimates as opposed to using nutrient shadow prices.

The reason to use these two sets of prices in estimation is to test the sensitivity of the second-stage blood pressure production function estimates to the inclusion of these two different price specifications in the first stage due to the potential measurement error problem in the shadow prices. Thus, the empirical estimation for the blood pressure production function consists of the two specifications: (a) the Cobb-Douglas blood pressure production function using food prices in the first-stage; and (b) the Cobb-Douglas blood pressure production function using nutrient shadow prices in the first stage. Each specification contains: (a) a full set of nutrient specification (ALL); (b) medical literature nutrient specification (MED); and (c) NHANES II nutrient specification (NHANES II). Within each price and nutrient specification, ordinary least squares (OLS) estimates and two-stage least squares (2SLS) estimates are presented to examine the sensitivity of effects of nutrients, exercise, and medication on blood pressure to the inclusion of prices, as well as other exogenous factors in the first stage.

The reduced-form health input demand Eqs. (6a)-(6c) show that the demand for health input depends on health endowment μ as well. Therefore the health inputs in epidemiological benchmark regression in Eq. (15) correlate with the error term which contains μ, making the underlying health production parameters inconsistent. Thus, it is crucial to examine the health endowment effect on the demand for health inputs. Although explicit measures of the health endowment are usually not available in survey data, the health endowment effect on each health input can be estimated empirically using the residuals from the consistent second-stage estimation as employed by Rosenzweig and Schultz (1983). The health endowment effect evaluates how the demand for health inputs differs due to difference in the exogenous component of health. The exogenous health endowment is a crucial determinant of the demand for health inputs (Rosenzweig & Schultz, 1983). This estimation procedure is discussed and the estimates of the endowment effects on health inputs are presented in the next section.

SECTION IV. EMPIRICAL RESULTS

The empirical results are presented in three parts in this section. Part A reports the first stage estimates of the reduced-form blood pressure input demand Eqs. (16), (17), and (18) and the reduced-form blood pressure equation using a log-linear approximation of Eq. (7). Part B reports the second stage consistent estimates of the blood pressure production parameters using Eq. (19). For comparison purposes and to simplify the discussion, the benchmark epidemiological regressions (EPID (OLS)) are also presented to allow comparison with the estimates of the health production (HPF (2SLS)) parameters. In both parts A and B, nutrient shadow prices and food prices are alternative regressors in the first-stage, reduced-form estimations. Since nutrient shadow prices are subject to potential measurement error as discussed earlier, the results are presented first in parts A and B using food prices as instruments in the first stage. Part C discusses the procedures to estimate endowment effects and presents the estimates of health endowment effects on the demand for blood pressure health inputs. Policy implications of the empirical findings using data from NHANES II are also summarized at the end of this section.

A. Estimates of the Reduced-Form Input Demand and Blood Pressure Equations

1. Food Prices

Reduced-form blood pressure input demand equations

Table 2 shows the OLS estimates of the reduced-form log-linear health input and blood pressure demand equations using food prices as identifying instruments. To capture the nonlinearity relationships between health inputs and age as well as education, preliminary OLS regressions included age-cube, age-fourth, and education-square terms as added regressors on the right-hand-side of the first stage. However, after replacing the endogenous choice variables of the blood pressure production function by the predicted values from the first stage, the statistical significance of most of the endogenous variables were insignificant as compared with the age-cube, age-fourth, and education-square terms which were not included in the first stage. Hence the first-stage results are reported in Table 2 and Table 3 using specifications in which age-cube, age-fourth, and education-square terms were not included as the right-hand-side regressors. Table 2 reports the results using food prices as identifying instruments, while Table 3 presents the results using nutrient shadow prices.

In general, food prices have no strongly significant effects on the eleven health input demand equations with few exceptions. Among the nine nutrients considered, calcium and sodium are the most responsive to food price variations. In the calcium equation, four food prices have significant effects on the intakes of calcium including price of meat, price of poultry, price of fruits and vegetables, and price of fats and oils. Price of meat and price of fats and oils appear to have significant effects on the intake of sodium as well.

Table 2. Estimates of log-linear input and blood pressure demand equation using food prices
(standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

REGRESSORS	LFAT	LCALC	LSODI	LPOTA	LCHOL	LVITC
INTERCEPT	5.73^{***}	4.57^{***}	$1.08\times10^{***}$	6.59^{***}	5.37^{***}	0.24
	(1.28)	(1.55)	(0.14×10)	(1.08)	(1.85)	(2.56)
PWHMILK	0.54×10^{-2}	9.48×10^{-2}	-4.39×10^{-2}	3.74×10^{-2}	2.81×10^{-2}	0.37×10^{-1}
	(5.75×10^{-2})	(6.99×10^{-2})	(6.19×10^{-2})	(4.87×10^{-2})	(8.32×10^{-2})	(1.15×10^{-1})
PE	0.60×10^{-2}	-2.89×10^{-2}	2.64×10^{-2}	-0.92×10^{-2}	-1.42×10^{-2}	-1.06×10^{-2}
	(1.60×10^{-2})	(1.94×10^{-2})	(1.72×10^{-2})	(1.35×10^{-2})	(2.31×10^{-2})	(3.20×10^{-2})
PSUGAR	0.15×10^{-2}	2.63×10^{-2}	-1.28×10^{-2}	1.30×10^{-2}	0.02×10^{-2}	1.62×10^{-2}
	(1.68×10^{-2})	(2.05×10^{-2})	(1.82×10^{-2})	(1.43×10^{-2})	(2.44×10^{-2})	(3.37×10^{-2})
PCOFFEE	-1.13×10^{-3}	1.86×10^{-3}	-1.78×10^{-3}	0.60×10^{-3}	-1.15×10^{-3}	2.89×10^{-3}
	(1.55×10^{-3})	(1.88×10^{-3})	(1.67×10^{-3})	(1.31×10^{-3})	(2.24×10^{-3})	(3.10×10^{-3})
PCOLA	-3.49×10^{-3}	-7.39×10^{-3}	-1.26×10^{-3}	-3.58×10^{-3}	-1.57×10^{-3}	-0.30×10^{-2}
	(5.94×10^{-3})	(7.22×10^{-3})	(6.40×10^{-3})	(5.03×10^{-3})	(8.60×10^{-3})	(1.19×10^{-2})
PMEATS	$1.00\times10^{-3**}$	$1.02\times10^{-3*}$	$1.22\times10^{-3**}$	$8.33\times10^{-4**}$	1.05×10^{-3}	1.44×10^{-3}
	(0.45×10^{-3})	(0.54×10^{-3})	(0.48×10^{-3})	(3.78×10^{-4})	(0.65×10^{-3})	(0.89×10^{-3})
PPOULTRY	0.34×10^{-2}	$-4.63\times10^{-2**}$	3.35×10^{-2}	-1.88×10^{-2}	-2.51×10^{-2}	-2.85×10^{-2}
	(1.89×10^{-2})	(2.30×10^{-2})	(2.04×10^{-2})	(1.60×10^{-2})	(2.74×10^{-2})	(3.79×10^{-2})
PFUVG	0.45×10^{-2}	$-8.71\times10^{-2**}$	5.36×10^{-2}	-3.37×10^{-2}	-2.09×10^{-2}	-3.09×10^{-2}
	(3.53×10^{-2})	(4.30×10^{-2})	(3.81×10^{-2})	(3.00×10^{-2})	(5.12×10^{-2})	(7.07×10^{-2})
PCEREALS	-2.09×10^{-2}	-4.60×10^{-2}	-0.65×10^{-2}	-2.30×10^{-2}	-0.44×10^{-2}	-0.10×10^{-1}
	(5.39×10^{-2})	(6.56×10^{-2})	(5.81×10^{-2})	(4.57×10^{-2})	(7.81×10^{-2})	(1.08×10^{-1})
PFAOL	-0.91×10^{-2}	$2.42\times10^{-2*}$	$-2.97\times10^{-2**}$	0.73×10^{-2}	1.16×10^{-2}	1.00×10^{-2}
	(1.18×10^{-2})	(1.44×10^{-2})	(1.27×10^{-2})	(1.00×10^{-2})	(1.71×10^{-2})	(2.36×10^{-2})
LNHRWAGE	3.18×10^{-2}	0.36×10^{-2}	0.56×10^{-2}	$3.40\times10^{-2*}$	4.68×10^{-2}	4.89×10^{-2}
	(2.20×10^{-2})	(2.68×10^{-2})	(2.37×10^{-2})	(1.87×10^{-2})	(3.19×10^{-2})	(4.41×10^{-2})
LNINCONE	3.38×10^{-2}	$4.48\times10^{-2*}$	$6.47\times10^{-2***}$	$4.38\times10^{-2**}$	-3.30×10^{-2}	$8.46\times10^{-2**}$
	(2.14×10^{-2})	(2.60×10^{-2})	(2.30×10^{-2})	(1.81×10^{-2})	(3.10×10^{-2})	(4.28×10^{-2})
NUMPERS	-9.94×10^{-3}	-1.72×10^{-2}	$-2.62\times10^{-2***}$	$-1.78\times10^{-2**}$	-0.40×10^{-2}	-2.80×10^{-2}
	(9.33×10^{-3})	(1.14×10^{-2})	(1.01×10^{-2})	(0.79×10^{-2})	(1.35×10^{-2})	(1.87×10^{-2})
AGE	$-1.19\times10^{-2**}$	$-2.08\times10^{-2***}$	-3.73×10^{-3}	-4.06×10^{-3}	-1.16×10^{-3}	$-2.40\times10^{-2**}$
	(0.56×10^{-2})	(0.69×10^{-2})	(6.08×10^{-3})	(4.78×10^{-3})	(8.18×10^{-3})	(1.13×10^{-2})
AGE^2	6.61×10^{-3}	$1.61\times10^{-2**}$	0.03×10^{-3}	3.52×10^{-3}	-1.68×10^{-3}	$3.47\times10^{-2***}$
	(6.40×10^{-3})	(0.78×10^{-2})	(6.89×10^{-3})	(5.42×10^{-3})	(9.26×10^{-3})	(1.28×10^{-2})
GENDER	$4.56\times10^{-1***}$	$3.74\times10^{-1***}$	$4.22\times10^{-1***}$	$3.05\times10^{-1***}$	$4.75\times10^{-1***}$	6.04×10^{-2}
	(0.33×10^{-1})	(0.40×10^{-1})	(0.35×10^{-1})	(0.28×10^{-1})	(0.47×10^{-1})	(6.54×10^{-2})
ED	$1.01\times10^{-2*}$	1.03×10^{-2}	1.91×10^{-3}	$1.53\times10^{-2***}$	-1.10×10^{-3}	$6.30\times10^{-2***}$
	(0.52×10^{-2})	(0.63×10^{-2})	(5.56×10^{-3})	(0.44×10^{-2})	(7.47×10^{-3})	(1.03×10^{-2})
R^2	0.19	0.12	0.12	0.14	0.09	0.06
ENDOWMENT[1]	0.63×10^{-1}	-1.36×10^{-1}	0.68×10^{-1}	3.85×10^{-2}	-0.10×10^{-1}	2.85×10^{-1}
	(1.13×10^{-1})	(1.31×10^{-1})	(1.17×10^{-1})	(9.25×10^{-2})	(1.53×10^{-1})	(2.09×10^{-1})

1. see p.59 for detail.

Table 2. Estimates of log-linear input and blood pressure demand equation using food prices (continued)
(standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

REGRESSORS	LRIBO	LFAAC	LOLAC	REEXER	MEDICINE	LSYS
INTERCEPT	1.11	5.11***	4.81***	2.17**	9.19×10^{-1}	5.83***
	(1.35)	(1.43)	(1.38)	(1.03)	(9.17×10^{-1})	(0.28)
PWHMILK	3.06×10^{-2}	-4.73×10^{-2}	-1.08×10^{-2}	2.80×10^{-2}	0.25×10^{-2}	$-3.17 \times 10^{-2**}$
	(6.06×10^{-2})	(6.42×10^{-2})	(6.22×10^{-2})	(4.62×10^{-2})	(4.13×10^{-2})	(1.27×10^{-2})
PE	-0.54×10^{-2}	1.85×10^{-2}	0.75×10^{-2}	0.17×10^{-2}	0.54×10^{-2}	$1.44 \times 10^{-2***}$
	(1.68×10^{-2})	(1.78×10^{-2})	(1.73×10^{-2})	(1.29×10^{-2})	(1.15×10^{-2})	(0.35×10^{-2})
PSUGAR	1.05×10^{-2}	-1.48×10^{-2}	-0.25×10^{-2}	0.54×10^{-2}	0.16×10^{-2}	$-6.12 \times 10^{-3*}$
	(1.78×10^{-2})	(1.88×10^{-2})	(1.82×10^{-2})	(1.36×10^{-2})	(1.21×10^{-2})	(3.72×10^{-3})
PCOFFEE	0.66×10^{-3}	-2.76×10^{-3}	-1.51×10^{-3}	0.34×10^{-3}	-0.07×10^{-3}	$-6.97 \times 10^{-4**}$
	(1.63×10^{-3})	(1.73×10^{-3})	(1.68×10^{-3})	(1.25×10^{-3})	(1.11×10^{-3})	(3.42×10^{-4})
PCOLA	-4.35×10^{-3}	2.08×10^{-3}	-2.11×10^{-3}	-4.09×10^{-3}	-1.31×10^{-3}	$2.34 \times 10^{-3*}$
	(6.26×10^{-3})	(6.63×10^{-3})	(6.42×10^{-3})	(4.78×10^{-3})	(4.26×10^{-3})	(1.31×10^{-3})
PMEATS	5.87×10^{-4}	$1.24 \times 10^{-3**}$	$1.06 \times 10^{-3**}$	4.52×10^{-4}	-0.47×10^{-4}	$-3.42 \times 10^{-4***}$
	(4.71×10^{-4})	(0.50×10^{-3})	(0.48×10^{-3})	(3.59×10^{-4})	(3.21×10^{-4})	(0.99×10^{-4})
PPOULTRY	-0.89×10^{-2}	1.21×10^{-2}	0.31×10^{-2}	-0.23×10^{-2}	1.10×10^{-2}	$2.15 \times 10^{-2***}$
	(1.99×10^{-2})	(2.11×10^{-2})	(2.05×10^{-2})	(1.52×10^{-2})	(1.36×10^{-2})	(0.42×10^{-2})
PFUVG	-2.04×10^{-2}	3.47×10^{-2}	1.31×10^{-2}	-1.26×10^{-2}	0.67×10^{-2}	$3.15 \times 10^{-2***}$
	(3.73×10^{-2})	(3.95×10^{-2})	(3.82×10^{-2})	(2.84×10^{-2})	(2.54×10^{-2})	(0.78×10^{-2})
PCEREALS	-2.74×10^{-2}	2.51×10^{-2}	-0.05×10^{-2}	-3.48×10^{-2}	-1.91×10^{-2}	0.25×10^{-2}
	(5.68×10^{-2})	(6.02×10^{-2})	(5.83×10^{-2})	(4.34×10^{-2})	(3.87×10^{-2})	(1.19×10^{-2})
PFAOL	-0.13×10^{-2}	-1.58×10^{-2}	-1.12×10^{-2}	-2.33×10^{-3}	-6.90×10^{-3}	$-1.27 \times 10^{-2***}$
	(1.24×10^{-2})	(1.32×10^{-2})	(1.28×10^{-2})	(9.50×10^{-3})	(8.48×10^{-3})	(0.26×10^{-2})
LNHRWAGE	1.03×10^{-2}	3.63×10^{-2}	2.46×10^{-2}	$-4.35 \times 10^{-2**}$	$-6.71 \times 10^{-2***}$	-2.41×10^{-3}
	(2.32×10^{-2})	(2.46×10^{-2})	(2.38×10^{-2})	(1.77×10^{-2})	(1.58×10^{-2})	(4.86×10^{-3})
LNINCONE	2.72×10^{-2}	2.55×10^{-2}	1.72×10^{-2}	-0.14×10^{-2}	0.97×10^{-2}	7.54×10^{-3}
	(2.25×10^{-2})	(2.39×10^{-2})	(2.31×10^{-2})	(1.72×10^{-2})	(1.54×10^{-2})	(4.72×10^{-3})
NUMPERS	-1.51×10^{-2}	-1.00×10^{-2}	-0.60×10^{-2}	-0.39×10^{-3}	$-1.39 \times 10^{-2**}$	1.42×10^{-3}
	(0.98×10^{-2})	(1.04×10^{-2})	(1.01×10^{-2})	(7.50×10^{-3})	(0.67×10^{-2})	(2.06×10^{-3})
AGE	$-2.22 \times 10^{-2***}$	$-1.24 \times 10^{-2**}$	$-1.07 \times 10^{-2*}$	2.21×10^{-3}	$1.17 \times 10^{-2***}$	-0.13×10^{-3}
	(0.59×10^{-2})	(0.63×10^{-2})	(0.61×10^{-2})	(4.54×10^{-3})	(0.41×10^{-2})	(1.25×10^{-3})
AGE^2	$2.01 \times 10^{-2***}$	6.24×10^{-3}	5.14×10^{-3}	-2.34×10^{-3}	-5.12×10^{-3}	$5.54 \times 10^{-3***}$
	(0.67×10^{-2})	(7.14×10^{-3})	(6.92×10^{-3})	(5.15×10^{-3})	(4.59×10^{-3})	(1.41×10^{-3})
GENDER	$4.04 \times 10^{-1***}$	$5.01 \times 10^{-1***}$	$4.99 \times 10^{-1***}$	$5.33 \times 10^{-2**}$	$-8.46 \times 10^{-2***}$	$4.94 \times 10^{-2***}$
	(0.34×10^{-1})	(0.37×10^{-1})	(0.35×10^{-1})	(2.63×10^{-2})	(2.35×10^{-2})	(0.72×10^{-2})
ED	$1.48 \times 10^{-2***}$	5.80×10^{-3}	7.45×10^{-3}	$2.25 \times 10^{-2***}$	3.43×10^{-3}	$-2.84 \times 10^{-3**}$
	(0.54×10^{-2})	(5.76×10^{-3})	(5.58×10^{-3})	(0.42×10^{-2})	(3.71×10^{-3})	(1.14×10^{-3})
R^2	0.13	0.18	0.18	0.03	0.12	0.34
ENDOWMENT[1]	-0.41×10^{-1}	1.07×10^{-1}	0.97×10^{-1}	$-1.72 \times 10^{-1**}$	$1.75 \times 10^{-1**}$	
	(1.14×10^{-1})	(1.25×10^{-1})	(1.21×10^{-1})	(0.83×10^{-1})	(0.78×10^{-1})	

1. see p.59 for detail.

Table 3. Estimates of log-linear input and blood pressure demand equation using nutrient shadow prices (standard errors in parentheses) (***, **, *, significant at 1%, 5%, 10% level)

REGRESSORS	LFAT	LCALC	LSODI	LPOTA	LCHOL	LVITC
INTERCEPT	3.90^{***}	6.80^{***}	6.26^{***}	6.45^{***}	6.46^{***}	1.09
	(1.01)	(1.23)	(1.09)	(0.86)	(1.47)	(2.03)
PFAT	$1.04x10^{-1}$	$-4.92x10^{-1}$	$4.65x10^{-1}$	$-0.45x10^{-1}$	$1.13x10^{-1}$	$6.90x10^{-1}$
	$(2.80x10^{-1})$	$(3.41x10^{-1})$	$(3.02x10^{-1})$	$(2.37x10^{-1})$	$(4.06x10^{-1})$	$(5.61x10^{-1})$
PCALC	-8.85	0.10x10	$-2.25x10^{**}$	-8.54	0.31x10	-2.11x10
	(8.50)	(1.03x10)	(0.92x10)	(7.21)	(1.23x10)	(1.70x10)
PSODI	$-1.03x10^{-1}$	-0.14	1.34	$5.14x10^{-1}$	-0.70	2.81
	$(9.91x10^{-1})$	(1.21)	(1.07)	$(8.40x10^{-1})$	(1.44)	(1.98)
PPOTA	1.20x10	0.57x10	$2.57x10^{*}$	1.38x10	-0.99x10	3.57x10
	(1.27x10)	(1.55x10	(1.37x10)	(1.08x10)	(1.84x10)	(2.55x10)
PCHOL	0.58x10	1.75x10	-0.04x10	$1.71x10^{*}$	-1.70x10	1.68x10
	(1.06x10)	(1.29x10)	(1.14x10)	(0.90x10)	(1.54x10)	(2.12x10)
PVITC	0.17	0.29	0.23	1.12	-0.28	2.83
	(1.15)	(1.40)	(1.24)	(0.98)	(1.67)	(2.31)
PRIBO	$-1.24x10^{-2}$	$-3.08x10^{-2}$	$-2.00x10^{-2}$	$-4.35x10^{-2}$	$-2.82x10^{-2}$	$-1.01x10^{-1}$
	$(3.54x10^{-2})$	$(4.30x10^{-2})$	$(3.81x10^{-2})$	$(3.00x10^{-2})$	$(5.12x10^{-2})$	$(0.71x10^{-1})$
PFAAC	$-1.00x10^{-1}$	$3.39x10^{-1}$	$-4.74x10^{-1*}$	$-0.19x10^{-1}$	$-0.33x10^{-1}$	$-7.62x10^{-1}$
	$(2.56x10^{-1})$	$(3.12x10^{-1})$	$(2.76x10^{-1})$	$(2.17x10^{-1})$	$(3.71x10^{-1})$	$(5.12x10^{-1})$
POLAC	$1.22x10^{-1}$	$-0.34x10^{-1}$	$3.81x10^{-1**}$	$1.32x10^{-1}$	$-0.43x10^{-1}$	$4.73x10^{-1}$
	$(1.57x10^{-1})$	$(1.91x10^{-1})$	$(1.69x10^{-1})$	$(1.33x10^{-1})$	$(2.28x10^{-1})$	$(3.14x10^{-1})$
LNHRWAGE	$3.24x10^{-2}$	$0.35x10^{-2}$	$0.65x10^{-2}$	$3.38x10^{-2*}$	$4.72x10^{-2}$	$5.08x10^{-2}$
	$(2.20x10^{-2})$	$(2.68x10^{-2})$	$(2.37x10^{-2})$	$(1.87x10^{-2})$	$(3.19x10^{-2})$	$(4.41x10^{-2})$
LNINCONE	$3.24x10^{-2}$	$4.20x10^{-2}$	$6.26x10^{-2***}$	$4.07x10^{-2**}$	$-2.99x10^{-2}$	$8.72x10^{-2**}$
	$(2.14x10^{-2})$	$(2.61x10^{-2})$	$(2.31x10^{-2})$	$(1.82x10^{-2})$	$(3.11x10^{-2})$	$(4.29x10^{-2})$
NUMPERS	$-1.16x10^{-2}$	$-1.85x10^{-2}$	$-2.86x10^{-2***}$	$-1.93x10^{-2**}$	$-0.51x10^{-2}$	$-2.92x10^{-2}$
	$(0.93x10^{-2})$	$(1.14x10^{-2})$	$(1.01x10^{-2})$	$(0.79x10^{-2})$	$(1.35x10^{-2})$	$(1.87x10^{-2})$
AGE	$-1.21x10^{-2**}$	$-2.06x10^{-2***}$	$-4.09x10^{-3}$	$-4.00x10^{-3}$	$-1.47x10^{-3}$	$-2.44x10^{-2**}$
	$(0.56x10^{-2})$	$(0.69x10^{-2})$	$(6.08x10^{-3})$	$(4.78x10^{-3})$	$(8.17x10^{-3})$	$(1.13x10^{-2})$
AGE^2	$6.77x10^{-3}$	$1.59x10^{-2**}$	$0.30x10^{-3}$	$3.39x10^{-3}$	$-1.28x10^{-3}$	$3.52x10^{-2***}$
	$(6.39x10^{-3})$	$(0.78x10^{-2})$	$(6.88x10^{-3})$	$(5.42x10^{-3})$	$(9.26x10^{-3})$	$(1.28x10^{-2})$
GENDER	$4.56x10^{-1***}$	$3.76x10^{-1***}$	$4.21x10^{-1***}$	$3.05x10^{-1***}$	$4.75x10^{-1***}$	$6.03x10^{-2}$
	$(0.33x10^{-1})$	$(0.40x10^{-1})$	$(0.35x10^{-1})$	$(0.28x10^{-1})$	$(0.47x10^{-1})$	$(6.55x10^{-2})$
ED	$1.09x10^{-2**}$	$1.11x10^{-2*}$	$3.00x10^{-3}$	$1.61x10^{-2***}$	$-0.02x10^{-3}$	$6.43x10^{-2***}$
	$(0.52x10^{-2})$	$(0.63x10^{-2})$	$(5.55x10^{-3})$	$(0.44x10^{-2})$	$(7.46x10^{-3})$	$(1.03x10^{-2})$
R^2	0.19	0.11	0.12	0.14	0.08	0.06
ENDOWMENT[1]	$0.45x10^{-1}$	$-1.46x10^{-1}$	$0.46x10^{-1}$	$2.48x10^{-2}$	$-0.36x10^{-1}$	$2.65x10^{-1}$
	$(1.12x10^{-1})$	$(1.31x10^{-1})$	$(1.16x10^{-1})$	$(9.23x10^{-2})$	$(1.53x10^{-1})$	$(2.08x10^{-1})$

1. see p.59 for detail.

Table 3. Estimates of log-linear input and blood pressure demand equation using nutrient shadow prices (continued)
(standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

REGRESSORS	LRIBO	LFAAC	LOLAC	REEXER	MEDICINE	LSYS
INTERCEPT	0.62	2.39^{**}	2.92^{***}	2.04^{**}	-2.31×10^{-1}	4.20^{***}
	(1.07)	(1.13)	(1.10)	(0.81)	(7.27×10^{-1})	(0.22)
PFAT	1.19×10^{-1}	-1.44×10^{-1}	2.83×10^{-1}	-2.33×10^{-1}	-0.17×10^{-1}	7.04×10^{-2}
	(2.95×10^{-1})	(3.13×10^{-1})	(3.03×10^{-1})	(2.25×10^{-1})	(2.01×10^{-1})	(6.20×10^{-2})
PCALC	-1.17×10	-1.18×10	-9.13	0.78	-3.22	-3.16^{*}
	(0.89×10)	(0.95×10)	(9.20)	(6.84)	(6.10)	(1.88)
PSODI	0.69	0.27	0.12	-7.07×10^{-1}	-1.42×10^{-1}	-0.22×10^{-1}
	(1.04)	(1.11)	(1.07)	(7.97×10^{-1})	(7.11×10^{-1})	(2.19×10^{-1})
PPOTA	1.85×10	1.31×10	1.60×10	-0.17×10	1.78	-1.27
	(1.34×10)	(1.42×10)	(1.38×10)	(1.02×10)	(9.13)	(2.82)
PCHOL	0.81×10	0.94×10	1.02×10	-1.47	1.54	1.59
	(1.12×10)	(1.18×10)	(1.15×10)	(8.53)	(7.62)	(2.35)
PVITC	0.43	0.58	0.42	-9.79×10^{-1}	-2.29×10^{-1}	1.32×10^{-1}
	(1.21)	(1.29)	(1.25)	(9.28×10^{-1})	(8.28×10^{-1})	(2.56×10^{-1})
PRIBO	-3.40×10^{-2}	-2.17×10^{-2}	-2.64×10^{-2}	2.02×10^{-2}	0.48×10^{-2}	1.93×10^{-3}
	(3.72×10^{-2})	(3.95×10^{-2})	(3.83×10^{-2})	(2.84×10^{-2})	(2.54×10^{-2})	(7.83×10^{-3})
PFAAC	-1.84×10^{-1}	-1.25×10^{-1}	-2.19×10^{-1}	1.51×10^{-1}	0.05×10^{-1}	-4.37×10^{-2}
	(2.69×10^{-1})	(2.86×10^{-1})	(2.77×10^{-1})	(2.06×10^{-1})	(1.84×10^{-1})	(5.67×10^{-2})
POLAC	2.08×10^{-1}	1.61×10^{-1}	1.32×10^{-1}	-0.31×10^{-1}	0.36×10^{-1}	3.46×10^{-2}
	(1.65×10^{-1})	(1.75×10^{-1})	(1.70×10^{-1})	(1.26×10^{-1})	(1.13×10^{-1})	(3.48×10^{-2})
LNHRWAGE	1.02×10^{-2}	3.73×10^{-2}	2.54×10^{-2}	$-4.30\times10^{-2**}$	$-6.74\times10^{-2***}$	-2.58×10^{-3}
	(2.32×10^{-2})	(2.46×10^{-2})	(2.38×10^{-2})	(1.77×10^{-2})	(1.58×10^{-2})	(4.88×10^{-3})
LNINCONE	2.36×10^{-2}	2.48×10^{-2}	1.74×10^{-2}	-0.17×10^{-2}	0.75×10^{-2}	6.15×10^{-3}
	(2.26×10^{-2})	(2.39×10^{-2})	(2.32×10^{-2})	(1.72×10^{-2})	(1.54×10^{-2})	(4.75×10^{-3})
NUMPERS	$-1.63\times10^{-2*}$	-1.21×10^{-2}	-0.76×10^{-2}	-0.91×10^{-3}	$-1.42\times10^{-2**}$	1.55×10^{-3}
	(0.98×10^{-2})	(1.04×10^{-2})	(1.01×10^{-2})	(7.51×10^{-3})	(0.67×10^{-2})	(2.07×10^{-3})
AGE	$-2.21\times10^{-2***}$	$-1.28\times10^{-2**}$	$-1.10\times10^{-2*}$	2.15×10^{-3}	$1.18\times10^{-2***}$	-0.09×10^{-3}
	(0.59×10^{-2})	(0.63×10^{-2})	(0.61×10^{-2})	(4.54×10^{-3})	(0.40×10^{-2})	(1.25×10^{-3})
AGE^2	$1.99\times10^{-2***}$	6.62×10^{-3}	5.47×10^{-3}	-2.30×10^{-3}	-5.26×10^{-3}	$5.46\times10^{-3***}$
	(0.67×10^{-2})	(7.14×10^{-3})	(6.92×10^{-3})	(5.14×10^{-3})	(4.59×10^{-3})	(1.42×10^{-3})
GENDER	$4.05\times10^{-1***}$	$5.01\times10^{-1***}$	$4.99\times10^{-1***}$	$5.34\times10^{-2**}$	$-8.46\times10^{-2***}$	$4.89\times10^{-2***}$
	(0.34×10^{-1})	(0.37×10^{-1})	(0.35×10^{-1})	(2.63×10^{-2})	(2.35×10^{-2})	(0.72×10^{-2})
ED	$1.51\times10^{-2***}$	6.93×10^{-3}	8.52×10^{-3}	$2.27\times10^{-2***}$	3.36×10^{-3}	$-3.08\times10^{-3***}$
	(0.54×10^{-2})	(5.75×10^{-3})	(5.58×10^{-3})	(0.41×10^{-2})	(3.70×10^{-3})	(1.14×10^{-3})
R^2	0.13	0.18	0.18	0.03	0.12	0.33
ENDOWMENT[1]	-0.47×10^{-1}	0.86×10^{-1}	0.75×10^{-1}	$-1.78\times10^{-1**}$	$1.78\times10^{-1**}$	
	(1.14×10^{-1})	(1.25×10^{-1})	(1.21×10^{-1})	(0.82×10^{-1})	(0.77×10^{-1})	

1. see p.59 for detail.

Except for potassium, wage appears to have no significant effect on the nutrient demand equations. This suggests that wages are not significant determinants of nutrients. Although the magnitudes are small, income elasticities of nutrients are significantly positive on four nutrients: calcium, sodium, potassium, and vitamin C. Since persons with low income were oversampled in NHANES II, the government income support programs to the low income group may have potential effects of improving nutrient consumption in that group. A good discussion of the effectiveness of consumer-oriented food subsidies in reaching income transfer goals is contained in Pinstrup-Andersen and Alderman (1988). The number of persons in the household reduces nutrient intake in general, but only significantly in sodium and potassium. Adding the square term of age captures the nonlinear effects of age on the demand for health inputs and allows for an examination of the curvature of age effect on health inputs. Of the nine nutrients, age appears to have nonlinear effects on the demands for calcium, vitamin C, and riboflavin. For the remainder of the nutrients, nonlinear effects are not significant. Men were found to consume more nutrients than women across all nutrient equations with the exception of the vitamin C equation.

Some findings from the exercise and medicine equations are worth discussing. None of the food prices had significant effects on the exercise and medicine equations. Wages, in contrast to nutrient equations, appear to have significantly negative effects on exercise and medication. Wage represents an opportunity cost of time. Labor supply curve slopes upward. Higher wages implies individuals have incentives to devote more time to work and, hence, less time is available for exercise. The nonlinear effects of age on exercise and medication equations are not statistically significant. Men tend to exercise more than women, and more educated individuals exercise more as compared with less educated individuals. Household composition affects individual member's medication demand. There is an inverse relationship between the number of persons in a household and medication demand by individuals. An increase in the number of persons results in less medication per person. Women take medicine more regularly as compared with men.

Consistent with the results reported by Strauss and Thomas (1994), the R^2's are not large in these first-stage health input demand regressions. There is considerable heterogeneity in the survey data, and particularly in these kinds of health input indicators. Rosenzweig and Schultz (1983) also claimed that inferences from nonexperimental data on health technology and the value of health inputs may be misleading if these inferences do not take into account the interdependence of the levels of health inputs and the preference orderings that occur because of exogenous health heterogeneity. In the empirical findings in the present study, the R^2's of the reduced form health input regressions for cholesterol, vitamin C, and exercise are 0.09, 0.06, and 0.03. This suggests exogenous health heterogeneity should be considered when estimating health production parameters.

Reduced-form blood pressure health equation

The last column of Table 2 presents the estimates of the reduced-form blood pressure equation which is the log-linear approximation of Eq. (7). The findings of food price effects on blood pressure are quite remarkable. Except for the price of cereals, all food prices appear to have statistically significant effects upon blood pressure. Price of whole milk, price of sugar, price of coffee, price of meat, and price of fats of oils have significantly negative effects on blood pressure, whereas price of eggs, price of cola, price of poultry, and price of fruits and vegetables have significantly positive effects on blood pressure. A negative food price effect upon blood pressure indicates that an increase in the price of the food will reduce blood pressure. Similarly, a positive food price effect on blood pressure implies that an increase in food price will increase blood pressure. At the sample means, a 10% increase in the prices of whole milk, sugar, coffee, meat, and fats and oils reduces the systolic blood pressure by 24%, 6.6%, 1.9%, 1.9%, and 23%. A similar percentage reduction in the prices of eggs, cola, poultry, and fruits and vegetables reduces the systolic blood pressure by 11%, 3.3%, 13%, and 17%. These results show that fluctuations in food prices significantly affect blood pressure.

Fluctuations in food prices may have potential effects in changing dietary patterns which in turn have potential effects of changing nutritional intakes due to different contents of nutrients contained in different foods. For example, milk is rich in calcium, while fruits and vegetables contain vitamin C. Egg yolk is high in cholesterol, while fats and oils contain fat and saturated fatty acid. Fluctuations in food prices have effects of changing food consumption patterns and, therefore, result in different combinations of nutrient intakes from those foods. Williamson-Gray (1982) found that subsidies on wheat bread in Brazil, which reduced the price of wheat bread, slightly reduced the calorie consumption since the increased bread consumption was offset by decreases in rice and other foods.

The price-induced changes in nutrient consumption are weighted by direct nutrient effects on health to derive food price effects on health. Hence, governmental food price-setting policies, through taxation or subsidization mechanisms, may serve as direct or indirect mechanisms to control blood pressure of the population. Empirical findings in the present study suggest that a tax levied on the price of whole milk, price of sugar, price of coffee, price of meat, or price of fats and oils, which increases the corresponding food prices, will lower the blood pressure of the population. Accordingly, a subsidy imposed on the price of eggs, price of cola, price of poultry, or price of fruits and vegetables, which decreases the respective food prices, will lower blood pressure. As discussed in his preface, Pinstrup-Andersen (1988a) addressed that one important goal of (consumer-oriented) food subsidy programs and policies is to reduce or eliminate calorie and nutrient deficiencies in low-income population groups. Hence, the increased nutrient consumption accompanied with the nutrient effects on health can be used to derive important policy implication concerning food price intentions to improve health. Thus, policy instruments, taxation and subsidization, which serve as mechanisms to alter food prices, have important implications for food price interventions to improve health of the population.

Other findings from the reduced-form blood pressure equation include the following. The linear age effect on blood pressure is insignificant while the squared term is strongly significant. This indicates blood pressure increases slowly in younger ages while it increases steeply in older ages. Males and less educated have higher blood pressure as shown in this reduced-form blood pressure equation. More education lowers blood pressure. Discussion of the endowment effects on the demand for health inputs reported in the bottom row of Tables 2 and 3 follows the presentation of the second stage results.

Taken together, joint significance tests of food prices and wages in the reduced-form health input and health equations show that the regression coefficients for food prices and wages were jointly different from zero at the 10 percent level with the exception of the cholesterol equation. This suggests that although food prices and wages are not significant determinants in the health input demand equations individually, they are jointly important factors in determining consumption demands for health inputs.

2. Shadow Prices

Reduced-form blood pressure input demand equations

Table 3 presents OLS estimates of the log-linear health input and blood pressure demand equations using nutrient shadow prices as identifying instruments. In general, nutrient shadow prices have no significant effects on the reduced-form health inputs and blood pressure demand equations. The only exception is the equation for sodium intake in which price of calcium and price of saturated fatty acid have negative effects on sodium intake, while price of potassium and price of oleic acid have positive effects. Wage appears to have no significant effects on nutrient health inputs except for the potassium equation in which the nutrient wage elasticity is positive. Income elasticities on the sodium, potassium, and vitamin C equations are positive and significant. Again, income support programs may have effects of increasing nutrient consumption. Nonlinear effects of age were found significant in the calcium, vitamin C, and riboflavin equations. Across all nutrient demand equations except vitamin C, men were also found to have more nutrient consumption than women. Education increases nutrient consumption.

Similar to findings with the previous first stage estimates using food prices as identifying instruments, wage appears to have significantly negative effects on the reduced-form exercise and medicine equations. Males and individuals with higher education tend to exercise more, while females appear to take medicine more regularly.

Reduced-form blood pressure health equation

Unlike the reduced-form using food prices, most shadow nutrient price effects in the reduced-form blood pressure equation are insignificant. The exception is the shadow price of calcium. At the sample mean, a 10% increase in the shadow price of calcium reduces the systolic blood pressure by 22%. The positive effect of male gender and the negative effect of education on blood pressure are similar to findings in the previous reduced-form regressions using food price specification.

B. Estimates of Blood Pressure Health Production Function

1. Food Prices

Table 4 shows the estimates for the three nutrient specifications of the health production relating behavioral inputs to blood pressure using food prices, while Table 5 presents the results using nutrient shadow prices. Note that the first column in Tables 4 and 5

Table 4. Estimates of household production functions for blood pressure:
Cobb-Douglas specification using food prices
(standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

	ALL		MED		NHANES II		Predicted
Covariates	EPID(OLS)	HPF(2SLS)	EPID(OLS)	HPF(2SLS)	EPID(OLS)	HPF(2SLS)	Sign
INTERCEPT	6.18^{***}	$1.04\times10^{***}$	6.15^{***}	7.00^{***}	6.10^{***}	6.16^{***}	
	(0.23)	(0.08×10)	(0.23)	(0.60)	(0.22)	(0.30)	
FAT	-1.83×10^{-2}	2.00×10^{-1}	9.53×10^{-3}	0.89×10^{-1}			+
	(2.00×10^{-2})	(2.87×10^{-1})	(8.24×10^{-3})	(1.44×10^{-1})			
CALCIUM	$-1.98\times10^{-2***}$	$-5.03\times10^{-1***}$	$-1.60\times10^{-2***}$	$-4.91\times10^{-1***}$			-
	(0.74×10^{-2})	(1.13×10^{-1})	(0.60×10^{-2})	(0.93×10^{-1})			
SODIUM	7.29×10^{-3}	$-3.60\times10^{-1***}$	4.94×10^{-3}	$-1.45\times10^{-1**}$			-/+
	(6.49×10^{-3})	(0.80×10^{-1})	(6.39×10^{-3})	(0.70×10^{-1})			
POTASSIUM	5.38×10^{-3}	1.28×10^{-1}	4.73×10^{-3}	$6.00\times10^{-1***}$			-
	(9.84×10^{-3})	(2.32×10^{-1})	(9.73×10^{-3})	(2.02×10^{-1})			
CHOLESTEROL	-5.03×10^{-3}	$-2.55\times10^{-1***}$	-2.84×10^{-3}	$-1.18\times10^{-1**}$			+
	(4.95×10^{-3})	(0.61×10^{-1})	(4.65×10^{-3})	(0.53×10^{-1})			
VITAMIN C	3.73×10^{-3}	1.94×10^{-2}	3.41×10^{-3}	-4.34×10^{-2}	3.80×10^{-3}	-0.00×10^{-2}	-
	(2.98×10^{-3})	(4.59×10^{-2})	(2.97×10^{-3})	(3.94×10^{-2})	(2.64×10^{-3})	(1.95×10^{-2})	
RIBOFLAVIN	3.00×10^{-3}	$3.53\times10^{-1***}$			$-1.07\times10^{-2*}$	$-1.52\times10^{-1*}$	-/+
	(8.25×10^{-3})	(1.24×10^{-1})			(0.61×10^{-2})	(0.83×10^{-1})	
FATTY ACID	$2.95\times10^{-2**}$	$8.94\times10^{-1***}$			1.31×10^{-2}	$4.58\times10^{-1***}$	-/+
	(1.47×10^{-2})	(2.07×10^{-1})			(1.28×10^{-2})	(1.23×10^{-1})	
OLEIC ACID	-0.22×10^{-2}	$-6.79\times10^{-1***}$			-0.43×10^{-2}	$-3.83\times10^{-1***}$	-/+
	(1.72×10^{-2})	(1.76×10^{-1})			(1.30×10^{-2})	(1.24×10^{-1})	
EXERCISE	$-1.29\times10^{-2**}$	$-1.78\times10^{-1*}$	$-1.32\times10^{-2**}$	-3.20×10^{-2}	$-1.30\times10^{-2**}$	-9.31×10^{-2}	-
	(0.63×10^{-2})	(0.96×10^{-1})	(0.63×10^{-2})	(9.12×10^{-2})	(0.63×10^{-2})	(7.82×10^{-2})	
MEDICINE	$1.75\times10^{-2**}$	$3.66\times10^{-1***}$	$1.70\times10^{-2**}$	$2.85\times10^{-1***}$	$1.77\times10^{-2**}$	$2.12\times10^{-1***}$	+
	(0.71×10^{-2})	(0.96×10^{-1})	(0.70×10^{-2})	(0.89×10^{-1})	(0.71×10^{-2})	(0.81×10^{-1})	
AGE	$-8.97\times10^{-1***}$	$-4.55\times10^{-1*}$	$-9.00\times10^{-1***}$	-1.18^{***}	$-8.95\times10^{-1***}$	$-9.64\times10^{-1***}$	-
	(1.28×10^{-1})	(2.70×10^{-1})	(1.27×10^{-1})	(0.24)	(1.27×10^{-1})	(1.76×10^{-1})	
AGE^2	$1.48\times10^{-1***}$	$7.17\times10^{-2**}$	$1.49\times10^{-1***}$	$1.62\times10^{-1***}$	$1.48\times10^{-1***}$	$1.50\times10^{-1***}$	+
	(0.18×10^{-1})	(3.65×10^{-2})	(0.18×10^{-1})	(0.33×10^{-1})	(0.18×10^{-1})	(0.26×10^{-1})	
GENDER	$5.04\times10^{-2***}$	$1.68\times10^{-1***}$	$5.14\times10^{-2***}$	$1.58\times10^{-1***}$	$5.20\times10^{-2***}$	$9.94\times10^{-2***}$	+
	(0.69×10^{-2})	(0.33×10^{-1})	(0.68×10^{-2})	(0.29×10^{-1})	(0.68×10^{-2})	(2.21×10^{-2})	
EDUCATION	$-2.48\times10^{-2***}$	$-3.44\times10^{-2*}$	$-2.53\times10^{-2***}$	$-3.71\times10^{-2**}$	$-2.39\times10^{-2***}$	0.71×10^{-2}	-
	(0.92×10^{-2})	(1.87×10^{-2})	(0.92×10^{-2})	(1.86×10^{-2})	(0.91×10^{-2})	(1.68×10^{-2})	
R^2	0.31	0.33	0.31	0.32	0.31	0.31	

Table 5. Estimates of household production functions for blood pressure:
Cobb-Douglas specification using nutrient shadow prices
(standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

Covariates	ALL EPID(OLS)	ALL HPF(2SLS)	MED EPID(OLS)	MED HPF(2SLS)	NHANES II EPID(OLS)	NHANES II HPF(2SLS)	Predicted Sign
INTERCEPT	6.18***	1.23×10***	6.15***	7.49***	6.10***	6.77***	
	(0.23)	(0.13×10)	(0.23)	(0.77)	(0.22)	(0.36)	
FAT	-1.83×10^{-2}	2.54×10^{-1}	9.53×10^{-3}	2.12×10^{-1}			+
	(2.00×10^{-2})	(4.81×10^{-1})	(8.24×10^{-3})	(1.67×10^{-1})			
CALCIUM	-1.98×10^{-2}***	-5.04×10^{-1}*	-1.60×10^{-2}***	-4.14×10^{-1}***			-
	(0.74×10^{-2})	(2.73×10^{-1})	(0.60×10^{-2})	(1.09×10^{-1})			
SODIUM	7.29×10^{-3}	-4.67×10^{-1}***	4.94×10^{-3}	-2.59×10^{-1}**			-/+
	(6.49×10^{-3})	(1.32×10^{-1})	(6.39×10^{-3})	(1.07×10^{-1})			
POTASSIUM	5.38×10^{-3}	-1.11×10^{-1}	4.73×10^{-3}	4.62×10^{-1}*			-
	(9.84×10^{-3})	(3.56×10^{-1})	(9.73×10^{-3})	(2.64×10^{-1})			
CHOLESTEROL	-5.03×10^{-3}	-3.55×10^{-1}***	-2.84×10^{-3}	-1.18×10^{-1}			+
	(4.95×10^{-3})	(1.12×10^{-1})	(4.65×10^{-3})	(0.99×10^{-1})			
VITAMIN C	3.73×10^{-3}	5.02×10^{-2}	3.41×10^{-3}	-0.02×10^{-2}	3.80×10^{-3}	-6.87×10^{-2}**	-
	(2.98×10^{-3})	(8.24×10^{-2})	(2.97×10^{-3})	(4.66×10^{-2})	(2.64×10^{-3})	(2.91×10^{-2})	
RIBOFLAVIN	3.00×10^{-3}	4.26×10^{-1}			-1.07×10^{-2}*	1.43×10^{-1}	-/+
	(8.25×10^{-3})	(3.00×10^{-1})			(0.61×10^{-2})	(1.27×10^{-1})	
FATTY ACID	2.95×10^{-2}**	1.15***			1.31×10^{-2}	5.65×10^{-1}**	-/+
	(1.47×10^{-2})	(0.40)			(1.28×10^{-2})	(2.87×10^{-1})	
OLEIC ACID	-0.22×10^{-2}	-7.73×10^{-1}***			-0.43×10^{-2}	-7.73×10^{-1}***	-/+
	(1.72×10^{-2})	(2.45×10^{-1})			(1.30×10^{-2})	(2.85×10^{-1})	
EXERCISE	-1.29×10^{-2}**	-2.99×10^{-1}*	-1.32×10^{-2}**	-1.55×10^{-1}	-1.30×10^{-2}**	2.08×10^{-1}**	-
	(0.63×10^{-2})	(1.71×10^{-1})	(0.63×10^{-2})	(1.19×10^{-1})	(0.63×10^{-2})	(1.02×10^{-1})	
MEDICINE	1.75×10^{-2}**	4.05×10^{-1}***	1.70×10^{-2}**	3.33×10^{-1}***	1.77×10^{-2}**	-1.32×10^{-1}	+
	(0.71×10^{-2})	(1.23×10^{-1})	(0.70×10^{-2})	(1.02×10^{-1})	(0.71×10^{-2})	(0.98×10^{-1})	
AGE	-8.97×10^{-1}***	-1.71×10^{-1}	-9.00×10^{-1}***	-9.42×10^{-1}***	-8.95×10^{-1}***	-9.69×10^{-1}***	-
	(1.28×10^{-1})	(3.07×10^{-1})	(1.27×10^{-1})	(2.59×10^{-1})	(1.27×10^{-1})	(1.97×10^{-1})	
AGE^2	1.48×10^{-1}***	3.53×10^{-2}	1.49×10^{-1}***	1.31×10^{-1}***	1.48×10^{-1}***	1.66×10^{-1}***	+
	(0.18×10^{-1})	(4.65×10^{-2})	(0.18×10^{-1})	(0.36×10^{-1})	(0.18×10^{-1})	(0.28×10^{-1})	
GENDER	5.04×10^{-2}***	2.09×10^{-1}***	5.14×10^{-2}***	1.70×10^{-1}***	5.20×10^{-2}***	7.86×10^{-2}***	+
	(0.69×10^{-2})	(0.79×10^{-1})	(0.68×10^{-2})	(0.63×10^{-1})	(0.68×10^{-2})	(2.78×10^{-2})	
EDUCATION	-2.48×10^{-2}***	-1.51×10^{-2}	-2.53×10^{-2}***	-3.48×10^{-2}*	-2.39×10^{-2}***	-1.89×10^{-2}	-
	(0.92×10^{-2})	(2.17×10^{-2})	(0.92×10^{-2})	(2.01×10^{-2})	(0.91×10^{-2})	(2.11×10^{-2})	
R^2	0.31	0.33	0.31	0.32	0.31	0.31	

lists the covariates used in the blood pressure production function with every covariate in natural logarithm except for the exercise, medicine, and gender variables since these three measures are dummy variables. The last column describes the ex-ante expected sign of the effect of the respective covariate on blood pressure. These expected signs were obtained from previous studies. When both positive and negative predicted signs are indicated, mixed effects were also found in previous studies. For example, Bursztyn (1987) found that salt elevated blood pressure, whereas McCarron et al. (1983, 1984) concluded that a higher intake of sodium is associated with lower mean systolic blood pressure and lower absolute risk of hypertension. Exhibit 1 reports F tests between different nutrient specifications, while Exhibit 2 presents Hausman tests for exogeneity of health inputs in the blood pressure production function.[1]

For comparative purposes, the EPID (OLS) estimates are also listed for each nutrient specification. Comparisons of both the EPID and HPF residuals across the full and the reduced subset of nutrient specifications indicate that the additional nutrients embodied in the full nutrient specification are jointly statistically significant at the one percent level in the HPF estimation but not in the EPID specification. The F values for blood pressure computed from the EPID residuals between full and medical nutrient specifications, and between full and NHANES II nutrient specification are 1.56 and 1.8, respectively, whereas the critical value at the one percent level are 3.78 and 3.02, respectively; while the F values computed from the HPF residuals are 12.67 and 12.61, respectively (Exhibit 1). To test the exogeneity of the nutrients, exercise, and medical care in the blood pressure production function

Exhibit 1. Joint significance tests of additional nutrients employed in the full nutrient specification

I. Food Prices:

1. Between full set and medical literature subset specifications (EPID (OLS)):
   $F=1.56 \sim F(3,1966)$

2. Between full set and NHANES II subset specifications (EPID (OLS)):
   $F=1.80 \sim F(5, 1966)$

3. Between full set and medical literature subset specifications (HPF (2SLS)):
   $F=12.67^{***} \sim F(3, 1966)$

4. Between full set and NHANES II subset specifications (HPF (2SLS)):
   $F=12.61^{***} \sim F(5,1966)$

II. Shadow Prices:

1. Between full set and medical literature subset specifications (EPID (OLS)):
   $F=1.56 \sim F(3,1966)$

2. Between full set and NHANES II subset specifications (EPID (OLS)):
   $F=1.80 \sim F(5,1966)$

3. Between full set and medical literature subset specifications (HPF (2SLS)):
   $F=13.62^{***} \sim F(3,1966)$

4. Between full set and NHANES II subset specifications (HPF (2SLS)):
   $F=12.46^{***} \sim F(5,1966)$

*** denotes significance at the 0.01 level.

Exhibit 2. Hausman tests for exogeneity of health inputs in blood pressure production function

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I. Food Prices:

1. All nutrient specification:
   $F=7.36^{***} \sim F(11,1955)$

2. Medical nutrient specification:
   $F=5.42^{***} \sim F(8,1961)$

3. NHANES II nutrient specification:
   $F=3.31^{***} \sim F(6,1965)$

II. Shadow Prices:

1. All nutrient specification:
   $F=6.39^{***} \sim F(11,1955)$

2. Medical nutrient specification:
   $F=3.90^{***} \sim F(8,1961)$

3. NHANES II nutrient specification:
   $F=2.18^{**} \sim F(6,1965)$

** and *** denote significance at the 0.05 and 0.01 level, respectively.

embedded in Eq. (2), Hausman's exogeneity test (see Maddala, 1992) was conducted.[1] The test statistics reported in part I of Exhibit 2 imply that, at the one percent significance level, the health inputs considered in this study cannot be treated as exogenous variables in the blood pressure production technology. The health inputs, including nutrients, exercise, and medication, are themselves behavioral choice variables in the blood pressure production function. The results from the exogeneity tests of the health inputs support the choice to use the two stage procedure.

A comparison of the EPID and the consistent HPF Cobb-Douglas blood pressure results using food prices indicates that neglect of the endogeneity of health inputs and the heterogeneity of the exogenous health endowment can affect the inferences drawn from estimates of the effects of self-selected health inputs on blood pressure. When examining the "ALL" nutrient specification (col. 2 and 3 in Table 4), calcium has about twenty-five times as large a beneficial effect on blood pressure according to the HPF point estimates than indicated by the EPID point estimates. The effects of calcium on blood pressure are robust according to both EPID and HPF estimation techniques, and they are statistically significant using either procedure.

Sodium appears to have no significant effect on blood pressure according to the EPID estimate which supports the findings by Harlan et al. (1984) using NHANES-I data. HPF estimate in this study indicates a significantly negative effect of sodium on blood pressure. Although most epidemiological studies may find that sodium (or salt) consumption increases blood pressure (e.g., Bennett & Cameron, 1984; Bursztyn, 1987), the present empirical HPF estimate of sodium shows a negative effect on blood pressure which supports the findings by McCarron et al. (1983, 1984) using the HANES-I (Health and Nutrition Examination Survey, I) data. Using a sample of normal blood pressure individuals, Sullivan et al. (1980) found that after the subjects had followed a high sodium diet, mean blood pressure fell 3.9%. In analyzing the effect of weight loss on the sensitivity of blood pressure to sodium in obese adolescents, Rocchini et al. (1989) also found the mean blood pressure of the nonobese group had significantly increased ($p < 0.001$) when they were changed from a high-salt to a low salt diet. As addressed by Weinberger et al. (1986), although considerable epidemiologic evidence linking sodium to blood pressure (Dahl, 1975), controversy regarding the role of sodium in hypertension still remains (Simpson, 1979). In controlled trails of the effect of changes in salt intake on blood pressure of healthy individuals conducted by Kirkendall et al. (1976) and Burstyn et al. (1980), salt intake was found to be inversely related to blood pressure. However, Wassertheil-Smoller and Lamport (1990) readdressed the conclusions by McCarron et al. (1983, 1984) and concluded that the evidence for the role of sodium on hypertension, both from cross-sectional and longitudinal studies is mixed. Therefore, the finding of strong negative effect of sodium on blood pressure in the present is supported by several prior observational and experimental studies.

The finding of sodium's effect on blood pressure according to EPID and HPF supports the claim that epidemiological studies of the associations between nutrients and blood pressure may not be correctly estimated. The HPF approach, which takes food prices into account in estimating the demand for nutrients, allows one to estimate consistent parameters of the relationships between blood pressure and nutrients. Riboflavin appears to have no appreciable effect on blood pressure according to the EPID estimates, whereas the HPF estimates suggest a statistically significant effect of riboflavin that is almost one hundred and twenty times the EPID point estimate. Saturated fatty acid has a significantly positive effect on blood pressure at five percent level of significance according to the EPID estimate, while the HPF estimate suggests an even greater significantly positive effect on blood pressure with the point estimate thirty times the EPID estimate. Oleic acid is insignificant according to the EPID, whereas it indicates a significantly beneficial effect on blood pressure according to the HPF. Exercise appears to have a significantly negative effect on blood pressure for both EPID and HPF estimation.

These results can be interpreted as more exercise is good for reducing systolic blood pressure and the result is robust whether the endogeneity concern is taken into account in the blood pressure production function. The HPF point estimate for exercise is almost fourteen times the EPID estimate. Medication has a significantly positive effect on blood pressure according to both EPID and HPF estimates. This indicates that if a person is taking medicine regularly, then he/she tends to have higher blood pressure as compared to those persons who do not take medicine regularly. The effects of exercise and medicine on blood pressure conform to this study's prior ex-ante expectations.

In terms of the exogenous variables, both of the AGE and AGE^2 terms are significant across all three nutrient specifications and two estimation techniques. This suggests the robust result that age has a U-shaped effect on blood pressure with the minimum occurring at early ages. According to the second-stage estimates of age and age-squared terms in the "ALL" nutrient specification, an increase in an individual's age first has a negative effect, but there is an increasing marginal effect on blood pressure. The minimum occurs at the age of 24 and increases thereafter. Older individuals have higher blood pressure than younger people. Males tend to have higher blood pressure than females for both EPID and HPF procedures and across all three nutrient specifications. Higher educated persons have lower blood pressure. This result is supported for both EPID and HPF procedures and across all three nutrient specifications with the exception of the HPF estimate in the NHANES II nutrient specification.

As shown in the medical literature and the NHANES II nutrient specifications (Table 4, col. 4, 5, 6, and 7), the findings are consistent with the "ALL" nutrient specification findings. Among the reduced subset of nutrient specifications considered, calcium, sodium, and oleic acid appear to have significantly negative effects on blood pressure, whereas saturated fatty acid has strongly positive effect on blood pressure in the second stage. As compared to the "ALL" nutrient specification, the one exception is the significantly negative effect of riboflavin on blood pressure at the ten percent level obtained in the second stage using the NHANES II nutrient specification. Exercise significantly reduces blood pressure only in the EPID estimation but not in the HPF stage. The insignificance of exercise in the HPF estimation may be due to the strong effects of other endogenous variables. Medication continues to have strong, positive effects on blood pressure in both EPID and HPF stages. The positive effect of medicine on blood pressure is robust according to both estimation techniques.

Taken together, the results obtained from the Cobb-Douglas blood pressure health production technology using food prices supports the intention to use the two-stage estimation procedure to capture the underlying health production technology parameters in the present study. The differences in terms of signs and significance between the EPID and HPF estimates of the health production parameters indicate the existence of endogeneity and measurement error problems associated with the health inputs. Among the eleven endogenous choice variables (nine nutrients plus exercise and medicine) specified in the "ALL" nutrient specification, seven have statistically significant (i.e., at least a ten percent level of significance) effects on blood pressure with the signs matching the prior ex-ante expectations. Similarly, among the six endogenous choices in the NHANES II specification, four covariates have significant effects on blood pressure. From the empirical findings, the "ALL" and NHANES II nutrient subsets are the best nutrient specifications of the health production technology embodied in health production Eq. (2).

2. Shadow Prices

Table 5 presents the empirical results of estimates of blood pressure production function using nutrient shadow prices in the first-stage. Similar findings were obtained using nutrient shadow prices instead of food prices in the first-stage. Comparisons of the HPF residuals between the "ALL" and reduced subsets of nutrient specifications, again, indicate that the additional nutrients considered in the "ALL" nutrient specification are jointly statistically significant. The F values computed from the HPF residuals are 13.62 and 12.46, respectively, for comparisons between full and medical literature nutrient specifications and full and NHANES II nutrient specifications (Exhibit 1). Hausman's exogeneity tests (Exhibit 2, part II) show that, at the five percent level of significance, health inputs cannot be treated as exogenous variables in the health production function. This confirms the intention to use the two-stage procedure to estimate consistent health production parameters in the present study. Calcium, sodium, saturated fatty acid, oleic acid, exercise, and medicine appear to have significant effects on blood pressure in the second-stage estimation (Table 5, col. 3) with the effects of calcium, saturated fatty acid, exercise, and medicine robust to both OLS and 2SLS estimation techniques. Across all three nutrient specifications, men still appear to have higher blood pressure than women. As compared to the previous specification using food prices in the first stage, the different findings of the effects of age, age squared, and education on blood pressure appear to be insignificant in the second stage in the full nutrient specification. The other different result is that the exercise effect on blood pressure is positive and significant at five percent level in the second-stage estimate of NHANES II specification (Table 5, col. 7).

However, in general, in comparisons between EPID and HPF regression results using either food prices or nutrient shadow prices in the reduced-form first stage estimations, the results using NHANES II data suggest that using two-stage procedure corrects the endogeneity and measurement error problems associated with the health inputs in the health production technology. In the present theoretical analysis, empirical results support that the nutrients, exercise, and medication are not exogenous in the presence of the health production function (Eq. 2). Hence, the epidemiological EPID regression estimates using Eq. (15) are inconsistent. Consistent estimates of the underlying health production parameters can be obtained by using the two-stage least squares procedure.

In general, since nutrient shadow prices are potentially subject to measurement error, food prices seem to be better instruments to identify the reduced-form input demand and health equations. Empirical results of the reduced-form health input equations using food prices perform slightly better than the ones using shadow prices. Furthermore, food prices have significant effects on the reduced-form blood pressure equation whereas nutrient shadow prices do not. The general insignificance of the shadow price effects on the reduced-form equations may be due to less variations of the shadow prices according to the small standard deviations of the shadow prices shown in Table 1. Moreover, shadow prices are unobserved directly but only implied in nutrient Eq. (3). From the policy perspective, manipulating food prices to improve health is easier than controlling for nutrient shadow prices since the shadow prices are unobserved.

C. Estimates of the Blood Pressure Health Endowment Effect

As discussed earlier, the exogenous health endowment μ embodied in health production technology (Eq. 2), which was not observed by the researcher, but, nevertheless, is perceived by the individual decision maker and has an important interpretation in the demand for health inputs. The effects of health endowment on health inputs affect the estimates of the health production parameters in the benchmark epidemiological regression of Eq. (15) because the health inputs are correlated with the error term which contains μ. Therefore, examining health endowment effect on the demand for health inputs is crucial for detecting the presence of health heterogeneity in the health production technology.

As discussed in Rosenzweig and Schultz (1983), the health endowment effect can be estimated using the two-stage least squares procedure to estimate the health production parameters. This is done as follows. Provided the health production function (Eq. 2) includes all significant health inputs, exogenous health endowment, and an error component that is assumed to be orthogonal to the choices of health input behaviors, as expressed in Eq. (19), the blood pressure health endowment effect can be empirically estimated. This was done using the residuals from the 2SLS blood pressure production function estimates (Eq. 19). The residuals are the blood pressure endowments. Regressing each of the blood pressure health inputs chosen by the individual on the 2SLS blood pressure residuals from Eq. (19) provides estimates of the effects of the blood pressure health endowment on health input demand behavior. The reason to regress each of the health inputs on initial health endowment is to examine the endowment effect on each of the health inputs. This will show the relationship between health input demand and exogenous health endowment. These endowment effect estimates are reported for each blood pressure input in the bottom row of Table 2 and Table 3. The significance level of the endowment effect is included. This endowment effect examines whether the initial health endowment has a significant effect on the demand for health inputs.

In general, the blood pressure health endowment effects for input demands of nutrients are insignificant. This indicates that the behavior of nutrient input demands does not depend significantly on blood pressure health endowment. However, different findings are observed for the blood pressure health endowment effects on exercise and medicine. For exercise, the estimate of the blood pressure health endowment effect is significantly negative at the five percent level. This shows that individuals with a higher blood pressure endowment were found to exercise less. Conversely, individuals with a lower blood pressure endowment were found to exercise more. The blood pressure health endowment effect on medicine is strongly positive. By the same argument, individuals with a higher blood pressure endowment tend to take medicine more regularly, while individuals with a lower blood pressure endowment tend to take medicine less regularly.

Although the blood pressure health endowment effect is not statistically significant in explaining the demand for nutrients, the findings of its effect on the demand for exercise and medication are quite striking. The correct signs of the blood pressure endowment effects on exercise and medicine suggest that the blood pressure health endowment is a determining factor for exercise and medicine taking demand equations; even though it is not observed by the researchers it is known to the individuals themselves. The low R^2's associated with the exercise and medication equations, 0.03 and 0.12, respectively, are also evidence of the presence of exogenous health heterogeneity (Strauss & Thomas, 1994). Neglect of the health endowment in health production technology yields misleading results concerning the reduced-form health input demand equations and hence the resulting reduced-form health equation. Exogenous variations in health endowment are termed "heterogeneity" (Rosenzweig & Schultz, 1983; Strauss & Thomas, 1994). The findings of significant effects of the health endowment on exercise and medication indicate that population heterogeneity biases estimates of the health production parameters. Health studies based on estimating the demand for health inputs and health production parameters need to consider the effect of health endowment even though it is usually unobserved in nonexperimental survey data. Health heterogeneity makes health inputs behavioral choice variables in health production technology (Rosenzweig & Schultz, 1983) so that two-stage estimation is necessary for estimating consistent health production parameters.

The empirical findings and the policy implications are briefly summarized as follows. With a few exceptions, food prices and nutrient shadow prices do not significantly affect the demand for nutrients, exercise, and medication. This implies health input demands are not very price responsive. However, in the reduced-form blood pressure equation, food prices appear to all have a significant impact on blood pressure with the exception of the price of cereals. In contrast, all nutrient shadow prices show no evident effects on blood pressure with the exception of the shadow price of calcium. According to the estimates of the reduced-form blood pressure equation using food prices, increases in the prices of whole milk, sugar, coffee, meat, and fats and oils, and reductions in the prices of eggs, cola, poultry, and fruits and vegetables will, *ceteris paribus*, significantly lower the systolic blood pressure of the population. At the sample means, a 10% increase in the prices of whole milk, sugar, coffee, meat, and fats and oils reduces the systolic blood pressure by 24%, 6.6%, 1.9%, 1.9%, and 23%. Similarly, a same percentage reduction in the prices of eggs, cola, poultry, and fruits and vegetables reduces the systolic blood pressure by 11%, 3.3%, 13%, and 17%. Hence, holding other variables constant, a tax levied on the prices of whole milk, sugar, coffee, meat, or fats and oils, and a subsidy imposed on the prices of eggs, cola, poultry, or fruits and vegetables, respectively, will lower blood pressure. Therefore, through taxation or subsidization mechanisms, government food price interventions may serve as policy instruments to improve the health of the population. These empirical findings of food price effects on health are also supported by Pitt and Rosenzweig's findings (1984, 1985) wherein increases in the price of sugar and reductions in the prices of vegetables and vegetable oils significantly lowered the incidence of illness among Indonesian farmers. Based on studies of consumer-oriented food subsidies in developing countries, Pinstrup-Andersen (1988b) concluded that:

> . . . consumer food subsidies can be a powerful and cost-effective policy tool to reach certain social, economic, and political goals, or they can be harmful to growth and equality. . . . the question is not whether consumer food subsidies are good or bad but when and how they are applied. (p. 340)

Thus, taxation or subsidization foods as policy tools to reduce or eliminate nutrient deficiencies and therefore to improve health of the low-income groups should consider when and how they are designed and implemented accordingly. Pinstrup-Andersen (1988b) further elaborated that food price subsidies are appropriate when:

> (a) development strategy is biased toward capital-intensive urban development; (b) too little emphasis is placed on expanding food production at lower unit costs and on reducing food marketing costs; (c) marketing institutions are not efficient in dealing with price fluctuations; and (d) the poor

> don't have efficient access to sufficient productive resources to assure a minimum living standard. (p. 333)

However, poor health is likely to be caused by a set of biological, socioeconomic, or other factors, only some of which will be affected by a food tax or subsidy per se. Thus, an integrated primary health care program, which may consist of growth monitoring, nutrition education, vaccinations, and various preventive and curative health measures, is still likely to be more cost effective than a food tax or subsidy program to improve health (Pinstrup-Andersen, 1988b).

Even though the effects of wages on exercise and medication equations are significant at the five percent level, wages were found to have no apparent impacts on blood pressure. The elasticities of wages on blood pressure are small, perhaps due to the compositional changes in the health inputs associated with the wage changes as implied by the right-hand-side of Eq. (8). Other findings from the reduced-form blood pressure equation are men and less educated individuals have higher blood pressure. The results conform to prior expectations. Higher education may improve health according to the results of this study.

According to the consistent two-stage HPF estimates of the health production technology using food prices in all nine nutrient specification, the significance and absolute values of the point estimates of the effects of health inputs on blood pressure are much larger than that of the EPID estimates. Due to differences in health endowment as shown in our estimates of health endowment effects, heterogeneity bias significantly contaminate the EPID estimates and, therefore, makes health inputs endogenous choices in health production technology. The differences between the magnitudes of the EPID and the two-stage HPF estimates are quite striking. Results suggest that increases in consumption of calcium, sodium, and oleic acid, while decreases in consumption of riboflavin and saturated fatty acid significantly lower systolic blood pressure. Hence, calcium, sodium, and oleic acid are identified to be healthy nutrients whereas riboflavin and saturated fatty acid are unhealthy nutrients. These findings are consistent with prior health studies by McCarron et al. (1984) and Bursztyn (1987). Other findings in the HPF estimates include more exercise lowers blood pressure, and women and higher educated individuals have lower blood pressure. According to the HPF estimates using nutrient shadow prices, these findings are almost identical with the results using food prices except that age and education turned out to be insignificant factors in determining blood pressure.

The importance of the effect of initial health endowment cannot be overemphasized when analyzing the effects of health inputs upon health in general. Health depends upon health endowment as well as health inputs and other exogenous factors. Using the residuals from the 2SLS estimation, which include the health endowment effect and an error component, the endowment effect on each health input was estimated. Across all blood pressure health inputs considered in this study, the endowment effects of blood pressure on exercise and medication are statistically significant while the endowment effects on nutrient demand equations are insignificant. This indicates the health endowment component is an important determinant of the demand for exercise and medication. Populations differ significantly due to exogenous health endowment in the health production technology.

Therefore, health inputs are, themselves, endogenously behavioral choice variables in the health production function. Note that this procedure of estimating the endowment effects on endogenous health inputs from the 2SLS residuals is conditional based on the inclusion of all significant health inputs in the second stage (Rosenzweig & Schultz, 1983).

Epidemiological studies of the association between nutrients and health need to consider prices as identifying instruments in the demand for nutrients and the demand for other health inputs as well. The argument lies upon the fact that fluctuations in prices may induce changes in nutrient consumption demand and in other health inputs, and the resulting changes in health inputs are weighted by the marginal productivities of health inputs to assess price impacts on health. The empirical estimates of the reduced-form health equation using food prices can be employed to derive useful policy implications concerning food price interventions to improve health.

SECTION V. CONCLUSIONS

This paper applies a household production approach to examine the sensitivity of estimates of the blood pressure production parameters to the inclusion of prices and to assess price effects on blood pressure as well. Specifically, the endogeneity of the health inputs due to the presence of health heterogeneity and the measurement error associated with the measures of health inputs were considered using a Cobb-Douglas blood pressure health production function. The empirical data used in this study were the second cycle of the National Health and Nutrition Examination Survey (NHANES II), conducted from 1976 to

1978. The two-stage least squares approach was used to estimate the effects of endogenous health inputs on blood pressure with prices, and other exogenous factors served as instruments to identify the first-stage reduced-form health inputs. The alternative prices specified in the first-stage were food prices and nutrient shadow prices where the latter were derived from the nutrient equation. These two sets of alternative prices were used to test the sensitivity of the second-stage blood pressure production function estimates to the inclusion of these two different price specifications in the first stage. However, it was shown that nutrients shadow prices are generally measured with error. Empirical results of the reduced-form equations indicated that shadow prices, in general, have no significant effects on health inputs and health due to the possibility of less variations in the shadow prices. Policies concerning price interventions to improve health using food prices as mechanism are easier than using shadow prices since the latter are unobserved. Hence, it was concluded that food prices are better instruments to identify the reduced-form input and health equations.

In general, it was found that although food prices are insignificant in explaining the demand for health inputs, they are important determinants of blood pressure. This may be due to the relative size of the considerable magnitudes of the marginal productivities of health inputs according to the HPF estimates and the compositional changes of the health inputs of the price changes as implied in Eq. (8). Therefore, findings from the reduced-form health equation suggest that estimating only the demand for health inputs is insufficient to derive policy implications concerning food price interventions designed to improve health (Pitt & Rosenzweig, 1985).

Consistent estimation of health production parameters is also equally important as estimating the demand for health inputs to assess food price impacts upon health. In view of the left-hand-side of Eq. (8), the reduced-form blood pressure equation provides estimates of the effects of prices on blood pressure. Consistent estimates of the marginal products of health inputs (HPF estimates) in conjunction with the estimates of the reduced-form health input demand equations comprise the price effect on blood pressure according to the right-hand-side of Eq. (8).

The results of significant endowment effects on health inputs confirmed the intention to use the two stage procedure to estimate consistent health production parameters. Hence, estimation based on either sides of Eq. (8) could be used to derive policy implications concerning price interventions to improve health. However, use of the reduced-form health Eq. (7) is sufficient for estimating direct price effects on health. Empirically, it was found that variations in food prices have a significant effect on the reduced-form blood pressure equation. This important finding was used to derive policy implications designed to improve health of the population.

Traditional epidemiological studies of the relationships between health inputs and health need to consider the problems of endogeneity caused by health heterogeneity and measurement error associated with the health inputs. Some final comments of this study are worth discussing. First, the proxy for health status, blood pressure, is also suspected to be subject to possible measurement error. However, in this study it was assumed that in NHANES II the blood pressure was measured without error. There are several alternatives to correct the problem of measurement error associated with the dependent variable in regression analysis but this is beyond the scope of the current study. Further studies in this area of economic aspects of health should further consider the problem of measurement error.

Second, the approach employed in this paper to estimate the health endowment effects had some problems due to the fact that omitted variables in the health production function may also be contained in the 2SLS residuals. This may be the reason for the inability to obtain significant endowment effects on all of the nutrients considered in the study. These issues are possible directions for future research in economic-health studies.

Third, the exogenous variables (i.e., mainly food prices and wages) served as instruments to identify the health input demand equations and the reduced-form health equation. They were assumed to be orthogonal to the exogenous health endowment. Nonetheless, it is possible for people with a poor health condition (low health endowment) to live in areas having low prices due to the low living expense concerns. In this paper, the possibility of correlations between exogenous health endowment and exogenous identifying instruments were excluded in the empirical analysis because data of prices and wages in metropolitan cities were used.

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FOOTNOTES

1. The Hausman exogeneity test of health inputs in the blood pressure production function was conducted by adding health inputs (which were not predicted from the reduced-form health input equations) to the 2SLS estimating Eq. (19) in addition to the regressors specified in that equation and testing the joint significance of the endogenous health inputs in Eq. (19). If the null hypothesis of exogeneity is rejected, then the health inputs cannot be treated as exogenous in the blood pressure production function (Maddala, 1992). From the U.S. NHANES II data, it was noted that the null hypothesis of exogeneity of health inputs was rejected. Hence, it is concluded that the health inputs cannot be treated as exogenous variables in the health production function of Eq. (2).

APPENDICES

Table A.1. Male participation probit procedure

Class Level Information

Class	Levels	Values
PRTPTN	2	0 1

Number of observations used = 32079

Probit Procedure

Data Set =WORK.MALE
Dependent Variable=PRTPTN

Weighted Frequency Counts for the Ordered Response Categories

Level	Count
0	3259
1	28820

Log Likelihood for NORMAL -9980.98093

Probit Procedure

Variable	DF	Estimate	Std Err	ChiSquare	Pr>Chi	Label/Value
INTERCPT	1	-1.6611735	0.111187	223.2129	0.0001	Intercept
SMSA	1	-0.1893134	0.020075	88.92688	0.0001	
NUMPERS	1	-0.0026261	0.012575	0.043611	0.8346	
KIDS06	1	0.00425847	0.021763	0.038288	0.8449	
KIDS618	1	0.03893865	0.015877	6.014946	0.0142	
MARSTAT	1	-0.0431171	0.032625	1.746671	0.1863	
RACE	1	-0.2547968	0.039573	41.45525	0.0001	
AGE	1	-0.0004632	0.00487	0.009048	0.9242	
AGESQ	1	0.00024068	0.000052	21.51222	0.0001	
ED	1	0.01049337	0.003075	11.64824	0.0006	
OTHINC	1	9.5316E-6	0.000025	0.150545	0.6980	
NE	1	-0.161462	0.027277	35.03927	0.0001	
MW	1	-0.1788241	0.027606	41.96186	0.0001	
SO	1	-0.0790639	0.026253	9.069563	0.0026	

Table A.2. Male wage equation

Dependent Variable: LNHRWAGE

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value
Model	80	2398.50975	29.98137	112.025
Error	28739	7691.43455	0.26763	
C Total	28819	10089.94430		

Root MSE	0.51733	R-square	0.2377
Dep Mean	1.87098	Adj R-sq	0.2356
C.V.	27.65030		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	-0.585113	0.22627459	-2.586	0.0097
SMSA	1	0.110359	0.01726827	6.391	0.0001
AGE	1	0.059554	0.00171777	34.670	0.0001
AGESQ	1	-0.000600	0.00002090	-28.689	0.0001
RACE	1	-0.099536	0.02373348	-4.194	0.0001
ED	1	0.042646	0.00469379	9.086	0.0001
EDSQ	1	0.000025937	0.00020006	0.130	0.8968
FULPRT	1	0.048099	0.01524920	3.154	0.0016
NE	1	-0.060944	0.02949981	-2.066	0.0388
MW	1	-0.002062	0.03038317	-0.068	0.9459
SO	1	-0.068325	0.02493465	-2.740	0.0061
MFG	1	-0.052090	0.01779799	-2.927	0.0034
WSRTTR	1	-0.250330	0.02034424	-12.305	0.0001
FNBU	1	-0.238646	0.02403826	-9.928	0.0001
PFRS	1	-0.201932	0.02014445	-10.024	0.0001
PROF	1	0.732584	0.03192131	22.950	0.0001
MASACL	1	0.742297	0.03067203	24.201	0.0001
CRAF	1	0.740310	0.02960345	25.008	0.0001
OPER	1	0.585771	0.02949085	19.863	0.0001
SERV	1	0.454525	0.03440830	13.210	0.0001
NEMFPR	1	0.072943	0.04099715	1.779	0.0752
MWMFPR	1	0.055032	0.04167441	1.321	0.1867
SOMFPR	1	0.082481	0.04467676	1.846	0.0649
NEMFMA	1	0.075707	0.03745273	2.021	0.0432
MWMFMA	1	0.038906	0.03811224	1.021	0.3073
SOMFMA	1	-0.001956	0.03809865	-0.051	0.9590
NEMFCR	1	-0.004255	0.03348477	-0.127	0.8989
MWMFCR	1	0.023059	0.03267691	0.706	0.4804
SOMFCR	1	-0.089025	0.03126830	-2.847	0.0044
NEMFOP	1	0.028137	0.03335554	0.844	0.3989
MWMFOP	1	0.119219	0.03207129	3.717	0.0002
SOMFOP	1	-0.018820	0.03106566	-0.606	0.5446
NEMFSE	1	-0.031704	0.09131301	-0.347	0.7284
MWMFSE	1	0.128750	0.07530526	1.710	0.0873
SOMFSE	1	-0.071468	0.07852697	-0.910	0.3628
NEWSPR	1	0.068957	0.11486262	0.600	0.5483
MWWSPR	1	0.217276	0.08607839	2.524	0.0116
SOWSPR	1	0.270846	0.10594829	2.556	0.0106
NEWSMA	1	0.062908	0.03749744	1.678	0.0934
MWWSMA	1	-0.042563	0.03806197	-1.118	0.2635
SOWSMA	1	-0.024225	0.03520812	-0.688	0.4914
NEWSCR	1	0.039361	0.05262787	0.748	0.4545

Table A.2. Male wage equation (continued)

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
MWWSCR	1	0.014180	0.05364653	0.264	0.7915
SOWSCR	1	-0.108182	0.05021136	-2.155	0.0312
NEWSOP	1	0.126028	0.04924889	2.559	0.0105
MWWSOP	1	0.138377	0.04747738	2.915	0.0036
SOWSOP	1	0.043081	0.04788225	0.900	0.3683
NEWSSE	1	-0.066193	0.05796680	-1.142	0.2535
MWWSSE	1	-0.058338	0.07760009	-0.752	0.4522
SOWSSE	1	-0.130148	0.07870425	-1.654	0.0982
NEFNPR	1	0.436742	0.06453180	6.768	0.0001
MWFNPR	1	0.064328	0.09631912	0.668	0.5042
SOFNPR	1	0.187886	0.07749132	2.425	0.0153
NEFNMA	1	0.237083	0.04439107	5.341	0.0001
MWFNMA	1	0.146715	0.04815574	3.047	0.0023
SOFNMA	1	0.173890	0.04394909	3.957	0.0001
NEFNCR	1	-0.031270	0.07051082	-0.443	0.6574
MWFNCR	1	-0.023776	0.07175089	-0.331	0.7404
SOFNCR	1	-0.063399	0.06702466	-0.946	0.3442
NEFNOP	1	0.033071	0.09248872	0.358	0.7207
MWFNOP	1	-0.144483	0.10327695	-1.399	0.1618
SOFNOP	1	-0.285669	0.08862677	-3.223	0.0013
NEFNSE	1	0.106637	0.06717067	1.588	0.1124
MWFNSE	1	0.032482	0.08946568	0.363	0.7166
SOFNSE	1	-0.105010	0.08697517	-1.207	0.2273
NEPFPR	1	0.045627	0.03626357	1.258	0.2083
MWPFPR	1	-0.092883	0.03719316	-2.497	0.0125
SOPFPR	1	-0.024551	0.03427647	-0.716	0.4738
NEPFMA	1	0.087278	0.04245859	2.056	0.0398
MWPFMA	1	-0.009652	0.04244085	-0.227	0.8201
SOPFMA	1	0.112846	0.03831673	2.945	0.0032
NEPFCR	1	0.065767	0.06057357	1.086	0.2776
MWPFCR	1	-0.039851	0.07153417	-0.557	0.5775
SOPFCR	1	0.023340	0.05551610	0.420	0.6742
NEPFOP	1	0.032966	0.06947759	0.474	0.6352
MWPFOP	1	-0.036160	0.08554206	-0.423	0.6725
SOPFOP	1	0.005038	0.07121575	0.071	0.9436
NEPFSE	1	0.153077	0.04303766	3.557	0.0004
MWPFSE	1	0.128975	0.04663809	2.765	0.0057
SOPFSE	1	0.029381	0.04433827	0.663	0.5076
LAMBDA	1	-0.027794	0.10007949	-0.278	0.7812

Table A.3. Female participation probit procedure

Class Level Information

Class	Levels	Values
PRTPTN	2	0 1

Number of observations used = 25842

Probit Procedure

Data Set =WORK.FEMALE
Dependent Variable=PRTPTN

Weighted Frequency Counts for the Ordered Response Categories

Level	Count
0	3235
1	22607

Log Likelihood for NORMAL -9143.295981

Probit Procedure

Variable	DF	Estimate	Std Err	ChiSquare	Pr>Chi	Label/Value
INTERCPT	1	-0.9998143	0.110571	81.76315	0.0001	Intercept
SMSA	1	-0.1518408	0.021222	51.1899	0.0001	
NUMPERS	1	0.01124407	0.013553	0.688251	0.4068	
KIDS06	1	0.3519676	0.022418	246.4922	0.0001	
KIDS618	1	0.12818208	0.0165	60.3493	0.0001	
MARSTAT	1	0.30528361	0.029544	106.7745	0.0001	
RACE	1	-0.2649019	0.036389	52.99408	0.0001	
AGE	1	-0.0335436	0.005011	44.80317	0.0001	
AGESQ	1	0.00059127	0.000056	109.8235	0.0001	
ED	1	-0.01244	0.003939	9.975232	0.0016	
OTHINC	1	0.00001264	0.000021	0.346578	0.5561	
NE	1	-0.1835944	0.029498	38.73762	0.0001	
MW	1	-0.1132556	0.02846	15.83669	0.0001	
SO	1	-0.1008556	0.027803	13.15912	0.0003	

Table A.4. Female wage equation

Dependent Variable: LNHRWAGE

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value
Model	80	1421.72095	17.77151	73.685
Error	22526	5432.83474	0.24118	
C Total	22606	6854.55568		

Root MSE	0.49110	R-square	0.2074
Dep Mean	1.37969	Adj R-sq	0.2046
C.V.	35.59518		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	0.259212	0.07742561	3.348	0.0008
SMSA	1	0.091556	0.00736238	12.436	0.0001
AGE	1	0.026479	0.00154161	17.176	0.0001
AGESQ	1	-0.000260	0.00001822	-14.247	0.0001
RACE	1	-0.010634	0.01069744	-0.994	0.3202
ED	1	-0.001531	0.00622366	-0.246	0.8057
EDSQ	1	0.001445	0.00026177	5.522	0.0001
FULPRT	1	0.004209	0.00811825	0.518	0.6042
NE	1	-0.049337	0.04434702	-1.113	0.2659
MW	1	-0.066738	0.04305149	-1.550	0.1211
SO	1	-0.101536	0.04307749	-2.357	0.0184
MFG	1	-0.162326	0.02912150	-5.574	0.0001
WSRTTR	1	-0.395029	0.02714504	-14.553	0.0001
FNBU	1	-0.255948	0.02918622	-8.769	0.0001
PFRS	1	-0.309785	0.02640444	-11.732	0.0001
PROF	1	0.618899	0.05611640	11.029	0.0001
MASACL	1	0.436128	0.05420321	8.046	0.0001
CRAF	1	0.451619	0.06477473	6.972	0.0001
OPER	1	0.261023	0.05346497	4.882	0.0001
SERV	1	0.238223	0.05553830	4.289	0.0001
NEMFPR	1	0.013965	0.07798672	0.179	0.8579
MWMFPR	1	-0.016890	0.08538574	-0.198	0.8432
SOMFPR	1	0.042329	0.08793748	0.481	0.6303
NEMFMA	1	0.032506	0.05454920	0.596	0.5512
MWMFMA	1	0.050235	0.05363536	0.937	0.3490
SOMFMA	1	-0.040246	0.05450141	-0.738	0.4603
NEMFCR	1	-0.086321	0.09401017	-0.918	0.3585
MWMFCR	1	0.052651	0.09183969	0.573	0.5665
SOMFCR	1	0.038260	0.08721627	0.439	0.6609
NEMFOP	1	0.005067	0.05083986	0.100	0.9206
MWMFOP	1	0.174161	0.05021527	3.468	0.0005
SOMFOP	1	0.005661	0.04983105	0.114	0.9095
NEMFSE	1	0.356704	0.25057733	1.424	0.1546
MWMFSE	1	0.281530	0.13208814	2.131	0.0331
SOMFSE	1	0.241233	0.13582623	1.776	0.0757
NEWSPR	1	0.145879	0.11764666	1.240	0.2150
MWWSPR	1	0.106924	0.12813522	0.834	0.4040
SOWSPR	1	0.393742	0.14954044	2.633	0.0085
NEWSMA	1	0.050270	0.05058488	0.994	0.3203
MWWSMA	1	0.025421	0.04876101	0.521	0.6021
SOWSMA	1	0.015386	0.04895349	0.314	0.7533
NEWSCR	1	0.181066	0.18359254	0.986	0.3240

Table A.4. Female wage equation (continued)

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
MWWSCR	1	0.235783	0.11409914	2.066	0.0388
SOWSCR	1	0.052503	0.12442790	0.422	0.6731
NEWSOP	1	0.077840	0.08451480	0.921	0.3570
MWWSOP	1	0.304944	0.09121544	3.343	0.0008
SOWSOP	1	0.157452	0.07673760	2.052	0.0402
NEWSSE	1	0.050484	0.05991239	0.843	0.3994
MWWSSE	1	0.042407	0.05546889	0.765	0.4446
SOWSSE	1	-0.003339	0.05637317	-0.059	0.9528
NEFNPR	1	0.034325	0.08987505	0.382	0.7025
MWFNPR	1	-0.219869	0.13577018	-1.619	0.1054
SOFNPR	1	0.034730	0.11767284	0.295	0.7679
NEFNMA	1	0.066438	0.05252630	1.265	0.2059
MWFNMA	1	0.037554	0.05237117	0.717	0.4733
SOFNMA	1	0.020946	0.05196211	0.403	0.6869
NEFNCR	1	-0.164723	0.25307354	-0.651	0.5151
MWFNCR	1	-0.219416	0.28977229	-0.757	0.4489
SOFNCR	1	-0.447131	0.49480877	-0.904	0.3662
NEFNOP	1	-0.038949	0.22544870	-0.173	0.8628
MWFNOP	1	-0.178611	0.13237886	-1.349	0.1773
SOFNOP	1	-0.099028	0.22528113	-0.440	0.6602
NEFNSE	1	0.193554	0.11000342	1.760	0.0785
MWFNSE	1	-0.001354	0.10944327	-0.012	0.9901
SOFNSE	1	0.073176	0.11332127	0.646	0.5185
NEPFPR	1	0.103176	0.04951644	2.084	0.0372
MWPFPR	1	0.075933	0.04874215	1.558	0.1193
SOPFPR	1	0.074962	0.04824013	1.554	0.1202
NEPFMA	1	0.093278	0.04938557	1.889	0.0589
MWPFMA	1	0.074585	0.04830807	1.544	0.1226
SOPFMA	1	0.087831	0.04775670	1.839	0.0659
NEPFCR	1	-0.134985	0.22760006	-0.593	0.5531
MWPFCR	1	0.175186	0.18306937	0.957	0.3386
SOPFCR	1	-0.013666	0.15337182	-0.089	0.9290
NEPFOP	1	-0.118999	0.10088791	-1.180	0.2382
MWPFOP	1	0.178544	0.09374842	1.905	0.0569
SOPFOP	1	-0.126290	0.08289903	-1.523	0.1277
NEPFSE	1	0.075610	0.05036974	1.501	0.1333
MWPFSE	1	-0.006740	0.04919787	-0.137	0.8910
SOPFSE	1	-0.072692	0.04880372	-1.489	0.1364
LAMBDA	1	0.081664	0.01473429	5.542	0.0001

Table A.5. Correlation matrix of food prices and logarithm of hourly wage rates

	PWHMILK	PE	PSUGAR	PCOFFEE	PCOLA	PMEATS	PPOULTRY	PFUVG	PCEREALS	PFAOL
PWHMILK	1.00	0.67	0.46	0.10	0.37	0.28	0.45	0.86	0.89	0.44
PE	0.67	1.00	0.48	-0.07	0.06	-0.15	0.01	0.55	0.64	0.31
PSUGAR	0.46	0.48	1.00	-0.65	0.18	-0.06	0.19	0.23	0.59	-0.03
PCOFFEE	0.10	-0.07	-0.65	1.00	0.25	0.59	0.20	0.31	-0.11	0.43
PCOLA	0.37	0.06	0.18	0.25	1.00	0.33	-0.07	0.39	0.04	-0.08
PMEATS	0.28	-0.15	-0.06	0.59	0.33	1.00	0.70	0.31	0.23	0.52
PPOULTRY	0.45	0.01	0.19	0.20	-0.07	0.70	1.00	0.26	0.62	0.57
PFUVG	0.86	0.55	0.23	0.31	0.39	0.31	0.26	1.00	0.62	0.65
PCEREALS	0.89	0.64	0.59	-0.11	0.04	0.23	0.62	0.62	1.00	0.36
PFAOL	0.44	0.31	-0.03	0.43	-0.08	0.52	0.57	0.65	0.36	1.00
PGRAIN	-0.11	-0.50	0.28	-0.29	-0.08	0.44	0.66	-0.31	0.13	-0.01
PSKMILK	0.94	0.58	0.39	0.03	0.17	0.22	0.46	0.85	0.86	0.47
PICECREM	0.69	0.25	0.05	0.62	0.53	0.71	0.51	0.75	0.49	0.60
PCHEESE	0.10	-0.20	0.27	-0.26	-0.41	0.21	0.67	-0.17	0.46	0.07
PTEA	0.33	0.23	-0.37	0.45	-0.36	0.33	0.62	0.25	0.39	0.62
PSTSNAK	0.81	0.42	0.36	0.16	-0.02	0.45	0.78	0.62	0.92	0.53
PLIQ	-0.22	-0.48	0.13	-0.27	-0.17	0.26	0.48	-0.54	0.09	-0.32
PFISH	0.31	-0.04	-0.09	0.05	-0.30	0.38	0.81	0.11	0.46	0.45
PORGMEAT	-0.14	-0.21	0.03	0.31	0.19	0.45	0.30	-0.35	0.02	-0.26
LNHRWAGE	0.00	0.06	0.02	-0.02	0.01	-0.02	-0.06	-0.01	0.00	-0.05

Table A.5. Correlation matrix of food prices and logarithm of hourly wage rates (continued)

	PGRAIN	PSKMILK	PICECREM	PCHEESE	PTEA	PSTSNAK	PLIQ	PFISH	PORGMEAT	LNHRWAGE
PWHMILK	-0.11	0.94	0.69	0.10	0.33	0.81	-0.22	0.31	-0.14	0.00
PE	-0.50	0.58	0.25	-0.20	0.23	0.42	-0.48	-0.04	-0.21	0.06
PSUGAR	0.28	0.39	0.05	0.27	-0.37	0.36	0.13	-0.09	0.03	0.02
PCOFFEE	-0.29	0.03	0.62	-0.26	0.45	0.16	-0.27	0.05	0.31	-0.02
PCOLA	-0.08	0.17	0.53	-0.41	-0.36	-0.02	-0.17	-0.30	0.19	0.01
PMEATS	0.44	0.22	0.71	0.21	0.33	0.45	0.26	0.38	0.45	-0.02
PPOULTRY	0.66	0.46	0.51	0.67	0.62	0.78	0.48	0.81	0.30	-0.06
PFUVG	-0.31	0.85	0.75	-0.17	0.25	0.62	-0.54	0.11	-0.35	-0.01
PCEREALS	0.13	0.86	0.49	0.46	0.39	0.92	0.09	0.46	0.02	0.00
PFAOL	-0.01	0.47	0.60	0.07	0.62	0.53	-0.32	0.45	-0.26	-0.05
PGRAIN	1.00	-0.05	-0.01	0.67	0.01	0.21	0.82	0.52	0.35	-0.05
PSKMILK	-0.05	1.00	0.58	0.11	0.40	0.79	-0.25	0.41	-0.30	0.00
PICECREM	-0.01	0.58	1.00	0.04	0.28	0.66	-0.17	0.21	0.19	-0.05
PCHEESE	0.67	0.11	0.04	1.00	0.24	0.59	0.77	0.58	0.32	-0.06
PTEA	0.01	0.40	0.28	0.24	1.00	0.52	0.01	0.80	-0.09	-0.01
PSTSNAK	0.21	0.79	0.66	0.59	0.52	1.00	0.15	0.57	0.14	-0.04
PLIQ	0.82	-0.25	-0.17	0.77	0.01	0.15	1.00	0.44	0.53	-0.02
PFISH	0.52	0.41	0.21	0.58	0.80	0.57	0.44	1.00	-0.08	-0.04
PORGMEAT	0.35	-0.30	0.19	0.32	-0.09	0.14	0.53	-0.08	1.00	0.00
LNHRWAGE	-0.05	0.00	-0.05	-0.06	-0.01	-0.04	-0.02	-0.04	0.00	1.00

Table A.6. Exercise equation probit procedure

Class Level Information

Class	Levels	Values
REEXER	2	2 1

Number of observations used = 1982

Probit Procedure

Dependent Variable=REEXER

Weighted Frequency Counts for the Ordered Response Categories

Level	Count
2	932
1	1050

Log Likelihood for NORMAL -1342.64536

Probit Procedure

Variable	DF	Estimate	Std Err	ChiSquare	Pr>Chi	Label/Value
INTERCPT	1	1.7117326	2.625483	0.425063	0.5144	Intercept
PWHMILK	1	0.07144163	0.118414	0.363993	0.5463	
PE	1	0.00450533	0.032889	0.018765	0.8910	
PSUGAR	1	0.01340981	0.034787	0.148597	0.6999	
PCOFFEE	1	0.00082677	0.003202	0.066669	0.7962	
PCOLA	1	-0.0103926	0.012223	0.722869	0.3952	
PMEATS	1	0.00117508	0.000929	1.601063	0.2058	
PPOULTRY	1	-0.0060822	0.038846	0.024516	0.8756	
PFUVG	1	-0.0324109	0.072759	0.198429	0.6560	
PCEREALS	1	-0.0886279	0.111176	0.63551	0.4253	
PFAOL	1	-0.0058423	0.02427	0.057945	0.8098	
LNHRWAGE	1	-0.1113002	0.045313	6.033053	0.0140	
LNINCOME	1	-0.0046253	0.044012	0.011044	0.9163	
NUMPERS	1	-0.0008793	0.019219	0.002093	0.9635	
AGE	1	0.00558699	0.011645	0.230192	0.6314	
AGESQ	1	-0.0058935	0.013199	0.199379	0.6552	
SEX	1	0.13718059	0.067292	4.155826	0.0415	
ED	1	0.05831651	0.010803	29.14022	0.0001	

Table A.7. Medication equation probit procedure

Class Level Information

Class	Levels	Values
MEDICINE	2	0 1

Number of observations used = 1982

Probit Procedure

Dependent Variable=MEDICINE

Weighted Frequency Counts for the Ordered Response Categories

Level	Count
0	1331
1	651

Log Likelihood for NORMAL -1126.333831

Probit Procedure

Variable	DF	Estimate	Std Err	ChiSquare	Pr>Chi	Label/Value
INTERCPT	1	-0.6461352	2.803989	0.0531	0.8178	Intercept
PWHMILK	1	-0.0133683	0.126739	0.011126	0.9160	
PE	1	-0.0123372	0.03515	0.123192	0.7256	
PSUGAR	1	-0.00621	0.037188	0.027886	0.8674	
PCOFFEE	1	-0.0000281	0.003416	0.000068	0.9934	
PCOLA	1	0.00404307	0.013107	0.095149	0.7577	
PMEATS	1	0.00014483	0.000986	0.021567	0.8832	
PPOULTRY	1	-0.0271771	0.041621	0.426357	0.5138	
PFUVG	1	-0.0123194	0.077804	0.025071	0.8742	
PCEREALS	1	0.05448303	0.119047	0.209451	0.6472	
PFAOL	1	0.01691901	0.025924	0.425937	0.5140	
LNHRWAGE	1	0.18777946	0.04759	15.56937	0.0001	
LNINCOME	1	-0.0285174	0.047845	0.355257	0.5512	
NUMPERS	1	0.0442314	0.021662	4.169384	0.0412	
AGE	1	-0.0442473	0.012838	11.87867	0.0006	
AGESQ	1	0.02574972	0.014283	3.249955	0.0714	
SEX	1	0.27450475	0.072094	14.4977	0.0001	
ED	1	-0.0101101	0.011203	0.814405	0.3668	

CHAPTER 2. A REEVALUATION OF THE IMPACT OF MEASUREMENT ERROR ON REGRESSION COEFFICIENTS USED IN THE STATE OF IOWA'S COMPARABLE WORTH SYSTEM

A paper prepared to be submitted to Industrial and Labor Relations Review

Shih-Neng Chen

ABSTRACT

A comparable worth pay analysis for the State of Iowa Merit Employment Pay System was conducted in 1984 by Arthur Young Consulting Company of Milwaukee. Greig (1987) suspected that Arthur Young's recommended pay plans were biased due to possible measurement error in the job evaluation. The presence of measurement error associated with the job evaluation factors will not only bias the estimates of the factor weights but also affect the estimates of other variables used in the pay analysis although the other variables were measured without error. Hence Greig explored the sensitivity analysis of the pay recommendations to various measurement error corrections. However, multicollinearity among several of the original Arthur Young's recommended thirteen job evaluation factors made estimation difficult. This paper aims to obtain unbiased estimates for the job factor weights in comparable worth pay analysis by correcting both the problems of measurement error and multicollinearity in the job evaluation factors simultaneously. Potential measurement error correlations between pairwise job evaluation factors are explored to analyze the sensitivity of the estimates for the job factor weights to various measurement error correlation specifications.

SECTION I. INTRODUCTION

Comparable worth pay analysis is used to evaluate pay by conducting a job evaluation to measure the level of each of several job factors, giving weights to each job evaluation factor, and then obtaining the value of each job classification by summing over the weighted factors. The value of each job classification is then translated into pay grade and pay. A comparable worth pay study was conducted in 1984 for the State of Iowa by Arthur Young Consulting Company of Milwaukee and actually implemented in 1985. Greig (1987) reexamined the pay recommendations based on Arthur Young Company's (1984) comparable worth pay analysis of the State of Iowa Merit Employment Pay System. Greig suspected that Arthur Young's recommended pay plans were biased due to possible measurement error in job evaluation. He explored the sensitivity of the pay recommendations to various measurement error corrections.

The Arthur Young pay analysis was based upon a set of job evaluation factors plus a factor representing percent female incumbents in each job classification. Holding job content constant, the coefficient on percent female incumbents in an occupation may be interpreted as a measure of pay structure discrimination against female jobs. However, there are other interpretations of this percent female coefficient as well. For example, holding job factors constant, the coefficient on percent female may reflect unmeasured job attributes which have different effects on male and female incentives to supply labor to the job classifications. If these attributes are also correlated with pay, then the coefficient will reflect these differential returns to unmeasured job attributes. Therefore, any unmeasured attributes influencing male and female supply of or demand for the jobs may be reflected in the coefficient on percentage female incumbents.

If the coefficient on percent female is interpreted as a measure of discrimination, then a significantly less than zero coefficient on percent female in current pay grade regression means that the current pay scheme is significantly discriminating against female jobs. One can therefore create a nondiscriminatory pay plan by predicting pay based upon the estimated regression coefficients with the coefficient for percent female restricted to zero.

A detailed discussion of the possible sources of measurement error in factor point pay analysis is contained in Greig et al. (1989). However, the percentage of female incumbents in each job classification is directly observed and measured without error. Regression analysis without correcting for measurement error problem will yield biased results, as shown in the next section. Nonetheless, the question of how measurement error in job evaluation factors affects the estimated coefficient on percent female remains. If measurement error in job evaluation factors biases the coefficient for percent female variable, then pay recommendations based upon the biased coefficient for percentage female will also be biased.

The original Arthur Young thirteen job evaluation factor points were examined to be highly intercorrelated. Positive correlations exist among several factors including several which were difficult to distinguish conceptually as well as empirically. For example, the factor "knowledge--from education" evaluates the least amount of time normally required for a person with the "typically required" training/education to acquire the knowledge and skills to perform the job satisfactorily while the factor "job complexity, judgement, and problem-solving" measures the complexity of duties, and the frequency and extent of judgement used in decision-making and problem-solving. These two factors are essentially measuring the same requirements to perform jobs satisfactorily. There are some other examples as well. This multicollinearity problem in both OLS and measurement-error corrected regressions proved limiting to Greig's original analysis. This multicollinearity problem resulted in EVCARP regression results with high R^2 but low individual t-ratios. EVCARP is a program for regression analysis of data containing measurement error in the explanatory variables. The model applied by Greig estimated the regression parameters under the assumption that the reliability ratios of the explanatory variables are known, or estimated from an external source. Reliability ratios were reported by the Arthur Young consultants.

The current study aims to reinvestigate Greig's results by taking into account the consideration of both the measurement error problem in the original Arthur Young analysis and the additional complication of multicollinearity among the factors. The current analysis is extended to allow for possible positive correlations between pairwise measurement errors of the job evaluation factors and therefore to explore the sensitivity of the effect of percentage female in each job classification on pay in measurement error corrected regressions. With the regression estimation corrected for measurement error and correlation problems, we can obtain unbiased estimates for the evaluation factor weights of job factors and for the coefficient on percent female incumbents.

The next section develops the statistical theory for regression with measurement error in the explanatory variables under the assumption of both independent measurement errors and correlated measurement errors. From this statistical foundation, we can derive parameter estimates corrected for measurement error. In particular, we show how measurement error in some regressors will affect parameter estimates for the variable without measurement error, e.g., percent female incumbents. A remedy for the problem of multicollinearity within Arthur Young job evaluation factors are also suggested to enhance the degree of explanatory power among regressors. Section V reports the empirical results of various measurement error corrections of the pay analysis and the last section gives conclusions of this paper.

SECTION II. THEORY OF MEASUREMENT ERROR MODELS IN REGRESSION ANALYSIS

A. Ordinary Least Squares of One Explanatory Variable with Measurement Error

The classical linear regression model with one independent variable is defined by

$$(1) \qquad Y_t = \beta_0 + \beta_1 x_t + e_t \qquad t = 1, 2, \dots, n$$

where x_t = true independent variable

and e_t = random disturbance term with $e_t \sim NI\,(0, \sigma_{ee})$

Linear model (1) is based upon a set of strong assumptions. One of these is that x_t must be <u>measured without error</u>. However, one sometimes is unable to observe x_t directly. Instead of observing x_t, one observes the sum

(2) $$X_t = x_t + u_t \qquad t = 1, 2, \ldots, n$$

where X_t = unbiased measure of x_t

x_t = unobserved variable

u_t = measurement error with $u_t \sim (0, \sigma_{uu})$

Combining (1) and (2) yields

$$Y_t = \beta_0 + \beta_1 X_t + v_t \qquad t = 1, 2, \ldots, n$$

where $v_t = e_t - \beta_1 u_t$. If ordinary least squares method is used, the least squares estimator is biased because v_t and X_t are correlated.

Let us now investigate the impact of the presence of measurement error on the least squares coefficient in the simple models (1) and (2), under the assumption that the x_t are random variables with $\sigma_{xx} > 0$. We assume

(3) $$[x_t, e_t, u_t]' \sim NI\{[\mu_x, 0, 0]', \operatorname{diag}[\sigma_{xx}, \sigma_{ee}, \sigma_{uu}]\}$$

where $\sim NI$ denotes distributed normally and independently, and $\operatorname{diag}[\sigma_{xx}, \sigma_{ee}, \sigma_{uu}]$ represents the diagonal matrix with elements σ_{xx}, σ_{ee}, and σ_{uu} along the diagonal.

It follows from the structural model (3) that the vector $[Y_t, X_t]'$, where Y_t is defined by (1) and X_t is defined in (2), is distributed as a bivariate normal vector with mean vector

$$E[(Y, X)] = (\mu_Y, \mu_X) = (\beta_0 + \beta_1 \mu_x, \mu_x)$$

and covariance matrix

$$(4) \qquad \begin{bmatrix} \sigma_{YY} & \sigma_{XY} \\ \sigma_{XY} & \sigma_{XX} \end{bmatrix} = \begin{bmatrix} \beta_1^2 \sigma_{xx} + \sigma_{ee} & \beta_1 \sigma_{xx} \\ \beta_1 \sigma_{xx} & \sigma_{xx} + \sigma_{uu} \end{bmatrix}$$

Let the regression coefficient estimated by using the observed variables be

$$(5) \qquad \hat{\beta}_M = [\sum_{t=1}^{n} (X_t - \bar{X})^2]^{-1} [\sum_{t=1}^{n} (X_t - \bar{X})(Y_t - \bar{Y})]$$

By the properties of the bivariate normal distribution, the expected value of $\hat{\beta}_M$ estimated from (5) is

$$(6) \qquad E(\hat{\beta}_M) = \sigma_{XY}/\sigma_{XX} = \beta_1 [\sigma_{xx}/(\sigma_{xx} + \sigma_{uu})] = \beta_1 (\sigma_{xx}/\sigma_{XX})$$

We conclude that, for the bivariate model with independent measurement error in X, the least squares regression coefficient is biased toward zero. The estimated coefficient when measurement error exists is biased by the ratio of the true variance of X to total variance of X. It is important to note that (6) is derived under the assumption that the measurement error in X_t, u_t, is independent of the true values, x_t, and of the errors, e_t.

One way to describe the effect of measurement error displayed in (6) is to say that the regression coefficient has been attenuated by the measurement error. The degree of attenuation is defined as $\kappa_{xx} = \sigma_{xx}/\sigma_{XX}$. The κ_{xx} is called a reliability ratio in statistics.

Because the bias in $\hat{\beta}_M$ as an estimator of β_1 is multiplicative, the test of the hypothesis that $\beta_1 = 0$ remains valid in the presence of independent measurement error (Fuller, 1987). The use of the t distribution for hypotheses other than $H_0 : \beta_1 = 0$ leads to biased tests in the presence of measurement error and will reduce the power of the test of $\beta_1 = 0$.

Fuller (1987) showed that the error in the estimator (5) is

$$\hat{\beta}_M - \beta_1 = \{\sum_{t=1}^{n} [(x_t - \bar{x})(v_t - \bar{v}) + (u_t - \bar{u})(v_t - \bar{v})]\}$$
$$\bullet\{\sum_{t=1}^{n} [(x_t - \bar{x})^2 + 2(x_t - \bar{x})(u_t - \bar{u}) + (u_t - \bar{u})^2]\}^{-1}$$

where $v_t = e_t - \beta_1 u_t$. The measurement error u_t produces biases both in the numerator and the denominator of $\hat{\beta}_M - \beta_1$.

The population squared correlation between x_t and Y_t is defined by

$$(R_{xY})^2 = (\sigma_{xY})^2/\sigma_{xx}\sigma_{YY} = (\sigma_{xx}/\sigma_{YY})(\beta_1)^2$$

while the population squared correlation between X_t and Y_t is

$$(R_{XY})^2 = (\sigma_{XY})^2/\sigma_{XX}\sigma_{YY} = (\sigma_{xx}/\sigma_{XX})(R_{xY})^2 = \kappa_{xx}(R_{xY})^2$$

since $\sigma_{eu} = \sigma_{xu} = 0$ implies $(\sigma_{XY})^2 = (\sigma_{xY})^2$.

Thus, the introduction of independent measurement error leads to a reduction in the squared correlation, where the factor by which the correlation is reduced is the factor by which the regression coefficient is biased toward zero. The correlation has been attenuated by the presence of measurement error. This argument holds true for all pairs of independent variables. We will show this later using the two independent variable case.

1. Estimation with Known Reliability Ratio

From equation (6) we know that the expected value of the least squares estimator $\hat{\beta}_M$ is the true β_1 multiplied by the reliability ratio κ_{xx}. Therefore, if we know the ratio $(\sigma_{xx}/\sigma_{XX})$, it is possible to construct an unbiased estimator of β_1. An unbiased estimator of the structural regression coefficient β_1 of model (1) is given by

(7) $$\hat{\beta}_1 = \hat{\beta}_M/\kappa_{xx}$$

where $\hat{\beta}_M$ is the least squares coefficient defined in (5). The coefficient (7) is sometimes called the regression coefficient corrected for attenuation.

An estimator of the squared correlation between x and Y is

(8) $$(\hat{R}_{xY})^2 = (\hat{R}_{XY})^2 / \kappa_{xx}$$

where $(\hat{R}_{XY})^2 = (m_{XY})^2/(m_{XX}\, m_{YY})$ and (m_{YY}, m_{XY}, m_{XX}) is the sample estimator of $(\sigma_{YY}, \sigma_{XY}, \sigma_{XX})$, for example,

$$m_{XY} = [\sum_{t=1}^{n} (X_t - \bar{X})(Y_t - \bar{Y})] / (n-1)$$

The estimator (8) is said to be the squared correlation corrected for attenuation. It is possible the squared correlation corrected for attenuation defined in (8) to exceed one. In this case, the maximum likelihood estimator for $(\hat{R}_{xY})^2$ is one (Fuller, 1987).

B. Ordinary Least Squares of Two Explanatory Variables with One Measured with Error and One Measured without Error

Let us now consider the two independent variable case in which one variable is measured with error and one is not. Suppose the linear regression model is

(9) $$Y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + e_t \qquad t = 1, 2, \ldots, n$$

$$X_{1t} = x_{1t} + u_{1t} \qquad t = 1, 2, \ldots, n$$

where X_{1t} = unbiased measure of x_{1t}

x_{1t} = true variable

x_{2t} = true variable

u_{1t} = measurement error with $u_{1t} \sim (0, \sigma_{uu})$

e_t = random disturbance term with $e_t \sim NI\,(0, \sigma_{ee})$

Assuming x_{it}, u_{1t}, and e_t are mutually uncorrelated for i = 1, 2. Model (9) can be rewritten as

(10)
$$\begin{aligned} Y_t &= \beta_0 + \beta_1(X_{1t} - u_{1t}) + \beta_2 x_{2t} + e_t \qquad t = 1, 2, \ldots, n \\ &= \beta_0 + \beta_1 X_{1t} + \beta_2 x_{2t} + v_t \end{aligned}$$

where $v_t = e_t - \beta_1 u_{1t}$. Note that v_t and X_{1t} are not independent. Hence the least squares estimator is biased.

The OLS regression using model (10) is

(11)
$$\hat{\beta}_{OLS} = (X'X)^{-1}(X'Y)$$

where $X = (\mathbf{1}, X_1, x_2)$, and Y, **1**, X_1, and x_2 are all nx1 vectors. It can be shown that

(12)
$$E\,[\hat{\beta}_{OLS}] = \beta - E\,[(X'X)^{-1}(X'u_1\beta_1)]$$

where $\beta = (\beta_0, \beta_1, \beta_2)'$ and $u_1 = (u_{11}, u_{12}, \ldots, u_{1n})'$.

For large samples, the least squares estimator $\hat{\beta}_{OLS}$ is also inconsistent and the inconsistency is

(13) $\text{plim}\,(\hat{\beta}_{OLS} - \beta) = \text{plim}\{[(X'X)/n]^{-1}(X'v)/n\}$

$= \text{plim}[(X'X)/n]^{-1}\,\text{plim}[(X'v)/n]$

where $v = e - u_1\beta_1$ nx1 vector. If we assume that the following limits exist:

$$plim\left[\frac{(X'X)}{n}\right]^{-1} = plim\begin{bmatrix} \frac{n}{n} & \frac{\Sigma X_{1t}}{n} & \frac{\Sigma x_{2t}}{n} \\ \frac{\Sigma X_{1t}}{n} & \frac{\Sigma X_{1t}^2}{n} & \frac{\Sigma X_{1t}x_{2t}}{n} \\ \frac{\Sigma x_{2t}}{n} & \frac{\Sigma X_{1t}x_{2t}}{n} & \frac{\Sigma x_{2t}^2}{n} \end{bmatrix}^{-1} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{12} & a_{22} & a_{23} \\ a_{13} & a_{23} & a_{33} \end{bmatrix}$$

$$\begin{aligned} \text{plim}[(X'v)/n] &= \text{plim}[X'(e - \beta_1 u_1)/n] \\ &= \text{plim}[\mathbf{1}'(e - \beta_1 u_1)/n,\ (X_1)'(e - \beta_1 u_1)/n,\ (x_2)'(e - \beta_1 u_1)/n]' \\ &= [0\ ,\ -\beta_1\sigma_{uu11}\ ,\ 0]' \end{aligned}$$

where σ_{uu11} is the variance of measurement error for X_1. Therefore expression (13) can be written as

$$plim(\hat{\beta}_{OLS} - \beta) = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{12} & a_{22} & a_{23} \\ a_{13} & a_{23} & a_{33} \end{bmatrix}\begin{bmatrix} 0 \\ -\beta_1\sigma_{uu11} \\ 0 \end{bmatrix} \tag{14}$$

$$= - \begin{bmatrix} a_{12}\beta_1\sigma_{uu11} \\ a_{22}\beta_1\sigma_{uu11} \\ a_{23}\beta_1\sigma_{uu11} \end{bmatrix}$$

From (14) we can see that the coefficient $\hat{\beta}_{OLS}$ is biased. In general, every element in plim ($\hat{\beta}_{OLS}$ - β) will be nonzero. In particular, the regression coefficient on the independent variable which is measured without error, $\hat{\beta}_2$, is still biased by the presence of measurement error in X_{1t}. Because $a_{22} > 0$ and $\sigma_{uu11} > 0$, $\hat{\beta}_1$ will be biased toward zero. The direction of bias of $\hat{\beta}_2$ depends on the signs of a_{23}, β_1, and β_2. Thus, if a variable is subject to measurement error, it will not only affect its own parameter estimate, but will also affect the parameter estimates of other variables that are measured without error.

The population squared correlation between x_{1t} and x_{2t} is defined by

$$(R_{xx12})^2 = (\sigma_{xx12})^2/(\sigma_{xx11}\sigma_{xx22})$$

while the population squared correlation between X_{1t} and x_{2t} is

$$(R_{Xx12})^2 = (\sigma_{Xx12})^2/(\sigma_{XX11}\sigma_{xx22}) = \kappa_{xx11}[(\sigma_{Xx12})^2/(\sigma_{xx11}\,\sigma_{xx22})] = \kappa_{xx11}(R_{xx12})^2$$

where κ_{xx11} is the reliability ratio for X_1. Because $0 < \kappa_{xx11} < 1$, independent measurement error leads to a reduction in the squared correlation between regressors. Similarly, if both independent variables are measured with error, under the assumption of independent measurement errors, the population squared correlation between X_{1t} and X_{2t} is

$$(R_{XX12})^2 = (\sigma_{XX12})^2/(\sigma_{XX11}\sigma_{XX22}) = \kappa_{xx11}\kappa_{xx22}[(\sigma_{xx12})^2/(\sigma_{xx11}\sigma_{xx22})]$$

$$= \kappa_{xx11}\kappa_{xx22}(R_{xx12})^2$$

Note that it is possible for the reliability corrected squared correlation coefficient $(R_{xx12})^2$ defined by the equation above to exceed one. In such cases, as discussed by Fuller (1987), the maximum likelihood estimator of $(R_{xx12})^2$ is one. Hence, it is possible to estimate the reliability corrected correlation matrix by using this derivation. A table of the reliability corrected correlation matrix of the original Arthur Young job evaluation factors under the assumption of independent measurement errors is reported in the Appendix (Table A.2). The existence of measurement error reduces the correlation coefficients. This indicates that the true correlation coefficients were underestimated due to the presence of measurement error in the job factors.

C. General Case under Independent Measurement Errors

Let us now consider the specific linear regression model used in this paper.

(15) $$Y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \beta_k x_{kt} + \gamma\, PF_t + e_t \qquad t = 1, 2, \dots, n$$

(16) $$X_{it} = x_{it} + u_{it} \qquad i = 1, 2, \dots, k \qquad t = 1, 2, \dots, n$$

where Y_t = current pay grade in t^{th} job classification (measured without error)

X_{it} = "measured" i^{th} evaluation factor in t^{th} job classification

x_{it} = "true" i^{th} evaluation factor in t^{th} job classification

u_{it} = measurement error with $u_{it} \sim (0, \sigma_{uuii})$

PF_t = percentage of female incumbents in t^{th} job classification (measured without error)

e_t = random disturbance term with $e_t \sim NI(0, \sigma_{ee})$

As shown in Fuller (1987), an estimator of $(\beta_1, \beta_2, \dots, \beta_k, \gamma)$ for (15) is obtained by

(17) $$(\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_k, \hat{\gamma})' = (\hat{H}_{xx})^{-1} \hat{H}_{xY}$$

where
$$\hat{H}_{ZZ} = m_{ZZ} - [1 - (1/n)]\hat{D}_{ZZ}\, \Lambda_{uu}\, \hat{D}_{ZZ} \quad \text{if } \hat{a} \geq 1$$
$$= m_{ZZ} - [\hat{a} - (1/n)]\hat{D}_{ZZ}\, \Lambda_{uu}\, \hat{D}_{ZZ} \quad \text{if } \hat{a} < 1$$
$$(\hat{D}_{ZZ})^2 = \mathrm{diag}\,(m_{YY}, m_{XX11}, m_{XX22}, \dots, m_{XXkk}, m_{PFPF})$$

$\Lambda_{uu} \quad = \text{diag}\,[0, (\sigma_{uu11}/\sigma_{XX11}), (\sigma_{uu22}/\sigma_{XX22}), \ldots, (\sigma_{uukk}/\sigma_{XXkk}), 0]$

$m_{ZZ} \quad = [\sum_{t=1}^{n} (Z_t - \overline{Z})'(Z_t - \overline{Z})] / (n-1)$

$Z_t \quad = (Y_t, X_{1t}, X_{2t}, \ldots, X_{kt}, PF_t)$

$\hat{a}$ is the smallest root of $|m_{ZZ} - a\,\hat{D}_{ZZ}\,\Lambda_{uu}\,\hat{D}_{ZZ}| = 0$

and $\hat{D}_{ZZ}\,\Lambda_{uu}\,\hat{D}_{ZZ} = \text{diag}\,[0, m_{XX11}(1-\kappa_{11}), m_{XX22}(1-\kappa_{22}), \ldots, m_{XXkk}(1-\kappa_{kk}), 0]$

1. Bias due to Measurement Error

(18) $$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_k X_{kt} + \gamma\, PF_t + v_t \qquad t = 1, 2, \ldots, n$$

$$= W_t\,\delta + v_t$$

where $W_t = (1, X_{1t}, X_{2t}, \ldots, X_{kt}, PF_t)$

$\delta = (\beta_0, \beta_1, \beta_2, \ldots, \beta_k, \gamma)'$

and $X_{it} = x_{it} + u_{it}$ is defined as in (16).

Model (18) can be rewritten as:

(19) $$Y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \ldots + \beta_k x_{kt} + \gamma\, PF_t + (v_t + \beta_1 u_{1t} + \beta_2 u_{2t} + \ldots + \beta_k u_{kt})$$

Comparing (15) and (19), we can obtain

$$v_t = e_t - \beta_1 u_{1t} - \beta_2 u_{2t} - \ldots - \beta_k u_{kt}$$

Suppose the OLS regression using model (18) is

$$(20) \qquad \hat{\delta}_M = (W'W)^{-1} W'Y$$

Under the assumption that x_{it}, u_{jt}, PF_t, and e_t are mutually uncorrelated for all i, j, it can be shown that, for large samples, the inconsistency due to regression in (20) is

$$(21) \qquad \text{plim}(\hat{\delta}_M - \delta) = \text{plim}[(W'W)^{-1} nn^{-1} W'(e - \beta_1 u_1 - \beta_2 u_2 - \dots - \beta_k u_k)]$$
$$= \text{plim}[(W'W)/n]^{-1}\ \text{plim}\{[W'(e - \beta_1 u_1 - \beta_2 u_2 - \dots - \beta_k u_k)]/n\}$$

where $\text{plim}\{[W'(e - \beta_1 u_1 - \beta_2 u_2 - \dots - \beta_k u_k)]/n\}$

$$= \text{plim}[\mathbf{1}'(v/n), (X_1)'(v/n), (X_2)'(v/n), \dots, (X_k)'(v/n), (PF)'(v/n)]'$$
$$= [0, -\beta_1\sigma_{uu11}, -\beta_2\sigma_{uu22}, \dots, -\beta_k\sigma_{uukk}, 0]'$$

$$(22) \qquad \text{plim}(\hat{\delta}_M - \delta) = \text{plim}[(W'W)/n]^{-1} [0, -\beta_1\sigma_{uu11}, -\beta_2\sigma_{uu22}, \dots, -\beta_k\sigma_{uukk}, 0]'$$

Thus the regression coefficient for PF_t, $\hat{\gamma}$, is also inconsistent due to the presence of measurement error of the X's although PF_t is measured without error. We conclude that the presence of measurement error will affect not only the variables measured with error but also affect the regression coefficient estimates for those variables measured without error.

D. Regressions under Correlated Measurement Errors

Previous discussions of the theory of measurement error in regression analysis were based upon an important assumption of independent measurement errors. However, in analyzing the Arthur Young's pay analysis, the measurement errors associated with job evaluation factors are likely to be correlated. For example, in measuring the job factors of knowledge from education and knowledge from experience required to perform the job satisfactorily, it is possible that the measurement errors associated with each factor are positively correlated. How is the problem of correlated measurement errors affects the regression results is considered in this section. We explore the possibility by allowing measurement error correlations to exist among job evaluation factors. Assuming the previous general case models (15) and (16) hold true with the measurement errors associated with the job evaluation factors positively correlated. This correlation can be expressed as follows:

(23) $$X_{it} = x_{it} + u_{it} \qquad t = 1, 2, \dots, n$$

$$X_{jt} = x_{jt} + u_{jt} \qquad t = 1, 2, \dots, n$$

where X_{it} = i^{th} job evaluation factor

u_{it} = measurement error in i^{th} job evaluation factor

X_{jt} = j^{th} job evaluation factor

u_{jt} = measurement error in j^{th} job evaluation factor

and x_{it}, u_{jt} uncorrelated for all i and j. u_{it} and u_{jt} are correlated.

Assuming u_{it} and u_{jt} are positively correlated. Because the correlation among the job evaluation measurement errors is unobserved, estimation was conducted under alternative maintained hypotheses that the correlation coefficient was 0.1, 0.2, or 0.3. The population squared correlation between X_i and X_j under model (23) is:

$$
\begin{aligned}
(24) \qquad (R_{XXij})^2 &= (\sigma_{XXij})^2/(\sigma_{XXii}\sigma_{XXjj}) \\
&= (\sigma_{xxij} + \sigma_{uuij})^2/[(\sigma_{XXii}\sigma_{XXjj})] \\
&= \kappa_{xxii}\kappa_{xxjj}\,\{[(\sigma_{xxij})^2 + 2\sigma_{xxij}\sigma_{uuij} + (\sigma_{uuij})^2]/(\sigma_{xxii}\,\sigma_{xxjj})\} \\
&= \kappa_{xxii}\kappa_{xxjj}\,(R_{xxij})^2 + \kappa_{xxii}\kappa_{xxjj}\,\{[2\sigma_{xxij}\sigma_{uuij} + (\sigma_{uuij})^2]/(\sigma_{xxii}\,\sigma_{xxjj})\}
\end{aligned}
$$

If the measurement errors, u_{it} and u_{jt}, are uncorrelated, then σ_{uuij} in (24) is zero. Hence, the second expression within the big bracket on the right-hand-side vanishes and the equation collapses to form:

$$
(24a) \qquad (R_{XXij})^2 = \kappa_{xxii}\kappa_{xxjj}\,(R_{xxij})^2
$$

However, if the measurement errors are correlated, then the second term on the right-hand-side of (24) is not zero. In either case, equation (24) allows us to compute the reliability corrected correlation matrix.

Since the reliability ratios, κ_{xxii} and κ_{xxjj}, are less than or equal to one, the result of (24a) again confirms that the existence of measurement error reduces the magnitude of the correlation coefficient between pairwise job factors under the independent measurement error assumption. A report of the reliability corrected true correlation matrix under the independent measurement error assumption of the original Arthur Young's thirteen job evaluation factors is attached in the Appendix (Table A.2). The true correlations show evidence of serious multicollinearity between job factors. The true correlation coefficients are greater than the observed correlation coefficients. In fact, several factors are perfectly or nearly perfectly correlated. These factors include Knowledge From Experience (KFE), Job Complexity, Judgement, and Problem-Solving (CJPS), Guidelines/Supervision Available (GSA), Scope and Effect (SE), and Impact of Errors (IE). These factors measure similar job attributes both conceptually and empirically. The measurement of these factors is discussed in detail in the next section. Thus, knowledge of the reliability ratios of the job factors and the statistical properties (independence or correlation) of the measurement errors associated with the job factors allow us to reconstruct the reliability corrected true correlation matrix even though the true job evaluation factors are not directly observed.

SECTION III. DATA AND ESTIMATION PROCEDURES

Arthur Young Factor Point model for the predicting pay is

$$Y_t = \alpha_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_{13} X_{13t} + \gamma\, PF_t + v_t \tag{25}$$

where Y_t = job classification pay grade $\quad t = 1, 2, \ldots, 758$ job classifications

X_{it} = job evaluation factor in t^{th} job classification $\quad i = 1, 2, \ldots, 13$

PF_t = percentage of female incumbents in t^{th} job classification

α_0 = intercept

β_j = evaluation factor weight for j^{th} factor $\quad j = 1, 2, \ldots, 13$

γ = coefficient for percentage female incumbents

v_t = random disturbance term

The definition of the original Arthur Young thirteen job evaluation factors (Arthur Young, 1984, p. 28) is contained in the Appendix (Exhibit A.1). The coefficient γ in equation (25) captures the effect of percent female incumbents on pay. It may represent a measure of whether the pay plan is systematically discriminatory against women. From a statistical point of view, if the coefficient γ is significantly less than zero then the pay plan scheme discriminates against women. Nonetheless, as discussed in the introduction section, there are other possible interpretations of this percent female coefficient as well. Both supply- and demand-side explanations of unmeasured job attributes affecting both male and female labor supply and/or firm pay decisions may be reflected on this percent female coefficient. The dependent variables used in (25) throughout this paper include current pay grade (PG), maximum salary (MS), and natural logarithm of maximum salary (LOGMS). OLS and EVCARP regressions will be applied to equation (25) to compare the evaluation factor weights and the measure of discrimination with and without correcting for measurement error problem.

The EVCARP regression will incorporate knowledge of reliability ratios associated with the evaluation factors. The reliability ratios in Arthur Young's analysis were the inter-rater team reliability. According to their final report "during the first few weeks of evaluation, 20 job classifications were evaluated by 2 teams, 6 job classifications were evaluated by 3 teams, and 2 job classifications were evaluated by 9 teams. They had the teams evaluate at least one job classification each day that had been done by another team. In total, 90 job classifications (98 separate pairs of comparisons), representing both male- and female-dominated classes, were evaluated by more than one team." (Arthur Young, 1984, p. 14). The reliability ratios were reported as follows:

	Reliability Ratio
Knowledge from Formal Training/Education (KFFTE)	0.92
Knowledge from Experience (KFE)	0.75
Complexity, Judgement, and Problem-Solving (CJPS)	0.85
Guidelines/Supervision Available (GSA)	0.73
Personal Contacts -- Purpose (PCP)	0.77
Personal Contacts -- Type (PCT)	0.78
Physical Demands (PD)	0.84
Mental/Visual Demands (MVD)	0.55
Supervision Exercised -- Nature (SENA)	0.91
Supervision Exercised -- Number (SENU)	0.94
Scope and Effect (SE)	0.73
Impact of Errors (IE)	0.74

Working Environment (WE)	0.71
Unavoidable Hazards/Risks (UHR)	0.86
Work Pace/Pressure (WPP)	0.61
Interruptions (I)	0.48

Arthur Young prioritized these aspects of job worth and finally determined that thirteen major factors (including some factors which combined elements of the larger lists) appeared to be most appropriate for use in the Comparable Worth study. Several of these thirteen factors were comprised of subfactors. These include factors of personal contacts (purpose and type), supervision exercised (nature and number), and work pace/pressure and interruptions. However, Arthur Young did not report the reliability coefficients for these combined factors. Hence, the reliability coefficients for these factors in this study were estimated from the reliability coefficients of the respective subfactors reported above by using a Monte Carlo simulation approach discussed below.

The Arthur Young Consultants and the Steering Committee established a final set of weights for each factor. The compensable factors were assigned weights as listed below (Arthur Young, 1984, p. 31):

	Factor Percent of Total
Knowledge from Formal Training/Education (KFFTE)	15%
Knowledge from Experience (KFE)	10%

Complexity, Judgement, and Problem-Solving (CJPS)	12%
Guidelines/Supervision Available (GSA)	5%
Personal Contacts (PC)	10%
Physical Demands (PD)	5%
Mental/Visual Demands (MVD)	5%
Supervision Exercised (SEN)	8%
Scope and Effect (SE)	10%
Impact of Errors (IE)	5%
Working Environment (WE)	5%
Unavoidable Hazards/Risks (UHR)	5%
Work Pace/Pressures and Interruptions (WI)	5%

After the relative weight of each factor was determined, each percentage was applied to the total number of points available for the evaluation system (1,000 points). For instance, Personal Contacts has a factor weight of 10%; thus, the highest degree would have a value of 100 points (1,000 x 10%). Arthur Young determined a constant value of 1.66 was most appropriate to be used to multiply or divide a base value to achieve the spread from the highest to lowest degree on most factors. Therefore, in their final point structure, succeeding values are then divided by 1.66 until a value is obtained for all degrees. Several of the factors contain multiple subfactors and are set up on a matrix. In these cases the same multiple is used along the diagonals and the square roots of the multiple ($(1.66)^{1/2} = 1.29$) is used for the intervening steps.

The formulas used by Arthur Young to generate the three combined factors discussed above are presented below. The formula used to obtain personal contact points (PC), a formula which combines information from degrees of personal contacts -- purpose (PCP) and personal contacts -- type (PCT) is:

$$PC = 100 / \{1.29^{**}[9-(PCP+PCT)]\}$$

where "100" is the highest point total for Personal Contacts, "1.29" is the constant deflator of the intervening steps, "**" is the power of the respective variable, and "9" is the sum of the total degrees of subfactors. Similarly, for factors of supervision exercised and work pace/pressure and interruptions, the formulas are expressed as:

$$SEN = 80 / \{1.29^{**}[12-(SENA+SENU)]\}$$

and

$$WI = 50 / \{1.29^{**}[6-(WPP+I)]\}$$

Direct computation of the reliability ratios of the nonlinear transformation is not straightforward. Hence, a Monto Carlo simulation approach is applied to estimate the reliability ratios for the combined factors. This is done as follows. First, by assuming the observed and the true factors have the same sample mean, it is possible to generate a set of observed variables with the same mean and variance using a random number generator.

Second, from the knowledge of the reliability ratio and the observed sample variance, we can compute the variance for the true variable. Using the observed sample mean and the true sample variance we can generate a set of true variables. Third, the nonlinear transformation is imposed on both the generated observed and true variables. This generates observed and true combined factors. The proportion of variation in the observed combined factor attributable to variation in the true combined factor is the reliability ratio for the combined factor. As a prior, the reliability ratio for the combined factor is most likely to be between the reliability ratios of the subfactors. We found that reliability ratios for factors of Personal Contacts, Supervision Exercised, and Work Pace/Pressure and Interruptions are 0.78, 0.92, and 0.55, respectively. An alternative approach to deriving reliability ratios would be to use a first order Taylor series expansion for the three combined factors.[1] Table 1 describes the summary of sample statistics used in this analysis.

OLS regressions using pay grade (PG), logarithm of maximum salary (LOGMS), and maximum salary (MS) as dependent variables using equation (25) are reported in Table 2 and Table 2.A. This regression includes the original Arthur Young 13 job evaluation factors and a factor which measures the percentage female (PF) incumbents in each job as regressors. Adding market wages (MW) as a factor can serve two main purposes (Greig et al., 1989, p. 140): (1) market wages can serve as a proxy for some relevant job factors which are difficult to measure or are excluded from the pay analysis, and (2) market wages can add information concerning how difficult it is to recruit qualified workers in a given occupation. However, as also addressed by Greig et al. (1989), if market wages are not a *bona fide* job characteristics

Table 1. Summary of sample statistics

Variable	N	Mean	Std Dev	Minimum	Maximum
LOGMS	758	6.5132309	0.2781830	5.8242286	7.5188243
MS	758	700.6808707	200.0132137	338.4000000	1842.4000000
PG	758	23.8126649	6.6926682	8.0000000	46.0000000
KFFTE	758	49.6174142	34.8960913	6.0000000	150.0000000
KFE	758	36.7387863	21.3025101	8.0000000	100.0000000
CJPS	758	23.9036939	17.7712594	6.0000000	120.0000000
GSA	758	17.8522427	9.2185737	6.0000000	50.0000000
PC	758	47.3773087	17.8920914	17.0000000	100.0000000
PD	758	17.7638522	9.7849215	11.0000000	50.0000000
MVD	758	12.6174142	4.7941855	11.0000000	50.0000000
SEN	758	10.0923483	12.8523541	0	80.0000000
SE	758	32.4894459	17.9935191	13.0000000	100.0000000
IE	758	18.4102902	9.3990780	6.0000000	50.0000000
WE	758	17.1569921	7.4250387	11.0000000	50.0000000
UHR	758	9.5079156	5.9928902	6.0000000	50.0000000
WI	758	30.9868074	7.7573733	18.0000000	50.0000000
PF	758	33.5179420	38.4039789	0	100.0000000
MW	758	9.4917678	3.0862908	3.3500000	19.2400000
KCGSI1	758	3.6156043	1.8867590	1.0902718	11.7427873
KCGSI	758	25.8788918	13.4891493	7.8000000	84.0000000

Note: KCGSI1 is the first principal component of KFE, CJPS, GSA, SE, and IE, while KCGSI is the average of KFE, CJPS, GSA, SE, and IE. See text for details.

Table 2. OLS regressions using original Arthur Young 13 job evaluation factors (without MW, standard errors in parentheses) (***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	Dependent Variable PG	LOGMS	MS
INTERCEPT	$1.00\times10^{***}$	5.95^{***}	$3.07\times10^{2***}$
	(0.06×10)	(0.03)	(0.17×10^{2})
KFFTE	$7.56\times10^{-2***}$	$3.09\times10^{-3***}$	1.80^{***}
	(0.34×10^{-2})	(0.15×10^{-3})	(0.09)
KFE	$8.25\times10^{-2***}$	$3.41\times10^{-3***}$	2.16^{***}
	(0.65×10^{-2})	(0.28×10^{-3})	(0.17)
CJPS	-1.19×10^{-2}	0.89×10^{-4}	1.80^{***}
	(0.88×10^{-2})	(3.75×10^{-4})	(0.24)
GSA	$1.01\times10^{-1***}$	$4.30\times10^{-3***}$	2.26^{***}
	(0.18×10^{-1})	(0.77×10^{-3})	(0.49)
PC	$3.43\times10^{-2***}$	$1.07\times10^{-3***}$	$6.29\times10^{-1***}$
	(0.64×10^{-2})	(0.27×10^{-3})	(1.73×10^{-1})
PD	$-4.54\times10^{-2***}$	$-1.09\times10^{-3**}$	0.71×10^{-1}
	(1.18×10^{-2})	(0.50×10^{-3})	(3.16×10^{-1})
MVD	$5.08\times10^{-2***}$	$1.99\times10^{-3***}$	1.68^{***}
	(1.70×10^{-2})	(0.72×10^{-3})	(0.46)
SEN	0.41×10^{-3}	-4.21×10^{-4}	-2.25×10^{-1}
	(8.28×10^{-3})	(3.53×10^{-4})	(2.22×10^{-1})
SE	$2.70\times10^{-2***}$	$1.17\times10^{-3***}$	1.43^{***}
	(0.91×10^{-2})	(0.39×10^{-3})	(0.24)
IE	$8.21\times10^{-2***}$	$3.41\times10^{-3***}$	2.64^{***}
	(1.53×10^{-2})	(0.65×10^{-3})	(0.41)
WE	$3.07\times10^{-2**}$	$1.46\times10^{-3**}$	3.83×10^{-1}
	(1.52×10^{-2})	(0.65×10^{-3})	(4.07×10^{-1})
UHR	1.67×10^{-2}	3.31×10^{-4}	-0.70×10^{-1}
	(1.58×10^{-2})	(6.74×10^{-4})	(4.25×10^{-1})
WI	$5.97\times10^{-2***}$	$2.08\times10^{-3***}$	4.51×10^{-1}
	(1.23×10^{-1})	(0.53×10^{-3})	(3.31×10^{-1})
PF	$-2.66\times10^{-2***}$	$-1.34\times10^{-3***}$	$-7.19\times10^{-1***}$
	(0.23×10^{-2})	(0.10×10^{-3})	(0.62×10^{-1})
R^2	0.90	0.90	0.92
Adj R^2	0.90	0.90	0.92

Table 2.A. OLS regressions using original Arthur Young 13 job evaluation factors (with MW, standard errors in parentheses) (***, **, *, significant at 1%, 5%, 10% level)

	Dependent Variable		
JOB FACTOR	PG	LOGMS	MS
INTERCEPT	8.68***	5.88***	2.67×10^{2}***
	(0.63)	(0.03)	(0.17×10^{2})
KFFTE	6.21×10^{-2}***	2.37×10^{-3}***	1.40***
	(0.37×10^{-2})	(0.16×10^{-3})	(0.10)
KFE	7.45×10^{-2}***	2.99×10^{-3}***	1.92***
	(0.64×10^{-2})	(0.27×10^{-3})	(0.17)
CJPS	-1.10×10^{-2}	1.36×10^{-4}	1.83***
	(0.85×10^{-2})	(3.54×10^{-4})	(0.23)
GSA	9.04×10^{-2}***	3.75×10^{-3}***	1.94***
	(1.76×10^{-2})	(0.73×10^{-3})	(0.47)
PC	3.90×10^{-2}***	1.31×10^{-3}***	7.69×10^{-1}***
	(0.62×10^{-2})	(0.26×10^{-3})	(1.66×10^{-1})
PD	-5.05×10^{-2}***	-1.36×10^{-3}**	-0.81×10^{-1}
	(1.14×10^{-2})	(0.47×10^{-3})	(3.02×10^{-1})
MVD	4.25×10^{-2}***	1.55×10^{-3}**	1.43***
	(1.64×10^{-2})	(0.68×10^{-3})	(0.44)
SEN	4.70×10^{-3}	-1.94×10^{-4}	-0.96×10^{-1}
	(8.00×10^{-3})	(3.33×10^{-4})	(2.13×10^{-1})
SE	2.99×10^{-2}***	1.32×10^{-3}***	1.52***
	(0.88×10^{-2})	(0.37×10^{-3})	(0.23)
IE	5.77×10^{-2}***	2.12×10^{-3}***	1.91***
	(1.51×10^{-2})	(0.63×10^{-3})	(0.40)
WE	2.32×10^{-2}	1.07×10^{-3}*	1.60×10^{-1}
	(1.46×10^{-2})	(0.61×10^{-3})	(3.89×10^{-1})
UHR	1.99×10^{-2}	5.01×10^{-4}	0.26×10^{-1}
	(1.52×10^{-2})	(6.36×10^{-4})	(4.05×10^{-1})
WI	5.78×10^{-2}***	1.98×10^{-3}***	3.95×10^{-1}
	(1.19×10^{-1})	(0.50×10^{-3})	(3.16×10^{-1})
PF	-2.26×10^{-2}***	-1.12×10^{-3}***	-5.97×10^{-1}***
	(0.23×10^{-2})	(0.10×10^{-3})	(0.61×10^{-1})
MW	2.93×10^{-1}***	1.55×10^{-2}***	8.83***
	(0.38×10^{-1})	(0.16×10^{-2})	(1.02)
R^2	0.91	0.91	0.93
Adj R^2	0.91	0.91	0.93

because the labor market systematically discriminates against female-dominated occupations, then market wages will be spurious information in a pay analysis. Note that *Bona fide* job factors refer to the factors that would affect worker productivity and the incentives needed to compensate for unpleasant job attributes. Hence, we use both with and without the market wage factor as a regressor in the regressions. Table 2 reports the OLS regressions without market wage while Table 2.A includes market wage. Note that in these regressions we have not corrected for the problems of measurement error and multicollinearity associated with the right-hand-side regressors.

In Table 2, the OLS regression using pay grade as dependent variable, percentage female variable has a significantly negative effect on pay. A 10% increase in the percent female incumbents in a job classification will reduce pay by 0.27% while in Table 2.A (MW included) a same proportion increase in the percent female will reduce pay by about 0.23%.

In Table 2 and Table 2.A, knowledge from education (KFFTE), knowledge from experience (KFE), guidelines/supervision available (GSA), personal contacts (PC), mental/visual demands (MVD), scope and effect (SE), impact of errors (IE), working environment (WE), work pace/pressures and interruptions (WI), and market wage (MW) significantly raise pay. In contrast, factors of physical demands (PD) and percent female (PF) have negative impacts on pay. Adding market wages to the analysis reduces the magnitude of the coefficient on percent female incumbents on all regressions. The overall explanatory power of these regressions is about ninety one percent. However, note that the OLS regressions reported in Tables 2 and 2.A have not corrected the problems of measurement error and multicollinearity associated with the job evaluation factors and hence the coefficient estimates are biased for both variables measured with and without error as already shown in the previous section. Therefore, pay recommendations based on job evaluation factor weights estimated from the OLS regressions without correcting problems of measurement error and multicollinearity were biased.

The EVCARP regressions which correct the problem of measurement errors using the same set of regressors as listed in Table 2 and Table 2.A yield high R^2 but low individual t-ratios for the estimates of the job evaluation factors. Multicollinearity was suspected to exist among regressors. An attempt to examine the correlation matrix of the original Arthur Young observed evaluation factors found that among the 13 factors 5 of them are highly intercorrelated with Pearson's correlation coefficients ranging from 0.67 to 0.83. These include the following five job factors: knowledge--from experience (KFE); job complexity, judgement, and problem-solving (CJPS); guidelines/supervision available (GSA); scope and effect (SE); and impact of errors (IE). The correlation matrix of the observed job factors is reported in the Appendix (Table A.1). These five job factors were defined by Arthur Young Company as follows:

Knowledge--from Experience:

This factor evaluates the least amount of time normally required for a person with the "typically required" training/education to acquire the knowledge and skills to perform the job satisfactorily.

Job Complexity, Judgement, and Problem-Solving:

This factor measures the complexity of duties, and the frequency and extent of judgement used in decision-making and problem-solving.

Guidelines/Supervision Available:

This factor covers the nature of guidelines and the judgement needed for application. Included are the extent and closeness of supervision required and received for methods to be followed, results to be obtained, and frequency of work progress review.

Scope and Effect:

This factor measures the relationship between the nature of the work, its purpose, breadth and depth, and the effect of work products or services within and outside the organizational unit.

Impact of Errors:

This factor measures the likely effect or probable consequences of potential errors made by an individual in the regular course of the work and the opportunity for making such errors.

Examining Arthur Young's definition of these five factors indicates that they do not differ conceptually nor do they differ empirically. All of these factors measure similar job attributes of either experience and judgement required to perform the job satisfactorily or scope of work and probable consequences of making potential errors.

Table 3 reports EVCARP regressions without market wage factor and Table 3.A presents EVCARP regressions with market wage factor. The determinantal matrix of the EVCARP regression is nearly singular, as indicated by the fact that the smallest root of the determinantal matrix is close to zero. Since the distribution of the smallest root for EV2 is not the same as that for the estimated error covariance matrix case (discussed below) we also computed the smallest root using information on the estimated error covariance matrix to perform an F-test of singularity in the determinantal matrix.

The smallest root can be used as a test of the hypothesis that the sum of squares and product matrix of the true values of the explanatory variables is singular. Fuller (1987) showed that if the rank of the matrix constructed from the true explanatory variables is k-1 (k is the number of total explanatory variables) the smallest root is approximately distributed as Snedecor's F with n-k+1 and d_f degrees of freedom, where d_f is the degrees of freedom for the error covariance matrix. The approximation assumes the sample is a simple random sample. The test statistic is

$$F = n\,(n-k+1)^{-1}\,\hat{\gamma}$$

where $\hat{\gamma}$ is the smallest root. For one to be comfortable with the analysis, the singularity F-test statistic reported should be large relative to the tabular value for the F-distribution to guarantee positive definiteness of the sum of squares and product matrix of the true explanatory variables. Multicollinearity among true job factors seriously affected the

Table 3. EVCARP regressions using original Arthur Young 13 job evaluation factors (without MW, standard errors in parentheses) (***, **, *, significant at 1%, 5%, 10% level)

	Dependent Variable		
JOB FACTOR	PG	LOGMS	MS
INTERCEPT	0.22×10	5.64	0.33×10^{3}
	(8.98×10)	(4.47)	(2.37×10^{3})
KFFTE	-0.00	-0.01×10^{-1}	0.51×10
	(2.85)	(1.42×10^{-1})	(7.62×10)
KFE	-0.11	-0.05×10^{-1}	0.11×10^{2}
	(7.34)	(3.67×10^{-1})	(1.96×10^{2})
CJPS	-0.36	-0.15×10^{-1}	0.08×10^{2}
	(7.35)	(3.67×10^{-1})	(1.95×10^{2})
GSA	0.32×10	0.14	-0.08×10^{3}
	(8.47×10)	(4.22)	(2.25×10^{3})
PC	0.14	0.05×10^{-1}	-0.17×10
	(2.46)	(1.22×10^{-1})	(6.53×10)
PD	0.10	0.05×10^{-1}	-0.25×10
	(3.12)	(1.56×10^{-1})	(8.28×10)
MVD	-0.17	-0.08×10^{-1}	0.10×10^{2}
	(7.48)	(3.73×10^{-1})	(1.99×10^{2})
SEN	-0.19×10^{-1}	-0.12×10^{-2}	-0.14×10
	(4.15×10^{-1})	(2.05×10^{-2})	(1.13×10)
SE	-0.15×10	-0.07	0.05×10^{3}
	(4.30×10)	(2.15)	(1.15×10^{3})
IE	0.13×10	0.06	-0.31×10^{2}
	(3.30×10)	(1.65)	(8.79×10^{2})
WE	-0.03	-0.01×10^{-1}	0.37×10
	(2.55)	(1.27×10^{-1})	(6.80×10)
UHR	-0.26	-0.12×10^{-1}	0.08×10^{2}
	(7.65)	(3.82×10^{-1})	(2.04×10^{2})
WI	0.48×10^{-1}	0.13×10^{-2}	0.06×10
	(6.95×10^{-1})	(3.43×10^{-2})	(1.86×10)
PF	-0.06×10^{-1}	-0.04×10^{-2}	-0.88
	(3.43×10^{-1})	(1.71×10^{-2})	(9.08)
SMALLEST ROOT	0.57	0.57	0.57
SINGULARITY F-TEST	0.58	0.58	0.58
R^2	0.97	0.97	0.98

Table 3.A. EVCARP regressions using original Arthur Young 13 job evaluation factors (with MW, standard errors in parentheses) (***, **, *, significant at 1%, 5%, 10% level)

	Dependent Variable		
JOB FACTOR	PG	LOGMS	MS
INTERCEPT	$0.48x10$	5.74^{***}	$2.22x10^{2}$
	$(1.16x10)$	(0.49)	$(2.34x10^{2})$
KFFTE	0.04	$0.15x10^{-2}$	$0.33x10$
	(2.01)	$(9.57x10^{-2})$	$(2.58x10)$
KFE	-0.06	$-0.02x10^{-1}$	$0.09x10^{2}$
	(7.80)	$(3.72x10^{-1})$	$(1.00x10^{2})$
CJPS	$-0.04x10$	$-0.13x10^{-1}$	$0.08x10^{2}$
	$(1.03x10)$	$(4.89x10^{-1})$	$(1.31x10^{2})$
GSA	$0.03x10^{2}$	0.12	$-0.08x10^{3}$
	$(1.09x10^{2})$	(5.21)	$(1.40x10^{3})$
PC	0.12	$0.04x10^{-1}$	$-0.10x10$
	(2.59)	$(1.23x10^{-1})$	$(3.32x10)$
PD	0.11	$0.05x10^{-1}$	$-0.28x10$
	(4.70)	$(2.24x10^{-1})$	$(6.01x10)$
MVD	-0.14	$-0.05x10^{-1}$	$0.08x10^{2}$
	(8.45)	$(4.02x10^{-1})$	$(1.09x10^{2})$
SEN	$-0.33x10^{-1}$	$-1.75x10^{-3}$	-0.82
	$(1.61x10^{-1})$	$(6.76x10^{-3})$	(3.21)
SE	$-0.15x10$	-0.06	$0.41x10^{2}$
	$(5.63x10)$	(2.68)	$(7.24x10^{2})$
IE	$0.13x10$	0.05	$-0.32x10^{2}$
	$(4.68x10)$	(2.23)	$(6.02x10^{2})$
WE	0.00	$0.06x10^{-2}$	$0.21x10$
	(1.83)	$(8.72x10^{-2})$	$(2.37x10)$
UHR	$-0.03x10$	$-0.10x10^{-1}$	$0.08x10^{2}$
	$(1.10x10)$	$(5.25x10^{-1})$	$(1.42x10^{2})$
WI	0.04	$0.14x10^{-2}$	$0.07x10$
	(1.05)	$(4.97x10^{-2})$	$(1.43x10)$
PF	$-0.13x10^{-1}$	$-0.75x10^{-3}$	-0.59
	$(1.58x10^{-1})$	$(7.46x10^{-3})$	(2.07)
MW	$-0.07x10$	-0.02	$0.26x10^{2}$
	$(2.94x10)$	(1.40)	$(3.78x10^{2})$
SMALLEST ROOT	0.57	0.57	0.57
SINGULARITY F-TEST	0.58	0.58	0.58
R^2	0.97	0.95	0.99

EVCARP regression results which yielded high R^2 but low individual t-ratios for the estimates as shown in Tables 3 and 3A. The next section develops a remedy for solving the problem of multicollinearity and hence to construct efficient estimates for the Arthur Young pay analysis.

SECTION IV. SOLUTIONS TO THE MULTICOLLINEARITY PROBLEM

A solution to the problem of multicollinearity in regression analysis that is often suggested is the principal component regression (Maddala, 1992). In our comparable worth pay analysis, we have 13 evaluation factors originally considered by Arthur Young Company. We can consider linear functions of these factors:

$$z_1 = a_1x_1 + a_2x_2 + \dots + a_{13}x_{13}$$

$$z_2 = b_1x_1 + b_2x_2 + \dots + b_{13}x_{13}$$

$$\vdots$$

$$z_{13} = g_1x_1 + g_2x_2 + \dots + g_{13}x_{13}$$

where x_i is the standardized variable of X_i and X_i is the original evaluation factors. Suppose we choose the a's so that the variance of z_1 is maximized subject to the condition that

$$a_1^2 + a_2^2 + \dots + a_{13}^2 = 1$$

This is called the normalization condition. z_1 is then said to be the first principal component. It is the linear function of the x's that has the highest variance (subject to the normalization rule). Corresponding to these we construct 13 linear functions $z_1, z_2, \ldots, z_{13}$. These are the principal components of the x's. They can be ordered so that

$$VAR(z_1) > VAR(z_2) > \ldots > VAR(z_{13})$$

z_1, the one with the highest variance is the first principal component, z_2 with the next highest variance is the second principal component, and so on. These principal components of the x's have the following important properties:

1. $VAR(z_1) + VAR(z_2) + \ldots + VAR(z_{13}) = VAR(x_1) + VAR(x_2) + \ldots + VAR(x_{13})$.
2. Unlike the x's, which are correlated, the z's are orthogonal or uncorrelated.

It is suggested to regress only a subset of the z's in regression analysis to correct for the multicollinearity problem. As noted above, the reliability corrected true correlations for factors of CJPS, GSA, SE, and IE show that they are nearly or perfectly correlated with factor KFE. Since five out of the thirteen job factors are highly intercorrelated, we perform the principal component analysis using these five factors to shrink down dimensionality. Among these five factors, the first two principal components explain about ninety one percent of the variation of the five factors while the first principal component explains nearly eighty percent of the variation. This implies the true dimensionality of the five factors is about two. Using only the first principal component has eighty percent explanatory power as compared to using all five factors. Combining the five factors into one using the first principal component in OLS and EVCARP regressions reduces the number of evaluation factors to nine rather than the thirteen factors as originally proposed by Arthur Young Company. The first eigenvector of the principal component (PRIN1) analysis is represented as:

$$\begin{array}{lccccc} & \text{KFE} & \text{CJPS} & \text{GSA} & \text{SE} & \text{IE} \\ \text{PRIN1} = [& 0.60, & 0.50, & 0.26, & 0.51, & 0.25] \end{array}$$

Hence, the first principal component KCGSI1 is therefore constructed as:

$$\text{KCGSI1} = 0.60(\text{KFE}/s_K) + 0.50(\text{CJPS}/s_C) + 0.26(\text{GSA}/s_G) + 0.51(\text{SE}/s_S) + 0.25(\text{IE}/s_I)$$

where s_i denotes the standard deviation of the corresponding job factors. In our empirical regressions we will be using this first principal component KCGSI1 as a regressor denoting a combination of the five factors including KFE, CJPS, GSA, SE, and IE, even though there are some problems with this procedure as addressed by Maddala (1992). One of the most important drawbacks of this method is the linear combination KCGSI1 does not have economic meaning.

However, another way of combining the five highly correlated job factors is to take a equally weighted average of these factors. For five job factors, the equal weight is 0.2. Hence, we can construct this equally weighted average of the five job factors as:

$$KCGSI = 0.2(KFE) + 0.2(CJPS) + 0.2(GSA) + 0.2(SE) + 0.2(IE)$$

Comparing KCGSI1 and KCGSI, it is easier to interpret the factor KCGSI because it gives equal weights to the five factors. As mentioned by Maddala (1992), principal components usually do not have economic meaning. However, we analyze the pay analysis using both measures of KCGSI1 and KCGSI to compare how sensitive the coefficient estimates are changed due to the different specifications of combining the five correlated job factors. Since both KCGSI1 and KCGSI are linear combinations of the five factors, we expect the empirical results using these two specifications to shrink down dimensionality of the job factors will be similar.

In order to run the regressions in EVCARP to correct the problem of measurement errors, we have to compute the reliability ratio for the combined factor KCGSI1 and KCGSI, respectively. For the first principal component KCGSI1, the reliability ratio is computed as follows:

(26) $$VAR(KCGSI1)$$

$$= VAR[0.60(KFE/s_K) + 0.50(CJPS/s_C) + 0.26(GSA/s_G) + 0.51(SE/s_S) +$$

$$0.25(IE/s_I)]$$

$$= VAR\{0.60[(k+u_K)/s_K] + 0.50[(c+u_C)/s_C] + 0.26[(g+u_G)/s_G] +$$

$$0.51[(s+u_S)/s_S] + 0.25[(i+u_I)/s_I]\}$$

$$= VAR[0.60(k/s_K) + 0.50(c/s_C) + 0.26(g/s_G) + 0.51(s/s_S) + 0.25(i/s_I)] +$$

$$VAR[0.60(u_K/s_K) + 0.50(u_C/s_C) + 0.26(u_G/s_G) + 0.51(u_S/s_S) + 0.25(u_I/s_I)]$$

where "VAR(•)" denotes variance of the respective expression inside the parenthesis, the lower case letter denotes the true variable of the corresponding job factor and the u_i is the measurement error associated with the factor. Under the assumption of independent measurement errors, it can be shown that

(26a) $$VAR[0.60(u_K/s_K) + 0.50(u_C/s_C) + 0.26(u_G/s_G) + 0.51(u_S/s_S) + 0.25(u_I/s_I)]$$

$$= (0.60/s_K)^2\sigma_{uuKK} + (0.50/s_C)^2\sigma_{uuCC} + (0.26/s_G)^2\sigma_{uuGG} +$$

$$(0.51/s_S)^2\sigma_{uuSS} + (0.25/s_I)^2\sigma_{uuII}$$

$$= (0.60)^2(1-\kappa_k) + (0.50)^2(1-\kappa_c) + (0.26)^2(1-\kappa_g) + (0.51)^2(1-\kappa_s) + (0.25)^2(1-\kappa_i)$$

$$= 0.23$$

Since the reliability ratios, κ_i 's, for the individual factors are known, the reliability ratio of the combined factor can be computed from the equation

$$[0.23/VAR(KCGSI1)] = 1 - \kappa_{kcgsi1}$$

The reliability ratio for KCGSI1, κ_{kcgsi1}, equals 0.94. Similarly, under the assumption of independent measurement errors, we can compute the reliability ratio for the weighted average KCGSI:

$$
\begin{aligned}
(27)\qquad & \mathrm{VAR(KCGSI)} \\
&= \mathrm{VAR(0.2KFE + 0.2CJPS + 0.2GSA + 0.2SE + 0.2IE)} \\
&= \mathrm{VAR}[0.2(k + c + g + s + i) + 0.2(u_K + u_C + u_G + u_S + u_I)] \\
&= \mathrm{VAR}[0.2(k + c + g + s + i)] + \mathrm{VAR}[0.2(u_K + u_C + u_G + u_S + u_I)]
\end{aligned}
$$

Under the assumption of independent measurement errors, the second term on the right-hand-side is

$$
\begin{aligned}
(27a)\qquad & \mathrm{VAR}[0.2(u_K + u_C + u_G + u_S + u_I)] \\
&= (0.2)^2[\sigma_{uuKK} + \sigma_{uuCC} + \sigma_{uuGG} + \sigma_{uuSS} + \sigma_{uuII}] \\
&= (0.2)^2[(1-\kappa_k)\sigma_{XXKK} + (1-\kappa_c)\sigma_{XXCC} + (1-\kappa_g)\sigma_{XXGG} + (1-\kappa_s)\sigma_{XXSS} + (1-\kappa_i)\sigma_{XXII}] \\
&= 11.77
\end{aligned}
$$

The reliability ratio of the combined factor KCGSI can be computed by replacing sample estimates for the σ_{XX}'s in Eq. (27a). The reliability ratio is calculated from the expression:

$$[11.77/\mathrm{VAR(KCGSI)}] = 1 - \kappa_{kcgsi}$$

Hence, the reliability ratio for KCGSI, κ_{kcgsi}, is 0.94.

Under the assumption of positively correlated measurement errors, the measurement error variance will be greater than under the assumption of independent measurement errors because the former involves pairwise correlations between measurement errors. Hence, the reliability ratios for the combined factors, KCGSI1 and KCGSI, will be less than 0.94. By the same derivation,[2] the reliability ratios for KCGSI1 and KCGSI under the correlated measurement error assumptions with the correlation coefficients 0.1, 0.2, and 0.3, are 0.91, 0.89, and 0.87, respectively.

An example of the matrix of measurement error variance ratios being used in EVCARP regression using first principal component KCGSI1 with measurement error correlation coefficient 0.1 is presented in the Appendix (Table A.3). The elements of the matrix are of the form

$$\lambda_{uuij} = (\sigma_{XXii}\,\sigma_{XXjj})^{-(1/2)}\sigma_{uuij}$$

where σ_{XXii} is the variance of the i-th observed job factor, and σ_{uuij} is the covariance between the error in the i-th job factor and the error in the j-th job factor. The covariance σ_{uuij} is computed using the hypothesized positive measurement error correlation coefficient ρ_{uuij}, 0.1, in this particular example. The formula used to compute the covariance σ_{uuij} is defined as:

$$\rho_{uuij} = \sigma_{uuij} / [(\sigma_{uuii}\,\sigma_{uujj})^{(1/2)}]$$

where σ_{uuii} is the variance of the measurement error of the i-th observed job factor. Independent measurement errors implies $\rho_{uuij} = 0$. Assumed measurement error correlations of 0.1, 0.2, and 0.3 are imposed on ρ_{uuij}, respectively, to compute measurement error covariances.

Note that the diagonal elements of the matrix of measurement error variance ratios are of the form

$$\lambda_{uuii} = 1 - \kappa_{xxii}$$

where κ_{xxii} is the reliability ratio for X_i.

OLS regressions using the combined factors generate coefficients on percent female that are larger in magnitude than those reported in Tables 2 and 2A. Therefore, use of the combined factor alone does not diminish the implied extent of discrimination against female jobs.

Tables 4 through 15 present the empirical results using both OLS and EVCARP regressions. The dependent variables used throughout the analysis are pay grade (PG), natural logarithm of maximum salary (LOGMS), and maximum salary (MS). In EVCARP runs, both independent measurement errors and positively correlated measurement errors with correlation coefficients ρ_{uuij}'s, 0.1, 0.2, and 0.3, are used to analyze the sensitivity of the

Table 4. Empirical results using first principal component KCGSI1
(dependent variable: PG, without MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	$1.14\times10^{***}$	8.36^{***}	-2.55	$-1.14\times10^{**}$	-9.57^{**}
	(0.06×10)	(1.99)	(3.75)	(0.55×10)	(4.56)
KFFTE	$6.56\times10^{-2***}$	$7.14\times10^{-2***}$	$7.65\times10^{-2***}$	$8.37\times10^{-2***}$	$8.23\times10^{-2***}$
	(0.31×10^{-2})	(0.47×10^{-2})	(0.63×10^{-2})	(0.81×10^{-2})	(0.69×10^{-2})
KCGSI1	1.79^{***}	2.10^{***}	1.89^{***}	1.77^{***}	1.95^{***}
	(0.08)	(0.23)	(0.30)	(0.29)	(0.19)
PC	$2.81\times10^{-2***}$	0.10×10^{-2}	$5.88\times10^{-2**}$	$1.07\times10^{-1***}$	$9.84\times10^{-2***}$
	(0.66×10^{-2})	(2.15×10^{-2})	(2.72×10^{-2})	(0.32×10^{-1})	(2.51×10^{-2})
PD	$-6.11\times10^{-2***}$	$-1.20\times10^{-1*}$	0.74×10^{-2}	$9.83\times10^{-2*}$	$9.04\times10^{-2**}$
	(1.22×10^{-2})	(0.62×10^{-1})	(5.72×10^{-2})	(5.67×10^{-2})	(4.25×10^{-2})
MVD	$4.53\times10^{-2**}$	$9.80\times10^{-2*}$	$3.24\times10^{-1***}$	$5.03\times10^{-1***}$	$4.52\times10^{-1***}$
	(1.77×10^{-2})	(5.28×10^{-2})	(0.80×10^{-1})	(1.07×10^{-1})	(0.85×10^{-1})
SEN	8.65×10^{-3}	-1.72×10^{-2}	-1.64×10^{-2}	-0.32×10^{-2}	-0.28×10^{-2}
	(8.55×10^{-3})	(1.62×10^{-2})	(1.99×10^{-2})	(2.22×10^{-2})	(1.94×10^{-2})
WE	$2.93\times10^{-2*}$	1.63×10^{-1}	$1.31\times10^{-1*}$	$1.53\times10^{-1***}$	$1.55\times10^{-1***}$
	(1.59×10^{-2})	(1.02×10^{-1})	(0.73×10^{-1})	(0.55×10^{-1})	(0.41×10^{-1})
UHR	$2.81\times10^{-2*}$	-0.36×10^{-2}	1.23×10^{-2}	2.36×10^{-2}	3.78×10^{-2}
	(1.60×10^{-2})	(4.20×10^{-2})	(3.53×10^{-2})	(3.60×10^{-2})	(3.03×10^{-2})
WI	$6.37\times10^{-2***}$	1.09×10^{-1}	$2.35\times10^{-1***}$	$2.99\times10^{-1***}$	$2.52\times10^{-1***}$
	(1.28×10^{-2})	(0.70×10^{-1})	(0.78×10^{-1})	(0.80×10^{-1})	(0.55×10^{-1})
PF	$-2.99\times10^{-2***}$	$-2.42\times10^{-2***}$	$-2.22\times10^{-2***}$	$-1.77\times10^{-2***}$	$-1.55\times10^{-2***}$
	(0.24×10^{-2})	(0.38×10^{-2})	(0.42×10^{-2})	(0.49×10^{-2})	(0.46×10^{-2})
SMALLEST ROOT		1.15	1.20	1.09	0.94
SINGULARITY F-TEST		1.17^{**}	1.21^{***}	1.10^{*}	0.95
R^2	0.89	0.93	0.97	0.99	0.99
Adj R^2	0.89				

Table 5. Empirical results using first principal component KCGSI1
(dependent variable: PG, with MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	9.80^{***}	7.54^{***}	-2.55	$-1.13\times10^{*}$	-9.56^{*}
	(0.63)	(1.94)	(3.73)	(0.59x10)	(5.00)
KFFTE	$5.08\times10^{-2***}$	$6.23\times10^{-2***}$	$7.64\times10^{-2***}$	$9.29\times10^{-2***}$	$9.13\times10^{-2***}$
	(0.35×10^{-2})	(0.59×10^{-2})	(0.86×10^{-2})	(1.33×10^{-2})	(1.21×10^{-2})
KCGSI1	1.56^{***}	1.93^{***}	1.88^{***}	1.92^{***}	2.10^{***}
	(0.08)	(0.24)	(0.31)	(0.28)	(0.20)
PC	$3.43\times10^{-2***}$	1.17×10^{-2}	$5.89\times10^{-2**}$	$1.03\times10^{-1***}$	$9.61\times10^{-2***}$
	(0.63×10^{-2})	(2.20×10^{-2})	(2.73×10^{-2})	(0.32×10^{-1})	(2.59×10^{-2})
PD	$-6.51\times10^{-2***}$	$-1.13\times10^{-1*}$	0.74×10^{-2}	$1.05\times10^{-1*}$	$9.87\times10^{-2**}$
	(1.16×10^{-2})	(0.60×10^{-1})	(5.74×10^{-2})	(0.62×10^{-1})	(4.93×10^{-2})
MVD	$3.56\times10^{-2**}$	$9.33\times10^{-2*}$	$3.24\times10^{-1***}$	$5.23\times10^{-1***}$	$4.73\times10^{-1***}$
	(1.69×10^{-2})	(4.77×10^{-2})	(0.84×10^{-1})	(1.28×10^{-1})	(1.07×10^{-1})
SEN	1.33×10^{-2}	-1.24×10^{-2}	-1.63×10^{-2}	-0.75×10^{-2}	-0.65×10^{-2}
	(0.82×10^{-2})	(1.53×10^{-2})	(2.02×10^{-2})	(2.32×10^{-2})	(2.05×10^{-2})
WE	2.09×10^{-2}	1.40×10^{-1}	$1.31\times10^{-1*}$	$1.66\times10^{-1***}$	$1.66\times10^{-1***}$
	(1.52×10^{-2})	(1.01×10^{-1})	(0.75×10^{-1})	(0.62×10^{-1})	(0.49×10^{-1})
UHR	$2.56\times10^{-2*}$	0.02×10^{-2}	1.23×10^{-2}	2.44×10^{-2}	3.95×10^{-2}
	(1.53×10^{-2})	(4.07×10^{-2})	(3.54×10^{-2})	(3.70×10^{-2})	(3.14×10^{-2})
WI	$5.96\times10^{-2***}$	1.09×10^{-1}	$2.35\times10^{-1***}$	$3.08\times10^{-1***}$	$2.61\times10^{-1***}$
	(1.23×10^{-2})	(0.67×10^{-1})	(0.80×10^{-1})	(0.89×10^{-1})	(0.65×10^{-1})
PF	$-2.48\times10^{-2***}$	$-2.26\times10^{-2***}$	$-2.22\times10^{-2***}$	$-1.95\times10^{-2***}$	$-1.74\times10^{-2***}$
	(0.24×10^{-2})	(0.36×10^{-2})	(0.42×10^{-2})	(0.50×10^{-2})	(0.46×10^{-2})
MW	$3.34\times10^{-1***}$	$1.69\times10^{-1***}$	0.19×10^{-2}	-1.76×10^{-1}	-1.79×10^{-1}
	(0.39×10^{-1})	(0.59×10^{-1})	(8.30×10^{-2})	(1.34×10^{-1})	(1.35×10^{-1})
SMALLEST ROOT		1.15	1.19	1.06	0.89
SINGULARITY F-TEST		1.16^{**}	1.21^{***}	1.07^{*}	0.90
R^2	0.90	0.93	0.97	0.99	0.99
Adj R^2	0.90				

Table 6. Empirical results using first principal component KCGSI1
(dependent variable: LOGMS, without MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	6.00***	5.91***	5.47***	5.05***	5.13***
	(0.03)	(0.09)	(0.16)	(0.24)	(0.20)
KFFTE	2.74×10^{-3}***	2.96×10^{-3}***	3.17×10^{-3}***	3.50×10^{-3}***	3.43×10^{-3}***
	(0.13×10^{-3})	(0.20×10^{-3})	(0.25×10^{-3})	(0.34×10^{-3})	(0.29×10^{-3})
KCGSI1	7.98×10^{-2}***	9.91×10^{-2}***	9.16×10^{-2}***	8.30×10^{-2}***	8.93×10^{-2}***
	(0.34×10^{-2})	(0.96×10^{-2})	(1.19×10^{-2})	(1.20×10^{-2})	(0.78×10^{-2})
PC	8.26×10^{-4}***	-7.13×10^{-4}	1.58×10^{-3}	3.94×10^{-3}***	3.65×10^{-3}***
	(2.77×10^{-4})	(9.40×10^{-4})	(1.12×10^{-3})	(1.38×10^{-3})	(1.06×10^{-3})
PD	-1.64×10^{-3}***	-4.47×10^{-3}*	0.74×10^{-3}	5.10×10^{-3}**	4.77×10^{-3}***
	(0.51×10^{-3})	(2.68×10^{-3})	(2.38×10^{-3})	(2.48×10^{-3})	(1.84×10^{-3})
MVD	1.84×10^{-3}**	3.47×10^{-3}	1.24×10^{-2}***	2.09×10^{-2}***	1.88×10^{-2}***
	(0.75×10^{-3})	(2.56×10^{-3})	(0.36×10^{-2})	(0.48×10^{-2})	(0.38×10^{-2})
SEN	-1.18×10^{-4}	-1.36×10^{-3}**	-1.44×10^{-3}*	-8.11×10^{-4}	-7.24×10^{-4}
	(3.60×10^{-4})	(0.69×10^{-3})	(0.82×10^{-3})	(9.27×10^{-4})	(8.06×10^{-4})
WE	1.41×10^{-3}**	7.88×10^{-3}*	6.29×10^{-3}**	6.81×10^{-3}***	6.76×10^{-3}***
	(0.67×10^{-3})	(4.39×10^{-3})	(3.01×10^{-3})	(2.37×10^{-3})	(1.76×10^{-3})
UHR	7.45×10^{-4}	-0.90×10^{-3}	-0.09×10^{-3}	0.48×10^{-3}	1.12×10^{-3}
	(6.72×10^{-4})	(1.85×10^{-3})	(1.46×10^{-3})	(1.52×10^{-3})	(1.29×10^{-3})
WI	2.24×10^{-3}***	3.03×10^{-3}	8.15×10^{-3}**	1.18×10^{-2}***	9.92×10^{-3}***
	(0.54×10^{-3})	(3.02×10^{-3})	(3.22×10^{-3})	(0.35×10^{-2})	(2.38×10^{-3})
PF	-1.45×10^{-3}***	-1.14×10^{-3}***	-1.06×10^{-3}***	-8.96×10^{-4}***	-8.19×10^{-4}***
	(0.10×10^{-3})	(0.16×10^{-3})	(0.17×10^{-3})	(2.02×10^{-4})	(1.91×10^{-4})
SMALLEST ROOT		1.15	1.20	1.09	0.94
SINGULARITY F-TEST		1.17**	1.21***	1.10*	0.95
R^2	0.89	0.93	0.96	0.99	0.99
Adj R^2	0.89				

Table 7. Empirical results using first principal component KCGSI1
(dependent variable: LOGMS, with MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	5.92^{***}	5.86^{***}	5.47^{***}	5.05^{***}	5.12^{***}
	(0.03)	(0.08)	(0.15)	(0.26)	(0.22)
KFFTE	$2.00\times10^{-3***}$	$2.48\times10^{-3***}$	$3.01\times10^{-3***}$	$3.76\times10^{-3***}$	$3.68\times10^{-3***}$
	(0.14×10^{-3})	(0.25×10^{-3})	(0.34×10^{-3})	(0.57×10^{-3})	(0.51×10^{-3})
KCGSI1	$6.84\times10^{-2***}$	$8.93\times10^{-2***}$	$8.90\times10^{-2***}$	$8.71\times10^{-2***}$	$9.31\times10^{-2***}$
	(0.33×10^{-2})	(0.98×10^{-2})	(1.19×10^{-2})	(1.14×10^{-2})	(0.80×10^{-2})
PC	$1.14\times10^{-3***}$	-1.06×10^{-4}	1.68×10^{-3}	$3.86\times10^{-3***}$	$3.62\times10^{-3***}$
	(0.26×10^{-3})	(9.37×10^{-4})	(1.11×10^{-3})	(1.41×10^{-3})	(1.10×10^{-3})
PD	$-1.84\times10^{-3***}$	-4.09×10^{-3}	0.68×10^{-3}	$5.34\times10^{-3*}$	$5.04\times10^{-3**}$
	(0.48×10^{-3})	(2.56×10^{-3})	(2.34×10^{-3})	(2.74×10^{-3})	(2.13×10^{-3})
MVD	$1.35\times10^{-3*}$	3.20×10^{-3}	$1.21\times10^{-2***}$	$2.16\times10^{-2***}$	$1.95\times10^{-2***}$
	(0.70×10^{-3})	(2.24×10^{-3})	(0.36×10^{-2})	(0.58×10^{-2})	(0.47×10^{-2})
SEN	1.18×10^{-4}	$-1.09\times10^{-3*}$	$-1.36\times10^{-3*}$	-9.24×10^{-4}	-8.20×10^{-4}
	(3.37×10^{-4})	(0.64×10^{-3})	(0.81×10^{-3})	(9.63×10^{-4})	(8.44×10^{-4})
WE	9.84×10^{-4}	6.58×10^{-3}	$5.99\times10^{-3**}$	$7.20\times10^{-3***}$	$7.09\times10^{-3***}$
	(6.25×10^{-4})	(4.24×10^{-3})	(3.03×10^{-3})	(2.66×10^{-3})	(2.07×10^{-3})
UHR	6.22×10^{-4}	-0.68×10^{-3}	-0.07×10^{-3}	0.50×10^{-3}	1.16×10^{-3}
	(6.28×10^{-4})	(1.74×10^{-3})	(1.43×10^{-3})	(1.56×10^{-3})	(1.33×10^{-3})
WI	$2.04\times10^{-3***}$	2.99×10^{-3}	$7.99\times10^{-3**}$	$1.21\times10^{-2***}$	$1.02\times10^{-2***}$
	(0.50×10^{-3})	(2.82×10^{-3})	(3.21×10^{-3})	(0.39×10^{-2})	(0.28×10^{-2})
PF	$-1.19\times10^{-3***}$	$-1.05\times10^{-3***}$	$-1.03\times10^{-3***}$	$-9.44\times10^{-4***}$	$-8.66\times10^{-4***}$
	(0.10×10^{-3})	(0.15×10^{-3})	(0.17×10^{-3})	(2.06×10^{-4})	(1.91×10^{-4})
MW	$1.68\times10^{-2***}$	$9.60\times10^{-3***}$	2.93×10^{-3}	-4.92×10^{-3}	-4.77×10^{-3}
	(0.16×10^{-2})	(2.43×10^{-3})	(3.26×10^{-3})	(5.68×10^{-3})	(5.63×10^{-3})
SMALLEST ROOT		1.15	1.19	1.06	0.89
SINGULARITY F-TEST		1.16^{**}	1.21^{***}	1.07^{*}	0.90
R^2	0.90	0.93	0.96	0.99	0.99
Adj R^2	0.90				

Table 8. Empirical results using first principal component KCGSI1
(dependent variable: MS, without MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	$3.11X10^{2***}$	$2.78x10^{2***}$	1.01x10	-4.08x10	-5.26x10
	$(0.16X10^{2})$	$(0.54x10^{2})$	(8.00x10)	(6.80x10)	(7.32x10)
KFFTE	1.79^{***}	1.84^{***}	1.92^{***}	1.99^{***}	2.02^{***}
	(0.08)	(0.13)	(0.15)	(0.14)	(0.14)
KCGSI1	$7.05x10^{***}$	$9.15x10^{***}$	$8.96x10^{***}$	$8.33x10^{***}$	$8.15x10^{***}$
	(0.21x10)	(0.77x10)	(0.77x10)	(0.50x10)	(0.45x10)
PC	$5.64x10^{-1***}$	$-2.49x10^{-1}$	$9.17x10^{-1}$	1.43^{***}	1.56^{***}
	$(1.69x10^{-1})$	$(6.02x10^{-1})$	$(6.45x10^{-1})$	(0.46)	(0.43)
PD	$0.15x10^{-1}$	-1.24	1.77	2.61^{***}	2.78^{***}
	$(3.13x10^{-1})$	(1.74)	(1.31)	(0.78)	(0.73)
MVD	1.72^{***}	3.00^{**}	8.14^{***}	8.65^{***}	8.63^{***}
	(0.46)	(1.40)	(1.74)	(1.41)	(1.50)
SEN	$-2.08x10^{-1}$	-1.15^{***}	-1.42^{***}	$-9.78x10^{-1**}$	$-7.81x10^{-1*}$
	$(2.20x10^{-1})$	(0.43)	(0.51)	$(4.34x10^{-1})$	$(4.12x10^{-1})$
WE	$3.79x10^{-1}$	3.95	3.20^{*}	2.69^{***}	2.68^{***}
	$(4.08x10^{-1})$	(3.03)	(1.83)	(0.96)	(0.83)
UHR	$1.50x10^{-1}$	-0.58	$-0.53x10^{-1}$	$3.42x10^{-1}$	$5.11x10^{-1}$
	$(4.11x10^{-1})$	(1.25)	$(9.29x10^{-1})$	$(7.23x10^{-1})$	$(7.12x10^{-1})$
WI	$5.41x10^{-1}$	-1.19	2.18	2.98^{***}	3.12^{***}
	$(3.30x10^{-1})$	(2.11)	(1.79)	(1.01)	(0.86)
PF	$-7.41x10^{-1***}$	$-4.93x10^{-1***}$	$-4.13x10^{-1***}$	$-4.19x10^{-1***}$	$-4.10x10^{-1***}$
	$(0.62x10^{-1})$	$(1.12x10^{-1})$	$(1.07x10^{-1})$	$(0.99x10^{-1})$	$(1.02x10^{-1})$
SMALLEST ROOT		1.15	1.20	1.09	0.94
SINGULARITY F-TEST		1.17^{**}	1.21^{***}	1.10^{*}	0.95
R^2	0.92	0.96	0.99	0.99	0.99
Adj R^2	0.92				

Table 9. Empirical results using first principal component KCGSI1
(dependent variable: MS, with MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	$2.66\text{x}10^{2***}$	$2.61\text{x}10^{2***}$	1.26x10	-3.97x10	-5.17x10
	$(0.16\text{x}10^{2})$	$(0.54\text{x}10^{2})$	(8.06x10)	(6.85x10)	(7.36x10)
KFFTE	1.38^{***}	1.66^{***}	1.99^{***}	2.05^{***}	2.08^{***}
	(0.09)	(0.17)	(0.20)	(0.20)	(0.20)
KCGSI	$6.44\text{x}10^{***}$	$8.80\text{x}10^{***}$	$9.09\text{x}10^{***}$	$8.43\text{x}10^{***}$	$8.24\text{x}10^{***}$
	(0.21x10)	(0.84x10)	(0.83x10)	(0.56x10)	(0.53x10)
PC	$7.33\text{x}10^{-1***}$	$-0.34\text{x}10^{-1}$	$8.65\text{x}10^{-1}$	1.41^{***}	1.55^{***}
	$(1.62\text{x}10^{-1})$	$(6.27\text{x}10^{-1})$	$(6.64\text{x}10^{-1})$	(0.46)	(0.43)
PD	$-0.94\text{x}10^{-1}$	-1.11	1.78	2.65^{***}	2.83^{***}
	$(2.97\text{x}10^{-1})$	(1.72)	(1.32)	(0.82)	(0.79)
MVD	1.46^{***}	2.90^{**}	8.25^{***}	8.77^{***}	8.74^{***}
	(0.43)	(1.29)	(1.86)	(1.57)	(1.71)
SEN	$-0.81\text{x}10^{-1}$	-1.06^{**}	-1.45^{***}	-1.00^{**}	$-8.01\text{x}10^{-1*}$
	$(2.09\text{x}10^{-1})$	(0.42)	(0.54)	(0.46)	$(4.33\text{x}10^{-1})$
WE	$1.50\text{x}10^{-1}$	3.49	3.32^{*}	2.76^{***}	2.74^{***}
	$(3.88\text{x}10^{-1})$	(3.04)	(1.90)	(1.03)	(0.91)
UHR	$0.84\text{x}10^{-1}$	-0.50	$-0.59\text{x}10^{-1}$	$3.49\text{x}10^{-1}$	$5.21\text{x}10^{-1}$
	$(3.90\text{x}10^{-1})$	(1.22)	$(9.39\text{x}10^{-1})$	$(7.30\text{x}10^{-1})$	$(7.21\text{x}10^{-1})$
WI	$4.31\text{x}10^{-1}$	-1.21	2.24	3.04^{***}	3.17^{***}
	$(3.14\text{x}10^{-1})$	(2.04)	(1.83)	(1.07)	(0.94)
PF	$-6.02\text{x}10^{-1***}$	$-4.60\text{x}10^{-1***}$	$-4.27\text{x}10^{-1***}$	$-4.32\text{x}10^{-1***}$	$-4.23\text{x}10^{-1***}$
	$(0.60\text{x}10^{-1})$	$(1.05\text{x}10^{-1})$	$(1.06\text{x}10^{-1})$	$(0.98\text{x}10^{-1})$	$(0.99\text{x}10^{-1})$
MW	9.05^{***}	3.41^{**}	-1.35	-1.15	-1.07
	(1.00)	(1.73)	(2.19)	(2.28)	(2.49)
SMALLEST ROOT		1.15	1.19	1.06	0.89
SINGULARITY F-TEST		1.16^{**}	1.21^{***}	1.07^{*}	0.90
R^2	0.93	0.97	0.99	0.99	0.99
Adj R^2	0.93				

Table 10. Empirical results using average KCGSI
(dependent variable: PG, without MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	$1.15\times10^{***}$	8.41^{***}	-2.49	$-1.14\times10^{**}$	-9.59^{**}
	(0.06×10)	(2.00)	(3.76)	(0.56×10)	(4.58)
KFFTE	$6.54\times10^{-2***}$	$7.12\times10^{-2***}$	$7.63\times10^{-2***}$	$8.36\times10^{-2***}$	$8.21\times10^{-2***}$
	(0.31×10^{-2})	(0.47×10^{-2})	(0.63×10^{-2})	(0.82×10^{-2})	(0.70×10^{-2})
KCGSI	$2.51\times10^{-1***}$	$2.94\times10^{-1***}$	$2.64\times10^{-1***}$	$2.47\times10^{-1***}$	$2.73\times10^{-1***}$
	(0.11×10^{-1})	(0.32×10^{-1})	(0.42×10^{-1})	(0.41×10^{-1})	(0.27×10^{-1})
PC	$2.81\times10^{-2***}$	0.09×10^{-2}	$5.88\times10^{-2**}$	$1.08\times10^{-1***}$	$9.86\times10^{-2***}$
	(0.66×10^{-2})	(2.15×10^{-2})	(2.72×10^{-2})	(0.32×10^{-1})	(2.52×10^{-2})
PD	$-6.11\times10^{-2***}$	$-1.20\times10^{-1*}$	0.69×10^{-2}	$9.87\times10^{-2*}$	$9.06\times10^{-2**}$
	(1.22×10^{-2})	(0.62×10^{-1})	(5.74×10^{-2})	(5.71×10^{-2})	(4.27×10^{-2})
MVD	$4.51\times10^{-2**}$	$9.75\times10^{-2*}$	$3.23\times10^{-1***}$	$5.04\times10^{-1***}$	$4.52\times10^{-1***}$
	(1.77×10^{-2})	(5.29×10^{-2})	(0.81×10^{-1})	(1.08×10^{-1})	(0.86×10^{-1})
SEN	8.78×10^{-3}	-1.69×10^{-2}	-1.60×10^{-2}	-0.27×10^{-2}	-0.23×10^{-2}
	(8.54×10^{-3})	(1.62×10^{-2})	(1.98×10^{-2})	(2.22×10^{-2})	(1.94×10^{-2})
WE	$2.93\times10^{-2*}$	1.64×10^{-1}	$1.31\times10^{-1*}$	$1.53\times10^{-1***}$	$1.55\times10^{-1***}$
	(1.59×10^{-2})	(1.02×10^{-1})	(0.73×10^{-1})	(0.55×10^{-1})	(0.41×10^{-1})
UHR	$2.72\times10^{-2*}$	-0.51×10^{-2}	1.11×10^{-2}	2.25×10^{-2}	3.68×10^{-2}
	(1.60×10^{-2})	(4.21×10^{-2})	(3.52×10^{-2})	(3.60×10^{-2})	(3.03×10^{-2})
WI	$6.34\times10^{-2***}$	1.08×10^{-1}	$2.34\times10^{-1***}$	$2.98\times10^{-1***}$	$2.52\times10^{-1***}$
	(1.28×10^{-2})	(0.70×10^{-1})	$(0..79\times10^{-1})$	(0.80×10^{-1})	(0.57×10^{-1})
PF	$-2.99\times10^{-2***}$	$-2.42\times10^{-2***}$	$-2.23\times10^{-2***}$	$-1.77\times10^{-2***}$	$-1.55\times10^{-2***}$
	(0.24×10^{-2})	(0.38×10^{-2})	(0.42×10^{-2})	(0.49×10^{-2})	(0.46×10^{-2})
SMALLEST ROOT		1.15	1.19	1.09	0.94
SINGULARITY F-TEST		1.17^{**}	1.21^{***}	1.10^{*}	0.95
R^2	0.89	0.93	0.97	0.99	0.99
Adj R^2	0.89				

Table 11. Empirical results using average KCGSI
(dependent variable: PG, with MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	9.81***	7.58***	-2.49	-1.14×10*	-9.57*
	(0.63)	(1.95)	(3.74)	(0.60×10)	(5.02)
KFFTE	5.07×10^{-2}***	6.22×10^{-2}***	7.62×10^{-2}***	9.28×10^{-2}***	9.12×10^{-2}***
	(0.35×10^{-2})	(0.59×10^{-2})	(0.86×10^{-2})	(1.34×10^{-2})	(1.22×10^{-2})
KCGSI	2.19×10^{-1}***	2.70×10^{-1}***	2.64×10^{-1}***	2.68×10^{-1}***	2.94×10^{-1}***
	(0.11×10^{-1})	(0.34×10^{-1})	(0.43×10^{-1})	(0.39×10^{-1})	(0.28×10^{-1})
PC	3.43×10^{-2}***	1.16×10^{-2}	5.88×10^{-2}**	1.04×10^{-1}***	9.63×10^{-2}***
	(0.63×10^{-2})	(2.20×10^{-2})	(2.73×10^{-2})	(0.33×10^{-1})	(2.60×10^{-2})
PD	-6.51×10^{-2}***	-1.13×10^{-1}*	0.69×10^{-2}	1.05×10^{-1}*	9.89×10^{-2}**
	(1.16×10^{-2})	(0.61×10^{-1})	(5.75×10^{-2})	(0.62×10^{-1})	(4.95×10^{-2})
MVD	3.55×10^{-2}**	9.29×10^{-2}*	3.23×10^{-1}***	5.24×10^{-1}***	4.74×10^{-1}***
	(1.69×10^{-2})	(4.78×10^{-2})	(0.84×10^{-2})	(1.29×10^{-2})	(1.08×10^{-2})
SEN	1.35×10^{-2}*	-1.21×10^{-2}	-1.59×10^{-2}	-0.70×10^{-2}	-0.61×10^{-2}
	(0.82×10^{-2})	(1.53×10^{-2})	(2.01×10^{-2})	(2.32×10^{-2})	(2.05×10^{-2})
WE	2.08×10^{-2}	1.41×10^{-1}	1.31×10^{-1}*	1.66×10^{-1}***	1.66×10^{-1}***
	(1.52×10^{-2})	(1.02×10^{-1})	(0.75×10^{-1})	(0.62×10^{-1})	(0.49×10^{-1})
UHR	2.49×10^{-2}	-0.12×10^{-2}	1.11×10^{-2}	2.32×10^{-2}	3.84×10^{-2}
	(1.53×10^{-2})	(4.08×10^{-2})	(3.53×10^{-2})	(3.70×10^{-2})	(3.14×10^{-2})
WI	5.95×10^{-2}***	1.08×10^{-1}	2.34×10^{-1}***	3.08×10^{-1}***	2.61×10^{-1}***
	(1.23×10^{-2})	(0.68×10^{-1})	(0.80×10^{-1})	(0.90×10^{-1})	(0.65×10^{-1})
PF	-2.48×10^{-2}***	-2.26×10^{-2}***	-2.22×10^{-2}***	-1.95×10^{-2}***	-1.74×10^{-2}***
	(0.24×10^{-2})	(0.36×10^{-2})	(0.42×10^{-2})	(0.50×10^{-2})	(0.46×10^{-2})
MW	3.33×10^{-1}***	1.68×10^{-1}***	0.14×10^{-2}	-1.78×10^{-1}	-1.80×10^{-1}
	(0.39×10^{-1})	(0.59×10^{-1})	(8.30×10^{-2})	(1.34×10^{-1})	(1.35×10^{-1})
SMALLEST ROOT		1.15	1.19	1.06	0.89
SINGULARITY F-TEST		1.16**	1.21***	1.07*	0.90
R^2	0.90	0.93	0.97	0.99	0.99
Adj R^2	0.90				

Table 12. Empirical results using average KCGSI
(dependent variable: LOGMS, without MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	6.01***	5.91***	5.47***	5.05***	5.13***
	(0.03)	(0.09)	(0.16)	(0.24)	(0.20)
KFFTE	2.73×10^{-3}***	2.98×10^{-3}***	3.16×10^{-3}***	3.50×10^{-3}***	3.43×10^{-3}***
	(0.13×10^{-3})	(0.20×10^{-3})	(0.25×10^{-3})	(0.34×10^{-3})	(0.29×10^{-3})
KCGSI	1.12×10^{-2}***	1.39×10^{-2}***	1.28×10^{-2}***	1.16×10^{-2}***	1.25×10^{-2}***
	(0.05×10^{-2})	(0.13×10^{-2})	(0.17×10^{-2})	(0.17×10^{-2})	(0.11×10^{-2})
PC	8.25×10^{-4}***	-7.18×10^{-4}	1.57×10^{-3}	3.95×10^{-3}***	3.66×10^{-3}***
	(2.77×10^{-4})	(9.42×10^{-4})	(1.12×10^{-3})	(1.39×10^{-3})	(1.07×10^{-3})
PD	-1.64×10^{-3}***	-4.51×10^{-3}*	0.71×10^{-3}	5.11×10^{-3}**	4.78×10^{-3}***
	(0.51×10^{-3})	(2.70×10^{-3})	(2.38×10^{-3})	(2.50×10^{-3})	(1.85×10^{-3})
MVD	1.83×10^{-3}**	3.44×10^{-3}	1.24×10^{-2}***	2.09×10^{-2}***	1.88×10^{-2}***
	(0.74×10^{-3})	(2.57×10^{-3})	(0.36×10^{-2})	(0.49×10^{-2})	(0.38×10^{-2})
SEN	-1.12×10^{-4}	-1.35×10^{-3}*	-1.43×10^{-3}*	-7.88×10^{-4}	-7.05×10^{-4}
	(3.59×10^{-4})	(0.69×10^{-3})	(0.82×10^{-3})	(9.28×10^{-4})	(8.06×10^{-4})
WE	1.41×10^{-3}**	7.93×10^{-3}*	6.30×10^{-3}**	6.81×10^{-3}***	6.76×10^{-3}***
	(0.67×10^{-3})	(4.41×10^{-3})	(3.01×10^{-3})	(2.38×10^{-3})	(1.76×10^{-3})
UHR	7.08×10^{-4}	-0.97×10^{-3}	-0.15×10^{-3}	0.43×10^{-3}	1.07×10^{-3}
	(6.72×10^{-4})	(1.85×10^{-3})	(1.46×10^{-3})	(1.52×10^{-3})	(1.29×10^{-3})
WI	2.23×10^{-3}***	2.97×10^{-3}	8.10×10^{-3}**	1.18×10^{-2}***	9.93×10^{-3}***
	(0.54×10^{-3})	(3.04×10^{-3})	(3.23×10^{-3})	(0.35×10^{-2})	(2.39×10^{-3})
PF	-1.45×10^{-3}***	-1.14×10^{-3}***	-1.06×10^{-3}***	-8.97×10^{-4}***	-8.19×10^{-4}***
	(0.10×10^{-3})	(0.16×10^{-3})	(0.17×10^{-3})	(2.02×10^{-4})	(1.91×10^{-4})
SMALLEST ROOT		1.15	1.19	1.09	0.94
SINGULARITY F-TEST		1.17***	1.21***	1.10*	0.95
R^2	0.89	0.93	0.96	0.99	0.99
Adj R^2	0.89				

Table 13. Empirical results using avergae KCGSI
(dependent variable: LOGMS, with MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	5.92***	5.86***	5.47***	5.04***	5.12***
	(0.03)	(0.08)	(0.15)	(0.26)	(0.22)
KFFTE	$1.99x10^{-3}$***	$2.47x10^{-3}$***	$3.00x10^{-3}$***	$3.76x10^{-3}$***	$3.68x10^{-3}$***
	($0.14x10^{-3}$)	($0.25x10^{-3}$)	($0.34x10^{-3}$)	($0.57x10^{-3}$)	($0.51x10^{-3}$)
KCGSI	$9.58x10^{-3}$***	$1.25x10^{-2}$***	$1.25x10^{-2}$***	$1.22x10^{-2}$***	$1.30x10^{-2}$***
	($0.47x10^{-3}$)	($0.14x10^{-2}$)	($0.17x10^{-2}$)	($0.16x10^{-2}$)	($0.11x10^{-2}$)
PC	$1.14x10^{-3}$***	$-1.12x10^{-4}$	$1.68x10^{-3}$	$3.88x10^{-3}$***	$3.62x10^{-3}$***
	($0.26x10^{-3}$)	($9.40x10^{-4}$)	($1.11x10^{-3}$)	($1.42x10^{-3}$)	($1.10x10^{-3}$)
PD	$-1.84x10^{-3}$***	$-4.12x10^{-3}$	$0.66x10^{-3}$	$5.36x10^{-3}$*	$5.05x10^{-3}$**
	($0.48x10^{-3}$)	($2.57x10^{-3}$)	($2.35x10^{-3}$)	($2.76x10^{-3}$)	($2.14x10^{-3}$)
MVD	$1.34x10^{-3}$*	$3.18x10^{-3}$	$1.21x10^{-2}$***	$2.17x10^{-2}$***	$1.95x10^{-2}$***
	($0.70x10^{-3}$)	($2.25x10^{-3}$)	($0.36x10^{-2}$)	($0.58x10^{-2}$)	($0.47x10^{-2}$)
SEN	$1.24x10^{-4}$	$-1.08x10^{-3}$*	$-1.34x10^{-3}$*	$-9.04x10^{-4}$	$-8.03x10^{-4}$
	($3.37x10^{-4}$)	($0.64x10^{-3}$)	($0.81x10^{-3}$)	($9.63x10^{-4}$)	($8.44x10^{-4}$)
WE	$9.84x10^{-4}$	$6.62x10^{-3}$	$6.01x10^{-3}$**	$7.20x10^{-3}$***	$7.10x10^{-3}$***
	($6.25x10^{-4}$)	($4.25x10^{-3}$)	($3.03x10^{-3}$)	($2.67x10^{-3}$)	($2.07x10^{-3}$)
UHR	$5.91x10^{-4}$	$-0.74x10^{-3}$	$-0.12x10^{-3}$	$0.45x10^{-3}$	$1.11x10^{-3}$
	($6.28x10^{-4}$)	($1.74x10^{-3}$)	($1.43x10^{-3}$)	($1.56x10^{-3}$)	($1.33x10^{-3}$)
WI	$2.03x10^{-3}$***	$2.93x10^{-3}$	$7.94x10^{-3}$**	$1.21x10^{-2}$***	$1.02x10^{-2}$***
	($0.51x10^{-3}$)	($2.84x10^{-3}$)	($3.22x10^{-3}$)	($0.40x10^{-2}$)	($0.28x10^{-2}$)
PF	$-1.19x10^{-3}$***	$-1.05x10^{-3}$***	$-1.03x10^{-3}$***	$-9.45x10^{-4}$***	$-8.67x10^{-4}$***
	($0.10x10^{-3}$)	($0.15x10^{-3}$)	($0.17x10^{-3}$)	($2.06x10^{-4}$)	($1.91x10^{-4}$)
MW	$1.68x10^{-2}$***	$9.54x10^{-3}$***	$2.90x10^{-3}$	$-4.98x10^{-3}$	$-4.84x10^{-3}$
	($0.16x10^{-2}$)	($2.44x10^{-3}$)	($3.26x10^{-3}$)	($5.70x10^{-3}$)	($5.64x10^{-3}$)
SMALLEST ROOT		1.15	1.19	1.06	0.89
SINGULARITY F-TEST		1.16**	1.21***	1.07*	0.90
R^2	0.90	0.93	0.96	0.99	0.99
Adj R^2	0.90				

Table 14. Empirical results using average KCGSI
(dependent variable: MS, without MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	$3.11X10^{2***}$	$2.80x10^{2***}$	1.27x10	-3.95x10	-5.16x10
	$(0.16X10^{2})$	$(0.55x10^{2})$	(8.03x10)	(6.81x10)	(7.32x10)
KFFTE	1.78^{***}	1.83^{***}	1.91^{***}	1.99^{***}	2.01^{***}
	(0.08)	(0.13)	(0.15)	(0.14)	(0.14)
KCGSI	9.87^{***}	$1.28x10^{***}$	$1.26x10^{***}$	$1.17x10^{***}$	$1.14x10^{***}$
	(0.29)	(0.11x10)	(0.11x10)	(0.70x10)	(0.06x10)
PC	$5.63x10^{-1***}$	$-2.56x10^{-1}$	$9.08x10^{-1}$	1.43^{***}	1.56^{***}
	$(1.69x10^{-1})$	$(6.04x10^{-1})$	$(6.47x10^{-1})$	(0.46)	(0.43)
PD	$0.12x10^{-1}$	-1.28	1.74	2.60^{***}	2.78^{***}
	$(3.13x10^{-1})$	(1.75)	(1.32)	(0.78)	(0.74)
MVD	1.71^{***}	2.97^{**}	8.10^{***}	8.63^{***}	8.61^{***}
	(0.46)	(1.41)	(1.75)	(1.41)	(1.50)
SEN	$-2.03x10^{-1}$	-1.14^{***}	-1.41^{***}	$-9.69x10^{-1**}$	$-7.71x10^{-1*}$
	$(2.20x10^{-1})$	(0.43)	(0.50)	$(4.33x10^{-1})$	$(4.11x10^{-1})$
WE	$3.78x10^{-1}$	4.00	3.22^{*}	2.69^{***}	2.68^{***}
	$(4.08x10^{-1})$	(3.05)	(1.84)	(0.96)	(0.83)
UHR	$1.18x10^{-1}$	-0.65	$-1.08x10^{-1}$	$2.98x10^{-1}$	$4.70x10^{-1}$
	$(4.10x10^{-1})$	(1.26)	$(9.30x10^{-1})$	$(7.22x10^{-1})$	$(7.11x10^{-1})$
WI	$5.31x10^{-1}$	-1.26	2.12	2.97^{***}	3.10^{***}
	$(3.30x10^{-1})$	(2.13)	(1.79)	(1.01)	(0.87)
PF	$-7.40x10^{-1***}$	$-4.91x10^{-1***}$	$-4.12x10^{-1***}$	$-4.19x10^{-1***}$	$-4.10x10^{-1***}$
	$(0.61x10^{-1})$	$(1.13x10^{-1})$	$(1.07x10^{-1})$	$(0.99x10^{-1})$	$(1.02x10^{-1})$
SMALLEST ROOT		1.15	1.19	1.09	0.94
SINGULARITY F-TEST		1.17^{**}	1.21^{***}	1.10^{*}	0.95
R^2	0.92	0.96	0.99	0.99	0.99
Adj R^2	0.92				

Table 15. Empirical results using average KCGSI
(dependent variable: MS, with MW, standard errors in parentheses)
(***, **, *, significant at 1%, 5%, 10% level)

JOB FACTOR	OLS	EVCARP $\rho_{uuij} = 0$	EVCARP $\rho_{uuij} = 0.1$	EVCARP $\rho_{uuij} = 0.2$	EVCARP $\rho_{uuij} = 0.3$
INTERCEPT	2.67×10^{2}***	2.64×10^{2}***	1.54×10	-3.83×10	-5.06×10
	(0.16×10^{2})	(0.54×10^{2})	(8.09×10)	(6.86×10)	(7.37×10)
KFFTE	1.38***	1.65***	1.98***	2.05***	2.07***
	(0.09)	(0.17)	(0.20)	(0.20)	(0.20)
KCGSI	9.01***	1.23×10***	1.27×10***	1.18×10***	1.15×10***
	(0.29)	(0.12×10)	(0.12×10)	(0.08×10)	(0.07×10)
PC	7.31×10^{-1}***	-0.45×10^{-1}	8.54×10^{-1}	1.40***	1.55***
	(1.62×10^{-1})	(6.30×10^{-1})	(6.67×10^{-1})	(0.46)	(0.43)
PD	-0.95×10^{-1}	-1.14	1.75	2.64***	2.82***
	(2.97×10^{-1})	(1.73)	(1.33)	(0.82)	(0.80)
MVD	1.45***	2.88**	8.22***	8.75***	8.73***
	(0.43)	(1.30)	(1.87)	(1.58)	(1.71)
SEN	-0.76×10^{-1}	-1.05**	-1.45***	-9.95×10^{-1}**	-7.93×10^{-1}*
	(2.09×10^{-1})	(0.42)	(0.54)	(4.55×10^{-1})	(4.33×10^{-1})
WE	1.50×10^{-1}	3.54	3.35*	2.77***	2.74***
	(3.88×10^{-1})	(3.07)	(1.91)	(1.03)	(0.91)
UHR	0.55×10^{-1}	-0.57	-1.15×10^{-1}	3.05×10^{-1}	4.80×10^{-1}
	(3.90×10^{-1})	(1.23)	(9.41×10^{-1})	(7.30×10^{-1})	(7.20×10^{-1})
WI	4.23×10^{-1}	-1.27	2.18	3.02***	3.15***
	(3.14×10^{-1})	(2.06)	(1.83)	(1.07)	(0.94)
PF	-6.02×10^{-1}***	-4.59×10^{-1}***	-4.27×10^{-1}***	-4.33×10^{-1}***	-4.23×10^{-1}***
	(0.60×10^{-1})	(1.06×10^{-1})	(1.07×10^{-1})	(0.98×10^{-1})	(0.99×10^{-1})
MW	9.00***	3.33*	-1.41	-1.21	-1.13
	(1.00)	(1.74)	(2.19)	(2.28)	(2.50)
SMALLEST ROOT		1.15	1.19	1.06	0.89
SINGULARITY F-TEST		1.16**	1.21***	1.07*	0.90
R^2	0.93	0.97	0.99	0.99	0.99
Adj R^2	0.93				

results of the pay analysis.

SECTION V. EMPIRICAL RESULTS

The empirical results consist of an extension of Arthur Young's and Greig's (1987) work on pay analysis. However, measurement error and multicollinearity problems associated with the original thirteen job evaluation factors were not taken into account in Arthur Young's analysis, whereas the latter was not considered in Greig's analysis. Hence, this study aims to correct these two problems simultaneously by exploring the possibility of positive measurement error correlations. Exhibit A.2 in the Appendix reports the F tests between OLS regression with combined factors and the OLS regressions using the original Arthur Young thirteen factors. When pay grade and logarithm of maximum salary are used as the dependent variables, the null hypotheses that the five factors can be combined into a single factor are rejected. The null hypothesis is accepted when maximum salary is used as the dependent variable. Nevertheless, the restriction is imposed throughout because the results reject the use of the separate factors when error corrections are imposed.

As the assumption of independent measurement errors is relaxed, the determinantal equation in EVCARP regressions is closer to singularity. The smallest root of the determinantal equation in each EVCARP regression is reported at the bottom of Table 4 through Table 15. Note that as more correlations of measurement errors are allowed, the smaller is the smallest root of the determinantal equation. As discussed earlier, for one to be comfortable with the analysis, the singularity F-test statistic should be large relative to the tabular value for the F-distribution. This is so in our analysis except for the EVCARP regressions under $\rho_{uuij} = 0.3$.

Tables 4 and 5 present the pay analysis using current pay grade as the dependent variable. Tables 4-9 present the regressions using the first principal component KCGSI1 as the combined factor. OLS regression indicates that the percentage female incumbents (PF) has a significantly negative impact on pay grade. Excluding market wage, a ten percentage point increase in female proportion in an occupation reduces the pay grade by almost 0.3 percentage points. Correcting for the problem of measurement error in EVCARP regression reduces the absolute magnitude of the percent female coefficient. For example, under the assumption of independent measurement errors, a ten-point increase in the percentage of women in a job classification reduces pay on average by about 0.24 percentage points, a reduction of 0.06 percentage points. Allowing assumed positive measurement error correlations between pairwise job factors reduces the coefficient on percent female incumbents even further. The lost pay grade from a 10 percentage point increase in percent female incumbents ranges from 0.22 to 0.16 percentage points as measurement error correlation coefficients range from 0.1 to 0.3.

Measurement error corrections also affects the coefficients on the other job evaluation factors. Under independent measurement errors, knowledge from education, KCGSI1, physical demands, and mental/visual demands are significant determinants of current pay grade. Personal contacts, working environment, unavoidable hazards/risks, and work pace/pressures and interruptions lose importance in determining pay although the latter have significant effects on pay according to the OLS regression. This implies the presence of measurement error associated with the Arthur Young job evaluation factors significantly biases the estimates of the job factor weights as the significance and magnitudes of estimates were different according to the OLS and EVCARP estimates. Allowing assumed positive measurement error correlations between pairwise job factors, several more job factors emerge as significant determinants of current pay grade as compared to the estimates under independent measurement errors. For instance, personal contacts, working environment, and work pace/pressures and interruptions again gain importance in explaining pay grade variation as assumed measurement error correlations are allowed. One important finding is the sign change of the factor physical demands. Under independent measurement errors, the job factor physical demands has a marginally significantly negative coefficient on pay. As assumed measurement error correlations are allowed from 0.2 to 0.3, the effects of physical demands on pay turn significantly positive. This finding supports our intention to allow positive measurement error correlations because we may not capture the correct sign of the effects of job factors on pay under the independent measurement error assumption. Nonetheless, the non-singularity test fails for 0.3 measurement error correlation. So the EVCARP results using $\rho_{uuij} = 0.3$ are invalid. Except for the job factor physical demands, the sign patterns of the significant job factor weights are consistent (all are positive) across the OLS and EVCARP regressions. In general, the absolute magnitudes of the coefficients on job factors in EVCARP regressions are greater than that of the coefficients in OLS regression and the standard errors of the coefficient estimates in EVCARP regressions are also greater.

Hence, with few exceptions, we conclude that OLS estimates which do not correct measurement error underestimates the magnitudes of the factor weights.

When the market wage factor is incorporated as an added regressor in the regression to predict pay (see Table 5), a ten percentage point increase in the percentage of female incumbents in a job classification reduces pay by about 0.25 percentage points as compared to the 0.3 percentage points with market wage excluded according to the OLS regressions. In EVCARP regression under $\rho_{uuij} = 0$, a ten percentage point increase in the percentage female incumbents in an occupation reduces pay by about 0.23 percentage points. There is a 0.02 percentage point difference between the OLS and EVCARP ($\rho_{uuij} = 0$) regressions. This indicates that adding market wage as a regressor in pay analysis reduces the difference between OLS and EVCARP regression estimates. As measurement error correlations are allowed, the effect of a ten percentage point increase in percent female incumbents falls from 0.22 to 0.17 percentage points. Market wages have significantly positive impacts on current pay grade both in the OLS and the EVCARP(under $\rho_{uuij} = 0$) regressions. A ten percentage point increase in the market wage induces an increase in pay grade level of 1.7 percentage points under the assumption of independent measurement errors as opposed to the 3.3 percentage point increase found in the OLS regression. Market wages lose significance in determining pay when measurement error correlations are allowed.

The measure of maximum salary in Arthur Young comparable worth pay analysis is computed by a positive linear transformation of total points obtained from job evaluation and therefore the results in terms of signs and statistical significance of employing maximum salary as the dependent variable in the pay analysis will be similar to the results using pay grade as the dependent variable. The regression coefficients on job factors and percent female incumbents can be interpreted as elasticities. The OLS regression implies that a 10 point increase in the percentage female incumbents in a job classification reduces maximum salary by 10.2 percentage points without measurement error correction. Under the assumption of independent measurement errors, a 10 point increase in the percent female incumbents within a job classification reduces maximum salary by 8 percentage points. When the assumption of independent measurement errors is relaxed, the percentage reductions in maximum salary due to a 10 point increase in percent female incumbents in a job classification falls from 7.4 to 5.7 percentage points as correlations range from 0.1 to 0.3. Without measurement error corrections, the average percentage adjustment in logarithm of maximum salary is 4.86%. This is taken by multiplying the regression coefficient on percent female incumbents by the mean of the percentage female incumbents over all job classifications which is 33.5. The comparable percentage reduction in logarithm of maximum salary is 3.8% and 3% under independent measurement errors and measurement error correlation of 0.2, respectively. The overstatement of the coefficient on percent female in OLS relative to EVCARP is on order of 38%.

Under the assumption of independent measurement errors, knowledge from education, KCGSI1 and working environment have strongly positive effects on logarithm of maximum salary whereas physical demands and supervision exercised have significantly negative effects. As error correlations are allowed, job factors gain in importance. Personal contacts, mental/visual demands, and work/pace pressures and interruptions emerge as significant determinants of maximum salary. Again, the relative magnitudes of job factor weights estimated using EVCARP regressions are greater than the factor weights estimated using OLS.

Adding market wages in the analysis of logarithm of maximum salary, a 10 point increase in percentage female incumbents reduces maximum salary by 7.4 percentage points as compared to 8 percentage points without market wage incorporated under independent measurement errors. Allowing positive measurement error correlations, the lost maximum salary from a 10 point increase in percentage female incumbents ranges from 7.2 to 6.1 percentage points as measurement error correlations range from 0.1 to 0.3. Market wage is a significant factor in determining logarithm of maximum salary under independent measurement errors. At the sample mean, a one dollar increase in market wage increases maximum salary by 6.7 dollars. However, allowing measurement error correlations, market wages lose importance in explaining logarithm of maximum salary. One finding from the inclusion of market wage as an added regressor is worth noting. In Table 6, under independent measurement errors, physical demands and working environment are important determinants of the logarithm of maximum salary. However, when market wage is considered in the analysis, these two job factors lose importance to explain logarithm of maximum salary. This finding implies that market wage may reflect job contents contained in factors of physical demands and working environment. This supports the interpretation that market wage is a *bona fide* job factor which affects worker productivity and the incentives needed to compensate for unpleasant job attributes as discussed by Greig et al. (1989). All other job factors appeared to have similar effects on logarithm of maximum salary as compared to the prior results.

The level of maximum salary is also used as dependent variable. The OLS coefficient on percent female incumbents without incorporating market wage is -0.74, while the point estimate in EVCARP ($\rho_{uuij} = 0$) is -0.49. As assumed measurement error correlations are allowed, the coefficients on percent female incumbents falls to -0.41. Correcting measurement error associated with job evaluation factors reduces the magnitude of the coefficient on percent female incumbents. As assumed measurement error correlations are considered, the magnitude of the coefficient on percent female reduces even more, while knowledge from education, KCGSI1, personal contacts, and mental/visual demands gain importance. As various measurement error corrections are performed, several other job evaluation factors emerge as significant determinants of maximum salary including supervision exercised, working environment, physical demands and work/pace pressures and interruptions. Supervision exercised has a significant negative effect on maximum salary in all EVCARP regressions but not in the OLS regression.

Adding market wages reduces the gap between the point estimates of percent female of OLS and EVCARP ($\rho_{uuij} = 0$) to 0.14 (0.60-0.46) as compared to 0.25 (0.74-0.49) when market wages were excluded. Allowing measurement error correlations, again, reduces the magnitudes of the coefficients on percent female incumbents. Market wage is still a significant factor in explaining maximum salary variation under independent measurement errors but not under the assumed correlated measurement errors. Under assumed measurement error correlations, market wages lose explanatory power since the job evaluation factors contain sufficient information to explain variation in maximum salary. This finding also holds for the other dependent variables. Correcting for measurement error also consistently allows more job factors to be significant determinants of maximum salary.

Almost identical findings were found when the weighted average of the five highly correlated factors is used as a regressor instead of using the first principal component. This is not unexpected since both the first principal component and the weighted average are linear combinations of the five correlated factors. Table 10 through Table 15 report the results using the weighted average approach for the five factors. Given the similarity in results, there is no need to repeat the discussion. The only difference in magnitudes of the coefficients on KCGSI relative to KCGSI1 is attributable to difference in the units of the two aggregates. Significance levels for the coefficients are virtually identical.

The bias caused by measurement error can be summarized with a table that compares relative magnitudes of the coefficient size. Table 16 presents the relative coefficient size that takes the OLS coefficients as a benchmark for comparison. Relative to the EVCARP coefficient under independent measurement errors, the OLS estimation overestimates the coefficient on percentage female incumbents by about 20 percent. Allowing 0.2 measurement error correlation, the OLS coefficient on percent female is about 40 percent higher relative to the EVCARP estimates. These magnitudes of relative coefficients are estimates of bias caused by measurement error. Similarly, relative to the EVCARP estimate

Table 16. Relative coefficient size

JOB FACTOR	OLS	OLS-MW	EVCARP $\rho_{uuij}=0$	EVCARP-MW $\rho_{uuij}=0$	EVCARP $\rho_{uuij}=0.1$	EVCARP-MW $\rho_{uuij}=0.1$	EVCARP $\rho_{uuij}=0.2$	EVCARP-MW $\rho_{uuij}=0.2$
Dependent Variable: Pay Grade								
KFFTE[a]	1.00	0.77	1.09	0.95	1.17	1.16	1.28	1.42
PF[a]	-1.00	-0.83	-0.81	-0.76	-0.74	-0.74	-0.59	-0.59
MW[b]		1.00		0.51		0.01		-0.53
Dependent Variable: Logarithm of Maximum Salary								
KFFTE[a]	1.00	0.73	1.08	0.91	1.16	1.10	1.28	1.37
PF[a]	-1.00	-0.82	-0.79	-0.72	-0.73	-0.71	-0.62	-0.65
MW[b]		1.00		0.57		0.17		-0.29
Dependent Variable: Maximum Salary								
KFFTE[a]	1.00	0.77	1.03	0.93	1.07	1.11	1.11	1.15
PF[a]	-1.00	-0.81	-0.67	-0.62	-0.56	-0.58	-0.57	-0.58
MW[b]		1.00		0.38		-0.15		-0.13

Notes: a. Relative to coefficients in OLS regression without market wage included.

b. Relative to coefficients in OLS regression with market wage included.

under independent measurement errors, the OLS estimate of the market wage is overestimated by about 50 percent. When maximum salary is used as the dependent variable, the magnitudes of overestimation of the OLS estimates are slightly larger than the overestimation when pay grade and logarithm of maximum salary are used as the dependent variables.

To illustrate the effects of measurement error on outcomes, predicted pay grade and maximum salary for each job using the parameter estimates with coefficient on percent female restricted to zero are obtained. A series of group means are computed to see how different groups are affected. Tables 17, 17.A and 17.B report group means for predicted pay grade, logarithm of maximum salary, and maximum salary, respectively, while Tables 18, 18.A, and 18.B show Student's t tests for subgroup means between various OLS and EVCARP regressions for predicted pay grade, logarithm of maximum salary, and maximum salary. Excluding market wages, OLS regression using 9 factors (first principal component approach) significantly overstated predicted pay grade for most of the subgroups as compared to the various EVCARP predictions.

Adding market wages in both OLS and EVCARP regressions reduces the differences between predicted pay grade under these two regressions. Allowing 0.1 and 0.2 measurement error correlations, the predicted pay grades for several of the job subgroups from OLS regression are not significantly different from the predicted pay grades from EVCARP regressions. To examine whether market wages capture measurement error information contained in the job factors, OLS regressions with market wages included are

Table 17. Group means of predicted pay grade

Subgroup	OLS13[a]	OLS13[a]-MW	OLS9[b]	OLS9[b]-MW	EVCARP $\rho_{uuij}=0$	EVCARP-MW $\rho_{uuij}=0$	EVCARP $\rho_{uuij}=0.1$	EVCARP-MW $\rho_{uuij}=0.1$	EVCARP $\rho_{uuij}=0.2$	EVCARP-MW $\rho_{uuij}=0.2$
Predicted Pay Grade										
81-100 PF job	21.7	21.3	22.3	21.3	21.5	21.4	21.5	21.1	21.0	21.1
21-80 PF job	24.3	23.9	24.8	23.9	24.2	24.1	24.3	23.9	24.0	24.0
0-20 PF job	26.0	25.8	26.4	25.7	26.0	26.0	26.1	25.7	26.1	26.0
Union	22.3	22.1	22.9	22.1	22.3	22.3	22.4	22.0	22.1	22.2
Not union	28.3	28.0	28.7	27.8	28.3	28.3	28.4	27.9	28.2	28.1
Managerial	32.5	32.2	33.0	32.1	32.5	32.6	33.0	32.5	33.2	33.1
Professional	28.3	27.8	28.7	27.7	28.2	28.2	28.4	28.0	28.3	28.2
Technical	21.6	21.7	22.0	21.5	21.7	21.7	21.8	21.5	21.8	21.7
Clerical	20.1	19.8	20.8	19.9	20.0	20.0	19.9	19.6	19.3	19.4
Service	18.5	18.3	19.2	18.3	18.5	18.3	18.3	18.0	18.0	18.1
<High school	16.3	16.0	17.1	16.2	15.8	15.7	15.5	15.2	14.9	15.1
High school	20.4	20.3	21.0	20.3	20.5	20.5	20.5	20.2	20.2	20.2
Technical school	23.1	23.1	23.4	22.9	23.0	23.1	23.1	22.8	23.0	22.8
>College	29.8	29.3	30.3	29.2	29.9	29.8	30.1	29.6	30.0	30.0
$0-5 MW	17.0	16.3	17.9	16.5	16.7	16.3	16.1	15.9	15.5	15.9
$5.01-7.5 MW	19.9	19.4	20.6	19.5	19.9	19.7	19.8	19.5	19.4	19.6
$7.51-10 MW	24.0	23.7	24.5	23.5	23.9	23.8	23.9	23.6	23.7	23.8
>$10 MW	28.4	28.3	28.7	28.2	28.5	28.6	28.7	28.3	28.7	28.5
Aggregate	24.7	24.4	25.1	24.3	24.6	24.6	24.7	24.3	24.5	24.5

Notes: a. OLS regression of original Arthur Young 13 job evaluation factors.
b. OLS regression of 9 job evaluation factors using first principal component approach.

Table 17.A. Group means of predicted logarithm of maximum salary

Subgroup	OLS13[a]	OLS13[a]-MW	OLS9[b]	OLS9[b]-MW	EVCARP $\rho_{uuij}=0$	EVCARP-MW $\rho_{uuij}=0$	EVCARP $\rho_{uuij}=0.1$	EVCARP-MW $\rho_{uuij}=0.1$	EVCARP $\rho_{uuij}=0.2$	EVCARP-MW $\rho_{uuij}=0.2$
Predicted Logarithm of Maximum Salary										
81-100 PF job	6.4	6.4	6.5	6.4	6.4	6.4	6.4	6.4	6.4	6.4
21-80 PF job	6.5	6.5	6.6	6.5	6.5	6.5	6.5	6.5	6.5	6.5
0-20 PF job	6.6	6.6	6.6	6.6	6.6	6.6	6.6	6.6	6.6	6.6
Union	6.4	6.4	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5
Not union	6.6	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7
Managerial	6.8	6.8	6.9	6.9	6.9	6.9	6.9	6.9	6.9	6.9
Professional	6.6	6.6	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7
Technical	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.4
Clerical	6.3	6.3	6.4	6.4	6.4	6.3	6.3	6.3	6.3	6.3
Service	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.3
<High school	6.2	6.2	6.2	6.2	6.2	6.2	6.2	6.2	6.2	6.2
High school	6.3	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.4
Technical school	6.4	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5
>College	6.7	6.7	6.8	6.7	6.8	6.8	6.8	6.8	6.8	6.8
$0-5 MW	6.2	6.2	6.3	6.2	6.2	6.2	6.2	6.2	6.2	6.2
$5.01-7.5 MW	6.3	6.3	6.4	6.3	6.4	6.3	6.3	6.3	6.3	6.3
$7.51-10 MW	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5
>$10 MW	6.6	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7
Aggregate	6.5	6.5	6.6	6.5	6.6	6.5	6.5	6.5	6.5	6.6

Notes: a. OLS regression of original Arthur Young 13 job evaluation factors.
b. OLS regression of 9 job evaluation factors using first principal component approach.

Table 17.B. Group means of predicted maximum salary

Subgroup	OLS13[a]	OLS13[a]-MW	OLS9[b]	OLS9[b]-MW	EVCARP $\rho_{uuij}=0$	EVCARP-MW $\rho_{uuij}=0$	EVCARP $\rho_{uuij}=0.1$	EVCARP-MW $\rho_{uuij}=0.1$	EVCARP $\rho_{uuij}=0.2$	EVCARP-MW $\rho_{uuij}=0.2$
Predicted Maximum Salary										
81-100 PF job	634.4	624.0	636.9	624.0	617.0	613.8	609.2	610.0	609.1	610.4
21-80 PF job	707.3	700.8	708.5	700.1	691.1	689.1	687.9	688.3	688.5	689.5
0-20 PF job	767.4	768.5	767.9	767.9	769.4	769.3	768.7	768.3	768.2	768.5
Union	654.4	650.7	655.8	650.2	646.0	644.7	642.8	642.9	642.2	642.8
Not union	832.9	830.8	833.7	830.2	828.5	827.5	826.0	826.0	826.4	827.1
Managerial	965.1	965.8	967.3	965.7	967.6	967.5	973.6	973.5	976.5	977.3
Professional	820.2	818.2	821.3	817.2	816.1	815.0	814.8	814.8	814.4	815.1
Technical	640.5	643.6	640.3	643.0	639.8	640.7	640.9	640.0	639.8	639.6
Clerical	592.0	582.2	593.8	582.1	570.1	567.3	562.5	563.2	560.5	561.6
Service	552.3	542.1	554.0	541.7	538.9	535.2	529.6	530.5	531.3	532.6
<High school	496.9	485.9	499.6	486.0	475.4	472.1	462.2	462.9	462.4	463.6
High school	601.6	596.4	602.9	596.2	589.5	588.0	585.7	585.8	585.3	586.0
Technical school	675.4	678.0	675.2	677.4	668.7	669.9	667.5	666.6	667.2	667.0
>College	871.8	868.1	873.1	867.2	871.2	869.1	870.7	871.1	870.7	871.8
$0-5 MW	511.7	488.1	514.8	487.9	489.9	481.7	470.7	473.3	471.1	473.9
$5.01-7.5 MW	588.2	572.1	589.9	571.7	569.9	564.5	563.6	565.3	562.9	564.9
$7.51-10 MW	696.8	690.3	699.0	690.1	683.1	680.9	679.6	680.0	681.8	682.9
>$10 MW	836.3	844.0	836.2	843.1	841.1	843.4	842.8	841.4	841.4	840.9
Aggregate	724.3	721.1	725.4	720.5	717.4	716.2	714.7	714.7	714.5	715.2

Notes: a. OLS regression of original Arthur Young 13 job evaluation factors.
b. OLS regression of 9 job evaluation factors using first principal component approach.

Table 18. Student's t tests for subgroup means of predicted pay grade between various OLS and EVCARP regressions

Subgroup	OLS13[a] OLS9[b]	OLS13[a]-MW OLS9[b]-MW	OLS9[b] EVCARP $\rho_{uuij}=0$	OLS9[b] EVCARP $\rho_{uuij}=0.1$	OLS9[b] EVCARP $\rho_{uuij}=0.2$	OLS9[b]-MW EVCARP-MW $\rho_{uuij}=0$	OLS9[b]-MW EVCARP-MW $\rho_{uuij}=0.1$
81-100 PF job	-16.21***	-1.73*	11.72***	4.90***	4.46***	-1.03	1.19
21-80 PF job	-15.79***	0.37	10.89***	4.54***	4.64***	-4.22***	0.00
0-20 PF job	-10.38***	4.05***	7.28***	2.41**	1.81*	-7.76***	-0.60
Union	-26.77***	-1.20	13.07***	5.41***	4.89***	-4.48***	0.78
Not Union	-8.01***	4.36***	9.21***	3.84***	3.59***	-8.63***	-0.66
Managerial	-4.35***	1.77*	6.06***	0.27	-0.83	-5.17***	-2.09**
Professional	-10.34***	2.75***	9.84***	2.66***	2.58***	-10.57***	-2.16**
Technical	-8.43***	2.79***	3.54***	0.74	0.60	-2.60***	0.29
Clerical	-17.57***	-3.84***	8.99***	3.89***	4.29***	-0.35	1.49
Service	-16.46***	-1.41	6.39***	4.88***	4.16***	-0.03	1.96**
<High school	-24.56***	-6.29***	12.30***	7.30***	6.03***	5.47***	4.28***
High school	-17.36***	-0.09	5.44***	2.58***	2.75***	-2.78***	0.62
Tech. school	-7.54***	4.81***	5.15***	1.96**	1.95*	-2.99***	1.27
>College	-10.24***	2.66***	11.09***	2.52**	2.00**	-13.44***	-3.77***
$0-5 MW	-19.20***	-3.24***	8.20***	5.43***	4.68***	1.29	1.81*
$5.01-7.5 MW	-20.52***	-1.75*	9.99***	4.89***	4.85***	-2.93***	-0.06
$7.51-10 MW	-14.84***	3.71***	10.72***	4.55***	3.90***	-4.21***	-0.16
>$10 MW	-8.00***	2.92***	5.59***	0.46	0.27	-7.85***	-0.35
Aggregate	-20.43***	2.86***	15.44***	6.36***	5.77***	-8.38***	0.19

Notes: a. OLS regression using 13 factors.
b. OLS regression using 9 factors.
c. ***, **, and * denote 0.01, 0.05, and 0.10 level of significance , respectively.

Table 18. Student's t tests for subgroup means of predicted pay grade between various OLS and EVCARP regressions (continued)

Subgroup	OLS9[b]-MW EVCARP-MW ρ_{uuij}=0.2	OLS9[b]-MW EVCARP ρ_{uuij}=0	OLS9[b]-MW EVCARP ρ_{uuij}=0.1	OLS9[b]-MW EVCARP ρ_{uuij}=0.2	OLS9[b] EVCARP-MW ρ_{uuij}=0	OLS9[b] EVCARP-MW ρ_{uuij}=0.1	OLS9[b] EVCARP-MW ρ_{uuij}=0.2
81-100 PF job	0.62	-2.35**	-0.56	1.00	14.58***	6.87***	3.89***
21-80 PF job	-0.41	-4.25***	-2.97***	-0.31	12.04***	8.08***	4.41***
0-20 PF job	-2.00**	-5.38***	-4.41***	-2.62***	6.83***	6.74***	2.27**
Union	-0.36	-4.25***	-2.77***	-0.30	13.98***	9.30***	4.64***
Not Union	-1.63	-6.57***	-4.70***	-2.16**	9.59***	8.85***	3.93***
Managerial	-3.25***	-3.41***	-4.26***	-3.94***	5.98***	3.26***	-0.36
Professional	-2.58***	-8.18***	-5.85***	-3.08***	10.61***	7.13***	2.85***
Technical	-0.49	-1.13	-1.50	-0.80	2.62***	2.64***	0.86
Clerical	1.48	-1.16	0.07	1.84*	11.75***	5.45***	3.79***
Service	0.68	-1.25	0.37	1.26	7.73***	6.57***	3.56***
<High school	2.86***	3.28***	3.16***	3.51***	14.46***	8.51***	5.28***
High school	0.23	-2.56**	-1.19	0.34	6.06***	4.53***	2.53**
Tech. school	0.42	-1.01	-1.34	-0.13	3.79***	4.65***	2.44**
>College	-4.46***	-11.16***	-7.87***	-4.88***	13.28***	7.67***	2.07**
$0-5 MW	1.08	-1.11	1.04	1.87*	12.28***	6.31***	3.70***
$5.01-7.5 MW	-0.37	-5.48***	-2.07**	0.53	14.97***	7.08***	3.74***
$7.51-10 MW	-1.08	-4.22***	-2.89***	-0.97	13.33***	7.93***	3.54***
>$10 MW	-1.33	-3.59***	-4.09***	-2.76***	2.73***	4.79***	1.61
Aggregate	-1.28	-7.18***	-4.84***	-1.47	16.47***	12.10***	5.70***

Notes: a. OLS regression using 13 factors.
b. OLS regression using 9 factors.
c. ***, **, and * denote 0.01, 0.05, and 0.10 level of significance, respectively.

Table 18.A. Student's t tests for subgroup means of predicted logarithm of maximum salary between various OLS and EVCARP regressions

Subgroup	OLS13[a] OLS9[b]	OLS13[a]-MW OLS9[b]-MW	OLS9[b] EVCARP $\rho_{uuij}=0$	OLS9[b] EVCARP $\rho_{uuij}=0.1$	OLS9[b] EVCARP $\rho_{uuij}=0.2$	OLS9[b]-MW EVCARP-MW $\rho_{uuij}=0$	OLS9[b]-MW EVCARP-MW $\rho_{uuij}=0.1$
81-100 PF job	-25.23***	-8.29***	9.95***	5.91***	3.90***	0.57	0.35
21-80 PF job	-34.62***	-14.01***	9.70***	6.60***	4.25***	-1.38	-1.09
0-20 PF job	-30.20***	-11.85***	2.30**	1.87*	0.37	-5.32***	-2.81***
Union	-47.72***	-16.26***	7.13***	5.62***	3.24***	-1.98**	-1.14
Not Union	-28.91***	-12.69***	7.27***	5.34***	3.29***	-5.15***	-2.46**
Managerial	-16.73***	-8.67***	6.20***	1.52	-0.52	-3.03***	-2.84***
Professional	-40.85***	-22.43***	8.53***	4.98***	2.71***	-6.67***	-3.59***
Technical	-26.50***	-2.80***	-0.68	-0.30	-0.79	-1.66*	-0.98
Clerical	-30.12***	-6.35***	7.50***	4.72***	3.61***	0.84	0.66
Service	-23.75***	-0.09	2.80***	3.87***	2.66***	0.65	0.94
<High school	-21.71***	-0.42	7.30***	6.46***	4.53***	5.17***	3.35***
High school	-28.61***	-3.75***	2.15**	2.37**	1.60	-1.22	-0.46
Tech. school	-33.93***	-5.00***	1.72*	1.74*	0.70	-1.06	-0.08
>College	-39.72***	-24.13***	9.97***	4.98***	2.34**	-9.30***	-5.51***
$0-5 MW	-18.01***	-1.15	5.79***	5.17***	3.86***	1.35	1.16
$5.01-7.5 MW	-31.53***	-4.82***	6.58***	5.37***	3.72***	-1.55	-1.40
$7.51-10 MW	-34.82***	-11.99***	7.74***	5.71***	3.25***	-1.38	-1.11
>$10 MW	-31.02***	-15.90***	2.40**	0.85	-0.45	-5.07***	-2.20**
Aggregate	-47.65***	-18.80***	9.64***	7.23***	4.22***	-4.55***	-2.34**

Notes: a. OLS regression using 13 factors.
b. OLS regression using 9 factors.
c. ***, **, and * denote 0.01, 0.05, and 0.10 level of significance, respectively.

Table 18.A. Student's t tests for subgroup means of predicted logarithm of maximum salary between various OLS and EVCARP regressions (continued)

Subgroup	OLS9[b]-MW EVCARP-MW ρ_{uuij}=0.2	OLS9[b]-MW EVCARP ρ_{uuij}=0	OLS9[b]-MW EVCARP ρ_{uuij}=0.1	OLS9[b]-MW EVCARP ρ_{uuij}=0.2	OLS9[b] EVCARP-MW ρ_{uuij}=0	OLS9[b] EVCARP-MW ρ_{uuij}=0.1	OLS9[b] EVCARP-MW ρ_{uuij}=0.2
81-100 PF job	0.09	-2.50**	0.27	0.72	15.39***	6.13***	3.10***
21-80 PF job	-1.05	-3.23***	-1.27	-0.34	12.76***	7.01***	3.34***
0-20 PF job	-2.80***	-4.42***	-2.77***	-2.48**	3.23***	2.02**	-0.11
Union	-1.36	-3.95***	-0.92	-0.54	9.89***	5.47***	2.29**
Not Union	-2.30**	-4.87***	-2.88***	-1.84*	9.50***	6.28***	2.60***
Managerial	-3.53***	-2.23**	-3.10***	-3.46***	7.07***	2.36**	-0.87
Professional	-3.31***	-6.11***	-3.87***	-2.61***	10.94***	5.70***	1.72*
Technical	-1.00	-1.05	-0.56	-0.94	-0.88	-0.70	-0.86
Clerical	0.94	-1.35	0.74	1.37	12.73***	4.68***	3.05***
Service	0.29	-1.82*	0.86	0.85	5.25***	3.96***	2.12**
<High school	2.34**	1.83*	3.41***	2.88***	10.15***	6.36***	3.95***
High school	-0.25	-2.37**	-0.27	0.06	3.84***	2.22**	1.24
Tech. school	-0.17	-0.31	0.37	-0.11	1.30	1.30	0.62
>College	-5.27***	-8.91***	-6.11***	-4.41***	14.24***	6.36***	1.06
$0-5 MW	0.74	-2.34**	0.90	1.39	11.73***	5.53***	3.09***
$5.01-7.5 MW	-1.05	-6.09***	-1.63	-0.19	14.09***	5.71***	2.68***
$7.51-10 MW	-1.55	-3.26***	-1.34	-0.88	11.35***	6.23***	2.38**
>$10 MW	-2.08**	-1.99**	-1.93*	-2.14**	0.54	0.71	-0.48
Aggregate	-2.42**	-6.00***	-2.46**	-1.52	13.13***	7.61***	3.08***

Notes: a. OLS regression using 13 factors.
b. OLS regression using 9 factors.
c. ***, **, and * denote 0.01, 0.05, and 0.10 level of significance , respectively.

Table 18.B. Student's t tests for subgroup means of predicted maximum salary between various OLS and EVCARP regressions

Subgroup	OLS13[a] OLS9[b]	OLS13[a]-MW OLS9[b]-MW	OLS9[b] EVCARP $\rho_{uuij}=0$	OLS9[b] EVCARP $\rho_{uuij}=0.1$	OLS9[b] EVCARP $\rho_{uuij}=0.2$	OLS9[b]-MW EVCARP-MW $\rho_{uuij}=0$	OLS9[b]-MW EVCARP-MW $\rho_{uuij}=0.1$
81-100 PF job	-6.61***	0.02	9.50***	6.60***	6.12***	5.01***	3.05***
21-80 PF job	-3.24***	4.46***	10.45***	8.28***	7.29***	6.72***	4.28***
0-20 PF job	-1.55	4.00***	-0.94	-0.35	-0.10	-0.89	-0.16
Union	-5.86***	4.37***	7.92***	6.10***	5.91***	4.83***	3.32***
Not Union	-1.90*	3.13***	2.83***	3.12***	2.87***	1.40	1.49
Managerial	-2.44**	0.31	-0.10	-1.34	-1.97**	-0.46	-1.26
Professional	-2.79***	5.14***	2.95***	2.75***	2.78***	1.31	0.92
Technical	0.41	2.88***	0.19	-0.14	0.10	0.93	0.68
Clerical	-3.93***	0.41	10.53***	6.14***	6.20***	5.93***	3.23***
Service	-4.64***	2.48**	6.10***	5.99***	4.93***	2.91***	2.84***
<High school	-8.89***	-0.61	9.05***	7.25***	6.55***	5.36***	4.17***
High school	-3.04***	0.85	5.86***	4.33***	4.05***	3.91***	2.46**
Tech. school	0.49	2.83***	2.95***	2.29**	2.23**	3.51***	3.09***
>College	-3.56***	4.93***	1.22	1.04	1.04	-1.17	-1.50
$0-5 MW	-8.13***	1.52	8.07***	6.01***	5.47***	2.03**	1.83*
$5.01-7.5 MW	-4.48***	2.80***	10.68***	7.46***	6.97***	3.91***	1.69*
$7.51-10 MW	-5.61***	0.75	9.24***	7.94***	6.15***	5.32***	3.50***
>$10 MW	0.13	4.87***	-2.93***	-2.64***	-2.00**	-0.15	0.59
Aggregate	-4.93***	5.31***	7.40***	6.39***	6.09***	4.12***	3.19***

Notes: a. OLS regression using 13 factors.
b. OLS regression using 9 factors.
c. ***, **, and * denote 0.01, 0.05, and 0.10 level of significance , respectively.

Table 18.B. Student's t tests for subgroup means of predicted maximum salary between various OLS and EVCARP regressions (continued)

Subgroup	OLS9b-MW EVCARP-MW ρ_{uuij}=0.2	OLS9b-MW EVCARP ρ_{uuij}=0	OLS9b-MW EVCARP ρ_{uuij}=0.1	OLS9b-MW EVCARP ρ_{uuij}=0.2	OLS9b EVCARP-MW ρ_{uuij}=0	OLS9b EVCARP-MW ρ_{uuij}=0.1	OLS9b EVCARP-MW ρ_{uuij}=0.2
81-100 PF job	2.75***	3.03***	3.32***	3.10***	11.49***	6.28***	5.71***
21-80 PF job	3.50***	4.58***	4.58***	3.96***	11.75***	8.05***	6.84***
0-20 PF job	-0.22	-0.81	-0.35	-0.12	-0.93	-0.16	-0.22
Union	3.08***	3.15***	3.42***	3.43***	8.99***	6.04***	5.58***
Not Union	1.06	0.76	1.53	1.35	3.53***	3.08***	2.54**
Managerial	-1.92*	-0.42	-1.35	-1.86*	-0.06	-1.26	-2.07**
Professional	0.74	0.54	0.95	1.04	3.68***	2.72***	2.44**
Technical	0.70	1.14	0.49	0.67	-0.17	0.07	0.15
Clerical	3.39***	4.06***	3.45***	3.66***	13.05***	5.85***	5.87***
Service	2.04**	1.06	3.14***	2.37**	7.85***	5.76***	4.64***
<High school	3.72***	3.47***	4.43***	4.01***	10.76***	7.00***	6.26***
High school	2.24**	2.76***	2.56**	2.44**	6.74***	4.24***	3.85***
Tech. school	2.84***	3.47***	2.90***	2.84***	2.46**	2.55**	2.28**
>College	-1.68*	-2.10**	-1.41	-1.32	2.55**	0.86	0.56
$0-5 MW	1.63	-0.58	2.22**	2.00**	12.00***	5.53***	5.02***
$5.01-7.5 MW	1.67*	0.84	2.18**	2.19**	15.30***	6.84***	6.35***
$7.51-10 MW	2.26**	3.46***	3.78***	2.67***	11.41***	7.56***	5.63***
>$10 MW	0.72	0.95	0.13	0.59	-4.76***	-2.03**	-1.79*
Aggregate	2.77***	2.52**	3.31***	3.21***	8.76***	6.29***	5.63***

Notes: a. OLS regression using 13 factors.
b. OLS regression using 9 factors.
c. ***, **, and * denote 0.01, 0.05, and 0.10 level of significance , respectively.

compared with EVCARP regressions excluded market wages. The comparisons show that the predicted pay grades are not significantly different according to the OLS and EVCARP predictions especially for low skilled jobs and low market wage jobs. Comparing OLS regression using 9 factors with EVCARP regression with market wages included in the latter, the overestimation of predicted pay grade in OLS regression was also significant. Similar results were found when predicted logarithm of maximum salary and maximum salary for each subgroup are compared between various measurement error corrections. Some findings are remarkable. Adding market wages, predicted logarithm of maximum salaries are not significantly different according to both OLS and EVCARP regressions for low skilled jobs and low market wage jobs. The only different finding when predicted maximum salaries for each subgroup are compared. Predicted maximum salaries for jobs not covered by union contracts, jobs requiring high skills, jobs with minimum college education requirement, and jobs with high market wages, are not significantly different according to both OLS and EVCARP regressions with market wages included. Adding market wages in the OLS regression only but not in the EVCARP regressions, predicted maximum salaries for the same subgroup jobs just stated are not significantly different under both OLS and EVCARP regressions.

Taken as a whole, this study shows that measurement error and multicollinearity in the original Arthur Young job evaluation factors led to underestimated job factor weights. Correcting for hypothesized measurement error correlation further increases the importance of job factors in explaining pay variation while market wages lose predictive power. Results are not sensitive to the use of principal component analysis or weighted averages of the highly correlated factors.

SECTION VI. CONCLUSIONS

This study evaluates the impacts of measurement errors on the regression coefficients used in the State of Iowa's comparable worth system. Specifically, corrections for measurement error and multicollinearity in the original Arthur Young's job evaluation factors are used to examine the sensitivity and statistical robustness of job evaluation factor weights to hypothesized positive measurement error correlations.

In general, the empirical findings from using the first principal component of the pay analysis can be summarized as follows:

1. The presence of measurement error causes downward bias on the estimated coefficient on percent female incumbents. The negative impact of percent female on pay is reduced by twenty to fifty percent when the problem of measurement error associated with the job factors is corrected. If the coefficient is taken to be a measure of discrimination against predominantly female jobs, the implication is that measurement errors caused the implied discrimination to be overstated. As a consequence, proposed comparable worth wage adjustments necessary to bring female jobs to parity with male jobs were too large.

2. Measurement error reduces the collinearity among job factors, allowing too many factors to be included in the pay analysis. Using reliability ratios, the "true" correlation matrix was estimated. Five factors, knowledge from education (KFE), complexity,

judgement, and problem-solving (CJPS), guidelines/supervision available (GSA), scope and effect (SE), and impact of errors (IE) were perfectly or nearly perfectly correlated. The OLS coefficients for these factors were only identified because of the measurement error.

3. The negative impact of percent female on pay is reduced as the correlation between measurement errors increases.

4. Including market wages in the pay analysis reduces the gap between the OLS point estimates and the EVCARP point estimates. Market wages decline in significance when corrections are made for measurement errors and measurement error correlations. This implies, as measurement error correlations are allowed, job factors contain sufficient information to explain pay variation.

5. Job evaluation factors gain importance under measurement error corrections.

6. Excluding market wages in the OLS regressions while including market wages in the EVCARP regressions, OLS predictions for pay grade, logarithm of maximum salary, and maximum salary were significantly overstated as compared to the EVCARP predictions.

7. The overall results of the reevaluation of the State of Iowa comparable worth system suggest that measurement error and multicollinearity associated with the job evaluation factors in comparable worth pay analysis are important concerns that need to be considered before conducting any statistical analysis to estimate job evaluation factor weights.

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FOOTNOTES

1. Suppose the general form for expressing the three combined factors is:

$$X_c = a / \{1.29^{**}[b - (X_{si} + X_{sj})]\}$$
$$= f(X_{si}, X_{sj})$$

where X_c is the combined factor, a is the highest point of the job factor, b is the sum of the levels of subfactors, X_{si} and X_{sj} are the levels of subfactors i and j, respectively. Assuming this relationship holds true for the true factors as well. First order Taylor series expansion of this general functional form about the sample means is expressed as:

$$x_c \approx f(\overline{x}_{si}, \overline{x}_{sj}) + [(\partial f / \partial x_{si})|(\overline{x}_{si}, \overline{x}_{sj})](x_{si} - \overline{x}_{si}) + [(\partial f / \partial x_{sj})|(\overline{x}_{si}, \overline{x}_{sj})](x_{sj} - \overline{x}_{sj})$$

where the lower case x denotes true job factor. Therefore the variance of x_c is approximated by:

$$\mathrm{VAR}(x_c)$$
$$\approx [(\partial f / \partial x_{si})|(\overline{x}_{si}, \overline{x}_{sj})]^2 \mathrm{VAR}(x_{si} - \overline{x}_{si}) + [(\partial f / \partial x_{sj})|(\overline{x}_{si}, \overline{x}_{sj})]^2 \mathrm{VAR}(x_{sj} - \overline{x}_{sj})$$
$$+ 2\, [(\partial f / \partial x_{si})|(\overline{x}_{si}, \overline{x}_{sj})]\, [(\partial f / \partial x_{sj})|(\overline{x}_{si}, \overline{x}_{sj})]\, \mathrm{COV}[(x_{si} - \overline{x}_{si})(x_{sj} - \overline{x}_{sj})]$$

The proportion of variation in the observed factor attributable to variation in the true factor is the reliability ratio.

2. Under the assumption of correlated measurement errors, the reliability ratios for KCGSI1 and KCGSI can be computed using equations (26a) and (27a) allowing covariance between measurement errors. For KCGSI1:

(26b) $$\mathrm{VAR}[a_K(u_K/s_K) + a_C(u_C/s_C) + a_G(u_G/s_G) + a_S(u_S/s_S) + a_I(u_I/s_I)]$$

$$= (a_K/s_K)^2\sigma_{uuKK} + (a_C/s_C)^2\sigma_{uuCC} + (a_G/s_G)^2\sigma_{uuGG} + (a_S/s_S)^2\sigma_{uuSS} + (a_I/s_I)^2\sigma_{uuII}$$

$$+ 2\Sigma\Sigma_{i\neq j}(a_i/s_i)(a_j/s_j)\sigma_{uuij}$$

$$= (a_K/s_K)^2\sigma_{uuKK} + (a_C/s_C)^2\sigma_{uuCC} + (a_G/s_G)^2\sigma_{uuGG} + (a_S/s_S)^2\sigma_{uuSS} + (a_I/s_I)^2\sigma_{uuII}$$

$$+ 2\Sigma\Sigma_{i\neq j}(a_i/s_i)(a_j/s_j)\, \rho_{uuij}\, [(1-\kappa_i)\sigma_{XXii}\,(1-\kappa_j)\sigma_{XXjj}]^{(1/2)}$$

where the a_i's are the constant coefficients in (26a) and the assumed measurement error correlation coefficients, ρ_{uuij}'s, are 0.1, 0.2, and 0.3. The measurement error variance computed above can be used to compute the reliability ratios for KCGSI1 under the assumed measurement error correlations 0.1, 0.2, and 0.3, respectively. Analogously, for KCGSI:

(27b) $$\mathrm{VAR}[0.2(u_K + u_C + u_G + u_S + u_I)]$$

$$= (0.2)^2[\sigma_{uuKK} + \sigma_{uuCC} + \sigma_{uuGG} + \sigma_{uuSS} + \sigma_{uuII} + 2\Sigma\Sigma_{i\neq j}\sigma_{uuij}]$$

$$= (0.2)^2\{\sigma_{uuKK} + \sigma_{uuCC} + \sigma_{uuGG} + \sigma_{uuSS} + \sigma_{uuII}$$

$$+ 2\Sigma\Sigma_{i\neq j}\rho_{uuij}\, [(1-\kappa_i)\sigma_{XXii}\,(1-\kappa_j)\sigma_{XXjj}]^{(1/2)}\}$$

APPENDICES

Exhibit A.1. Arthur Young thirteen job evaluation factors

Knowledge--from Formal Training/Education:

This factor measures the academic preparation and/or technical training at the entry level considered to be "normal" or "typically required" to perform the work. This factor represents the requirements for the job, not the particular educational background of the person holding the job.

Knowledge--from Experience:

This factor evaluates the least amount of time normally required for a person with the "typically required" training/education to acquire the knowledge and skills to perform the job satisfactorily.

Job Complexity, Judgement, and Problem-Solving:

This factor measures the complexity of duties, and the frequency and extent of judgement used in decision-making and problem-solving.

Guidelines/Supervision Available:

This factor covers the nature of guidelines and the judgement needed for application. Included are the extent and closeness of supervision required and received for methods to be followed, results to be obtained, and frequency of work progress review.

Personal Contacts:

This factor measures the responsibility for effective handling of personal contacts with persons not in the supervisory chain. Discussed is the frequency, purpose, importance, setting and person(s) contacted.

Physical Demands:

This factor measures physical effort and fatigue. Considered is the effort, strength, stamina, and endurance necessary to perform the job.

Mental/Visual Demands:

This factor measures the coordination and dexterity of mind, eye, and hand. This factor includes duration and intensity of the coordination and not intelligence or mental development.

Supervision Exercised:

This factor measures the nature and magnitude for supervising subordinates. Indicated are the number of people supervised and the type of supervisory responsibility.

Scope and Effect:

This factor measures the relationship between the nature of the work, its purpose, breadth and depth, and the effect of work products or services within and outside the organizational unit.

Impact of Errors:

This factor measures the likely effect or probable consequences of potential errors made by an individual in the regular course of the work and the opportunity for making such errors.

Working Environment:

This factor evaluates the conditions under which the job must be performed and the extent to which conditions, i.e., heat, cold, rain, snow, dirty, or bloody conditions, fumes, noises, unpleasant social encounters, etc., make the job unpleasant.

Unavoidable Hazards/Risks:

This factor measures the hazards connected with the performance of the job or the extent and seriousness of potential bodily injury that normally exists in performing the job.

Work Pace/Pressure and Interruptions:

This factor measures the degree to which the employee is able to maintain continuity of work and to plan the scheduling and priority of job tasks in advance. Indicated are the changes in work volume and frequency of interruptions.

Exhibit A.2. F tests between OLS with combined factors and OLS with original 13 factors

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A. Dependent Variable: Pay Grade

1. First principal component[1]:
   $F = 19.06^{***} \sim F(4, 743)$
   $F\text{-}MW^3 = 15.33^{***} \sim F(4, 742)$

2. Equally weighted average[2]:
   $F = 18.95^{***} \sim F(4, 743)$
   $F\text{-}MW^3 = 15.37^{***} \sim F(4, 742)$

B. Dependent Variable: Logarithm of Maximum Salary

1. First principal component[1]:
   $F = 14.00^{***} \sim F(4, 743)$
   $F\text{-}MW^3 = 10.28^{***} \sim F(4, 742)$

2. Equally weighted average[2]:
   $F = 13.87^{***} \sim F(4, 743)$
   $F\text{-}MW^3 = 10.33^{***} \sim F(4, 742)$

C. Dependent Variable: Maximum Salary

1. First principal component[1]:
   $F = 2.22 \sim F(4, 743)$
   $F\text{-}MW^3 = 0.56 \sim F(4, 742)$

2. Equally weighted average[2]:
   $F = 1.90 \sim F(4, 743)$
   $F\text{-}MW^3 = 0.46 \sim F(4, 742)$

Note: 1. The null hypothesis to be tested is
$H_0 : (s_K/0.60)\beta_K = (s_C/0.50)\beta_C = (s_G/0.26)\beta_G = (s_S/0.51)\beta_S = (s_I/0.25)\beta_I$.
2. The null hypothesis to be tested is $H_0 : \beta_K = \beta_C = \beta_G = \beta_S = \beta_I$.
3. OLS regression with market wage included.
4. *** denotes significance at the 0.01 level.

Table A.1. Observed correlation matrix

	KFFTE	KFE	CJPS	GSA	PC	PD	MVD	SEN	SE	IE	WE	UHR	WI	PF	MW
KFFTE	1.00	0.31	0.65	0.59	0.56	-0.49	-0.12	0.22	0.55	0.56	-0.35	-0.19	0.30	-0.17	0.66
KFE	0.31	1.00	0.67	0.73	0.43	-0.32	-0.15	0.64	0.71	0.68	-0.22	-0.12	0.50	-0.33	0.50
CJPS	0.65	0.67	1.00	0.81	0.60	-0.39	-0.13	0.51	0.78	0.74	-0.30	-0.19	0.47	-0.24	0.60
GSA	0.59	0.73	0.81	1.00	0.61	-0.44	-0.15	0.57	0.83	0.74	-0.32	-0.19	0.48	-0.27	0.59
PC	0.56	0.43	0.60	0.61	1.00	-0.50	-0.26	0.32	0.64	0.58	-0.26	-0.14	0.43	-0.11	0.40
PD	-0.49	-0.32	-0.39	-0.44	-0.50	1.00	0.02	-0.20	-0.43	-0.36	0.63	0.36	-0.32	-0.10	-0.26
MVD	-0.12	-0.15	-0.13	-0.15	-0.26	0.02	1.00	-0.17	-0.20	-0.16	-0.07	-0.02	-0.16	0.15	-0.09
SEN	0.22	0.64	0.51	0.57	0.32	-0.20	-0.17	1.00	0.56	0.51	-0.12	0.01	0.45	-0.21	0.31
SE	0.55	0.71	0.78	0.83	0.64	-0.43	-0.20	0.56	1.00	0.78	-0.30	-0.18	0.49	-0.26	0.55
IE	0.56	0.68	0.74	0.74	0.58	-0.36	-0.16	0.51	0.78	1.00	-0.19	0.00	0.50	-0.32	0.63
WE	-0.35	-0.22	-0.30	-0.32	-0.26	0.63	-0.07	-0.12	-0.30	-0.19	1.00	0.53	-0.12	-0.21	-0.14
UHR	-0.19	-0.12	-0.19	-0.19	-0.14	0.36	-0.02	0.01	-0.18	0.00	0.53	1.00	-0.06	-0.18	-0.06
WI	0.30	0.50	0.47	0.48	0.43	-0.32	-0.16	0.45	0.49	0.50	-0.12	-0.06	1.00	-0.13	0.33
PF	-0.17	-0.33	-0.24	-0.27	-0.11	-0.10	0.15	-0.21	-0.26	-0.32	-0.21	-0.18	-0.13	1.00	-0.40
MW	0.66	0.50	0.60	0.59	0.40	-0.26	-0.09	0.31	0.55	0.63	-0.14	-0.06	0.33	-0.40	1.00

Table A.2. Reliability corrected correlation matrix under $\rho_{uuij} = 0$

	KFFTE	KFE	CJPS	GSA	PC	PD	MVD	SEN	SE	IE	WE	UHR	WI	PF	MW
KFFTE	1.00	0.38	0.74	0.72	0.66	-0.55	-0.17	0.23	0.68	0.68	-0.43	-0.22	0.42	-0.18	0.69
KFE	0.38	1.00	0.84	0.98	0.56	-0.40	-0.23	0.77	0.95	0.91	-0.31	-0.14	0.77	-0.39	0.58
CJPS	0.74	0.84	1.00	1.00	0.74	-0.46	-0.18	0.57	0.99	0.93	-0.38	-0.22	0.69	-0.26	0.65
GSA	0.72	0.98	1.00	1.00	0.81	-0.56	-0.24	0.70	1.00	1.00	-0.44	-0.24	0.76	-0.32	0.69
PC	0.66	0.56	0.74	0.81	1.00	-0.62	-0.40	0.38	0.85	0.77	-0.35	-0.17	0.65	-0.12	0.46
PD	-0.55	-0.40	-0.46	-0.56	-0.62	1.00	0.03	-0.22	-0.54	-0.45	0.81	0.42	-0.47	-0.11	-0.29
MVD	-0.17	-0.23	-0.18	-0.24	-0.40	0.03	1.00	-0.24	-0.31	-0.26	-0.11	-0.04	-0.29	0.21	-0.12
SEN	0.23	0.77	0.57	0.70	0.38	-0.22	-0.24	1.00	0.68	0.62	-0.15	0.01	0.63	-0.22	0.32
SE	0.68	0.95	0.99	1.00	0.85	-0.54	-0.31	0.68	1.00	1.00	-0.41	-0.22	0.77	-0.30	0.64
IE	0.68	0.91	0.93	1.00	0.77	-0.45	-0.26	0.62	1.00	1.00	-0.27	0.00	0.78	-0.37	0.74
WE	-0.43	-0.31	-0.38	-0.44	-0.35	0.81	-0.11	-0.15	-0.41	-0.27	1.00	0.68	-0.19	-0.25	-0.16
UHR	-0.22	-0.14	-0.22	-0.24	-0.17	0.42	-0.04	0.01	-0.22	0.00	0.68	1.00	-0.09	-0.19	-0.06
WI	0.42	0.77	0.69	0.76	0.65	-0.47	-0.29	0.63	0.77	0.78	-0.19	-0.09	1.00	-0.18	0.45
PF	-0.18	-0.39	-0.26	-0.32	-0.12	-0.11	0.21	-0.22	-0.30	-0.37	-0.25	-0.19	-0.18	1.00	-0.40
MW	0.69	0.58	0.65	0.69	0.46	-0.29	-0.12	0.32	0.64	0.74	-0.16	-0.06	0.45	-0.40	1.00

Table A.3. Matrix of measurement error variance ratios using KCGSI1 under $\rho_{uuij} = 0.1$

	KFFTE	KCGSI1	PC	PD	MVD	SEN	WE	UHR	WI	PF	MW
KFFTE	0.08	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.02	0.00	0.00
KCGSI1	0.01	0.09	0.01	0.01	0.02	0.01	0.02	0.01	0.02	0.00	0.00
PC	0.01	0.01	0.22	0.02	0.03	0.01	0.03	0.02	0.03	0.00	0.00
PD	0.01	0.01	0.02	0.16	0.03	0.01	0.02	0.02	0.03	0.00	0.00
MVD	0.02	0.02	0.03	0.03	0.45	0.02	0.04	0.03	0.05	0.00	0.00
SEN	0.01	0.01	0.01	0.01	0.02	0.08	0.02	0.01	0.02	0.00	0.00
WE	0.02	0.02	0.03	0.02	0.04	0.02	0.29	0.02	0.04	0.00	0.00
UHR	0.01	0.01	0.02	0.02	0.03	0.01	0.02	0.14	0.03	0.00	0.00
WI	0.02	0.02	0.03	0.03	0.05	0.02	0.04	0.03	0.45	0.00	0.00
PF	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MW	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

GENERAL CONCLUSIONS

Measurement error can be corrected using various approaches in studies of the economics of human resources. In the field of health, measurement error associated with the health inputs can be corrected using prices as instruments. In the comparable worth pay analysis, knowledge of reliability ratios of the job factors allows us to correct the measurement error associated with the job factors.

Household production technology applies the concept of production function by employing "inputs" in a "household production function" to produce "commodities." These commodities are the arguments of the household's utility function. In one field, health, household production function approach is particularly applicable (Rosenzweig & Schultz, 1983). The first chapter in this dissertation applies this approach to study the associations between one indicator of health, blood pressure, and health inputs. Traditional epidemiological correlations between blood pressure and health inputs are flawed due to the several reasons. Endogeneity and measurement error associated with the health inputs are major reasons contributing to the explanation of the biased health production parameters in the traditional epidemiological studies. Two stage least squares approach was employed in the health production technology to correct for these biases. Prices, wages, and other exogenous variables in the health production function serve as identifying instruments in the first stage to predict health inputs. Results from the traditional epidemiological approach and the household production approach to assess the relationships between blood pressure and health inputs were compared to examine the sensitivity of estimates of blood pressure production parameters.

The second chapter examines the problems of measurement error and multicollinearity of the job evaluation factors in State of Iowa's comparable worth pay analysis originally conducted by Arthur Young Company (1984). This study obtains consistent estimates of the factor weights associated with the job evaluation factors in the comparable worth pay analysis. In the meantime, assumed possible positive measurement error correlations were explored to analyze the sensitivity of the results due to different measurement error correlation assumptions. Proportion of female incumbents in each job classification and/or market wage were also included as regressors in addition to the job evaluation factors to examine their impacts on pay. Job factors gain in importance while market wages and percent female incumbents fall in importance when measurement error corrections are imposed.

Conclusions of the two chapters indicate that measurement error of health inputs and of job factors indeed bias their marginal impacts on health and pay, respectively. Policy analysis should critically examine the measurement error problem associated with the variables and derive appropriate policy implications.