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THE ROLE OF QUALITY IN THE DEMAND FOR HEALTH CARE CEBU, PHILIPPINES

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ABSTRACT

A mixed multinominal logit model is used in this document to estimate the effects of quality price, distance, and individual demand for health care on Cebu Island in the Philippines. Data collected from both households and health care facilities ensures that information concerning individual characteristics and facility attributes of all relevant obstetric care alternatives — alternatives that vary greatly in quality and price — are included.

Estimation results confirm that factors such as facility crowding, practitioner training, patient education, and family economic level are all important considerations that influence consumer choice.

TABLE OF CONTENTS

LIST OF EXHIBITS iv

ACKNOWLEDGEMENTS v

FOREWORD vi

EXECUTIVE SUMMARY vii

1.0 INTRODUCTION 9

2.0 THEORY 12

2.1 MODEL OF THE DEMAND FOR HEALTH CARE 12
2.2 COMPARATIVE STATICS ANALYSIS 15

3.0 ECONOMETRICS 17

4.0 DATA 21

4.1 VARIABLE SPECIFICATION 21
4.1.1 Dependent Variable: Choice of Delivery Alternative . . . 21
4.1.2 Independent Variables: Facility Characteristics 23
4.1.3 Independent Variables: Individual Characteristics 25

5.0 RESULTS 27

5.1 ESTIMATION RESULTS 27
5.2 SIMULATION RESULTS 29
5.3 ELASTICITIES 30

6.0 CONCLUSION 32

EXHIBITS 34

APPENDIX 35
Mathematical Assumptions used in Comparative Statics Analysis . 35
Huber-White Adjustment of Standard Errors 36

REFERENCES 37

LIST OF EXHIBITS

Exhibit 1. Percent Distribution of Sample Women by Choice of Delivery Arrangement and Urban-Rural Status 35

Exhibit 2. Descriptive Statistics for Variables in Multinomial Logit Model for All Households (Sample Size = 3,118) 36

Exhibit 3. Multinomial Logit Model of Obstetric Provider Choice with Adjusted T-statistics 38

Exhibit 4. Multinomial Logit Model of Obstetric Provider Choice, Comparison of Adjusted and Unadjusted Results for Conditional Variables 40

Exhibit 5. Mean Simulated Probabilities of Choosing Delivery Alternatives — All Households 41

Exhibit 6. Mean Simulated Probabilities of Choosing Delivery Alternatives — HHs in Bottom Asset Quartile 42

Exhibit 7. Mean Simulated Probabilities of Choosing Delivery Alternatives — HHs in Top 3 Asset Quartiles 43

Exhibit 8. Demand Elasticities with Respect to Own Price 44

Exhibit 9. Assumptions Concerning the Determinants of Matrices Used in Comparative Statics Analysis 45

Exhibit 10. Results of the Comparative Statics Analysis 46

Exhibit 11. Probit of Labor Force Participation of Women with Huber Standard Errors 50

Exhibit 12. Regression of Log Wages of Women with Huber Standard Errors . 51

Exhibit 13. Probit of Labor Force Participation of Spouses with Huber Standard Errors 53

Exhibit 14. Regression of Log Wages of Spouses with Huber Standard Errors 56

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FOREWORD

The Health Financing and Sustainability (HFS) Project provides technical assistance, and conducts applied research, training, and information dissemination to developing countries in health economics, health sector policy development, and health services management. The Applied Research (AR) component of the project provides opportunities to increase knowledge of the complex issues underlying health financing problems, and augments the supply of qualified individuals who can contribute to policy analysis and reform. HFS is emphasizing the following policy areas for applied research activities: cost recovery, productive efficiency, social financing, and private sector development in the health sector.

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Other small applied research studies are done in conjunction with technical assistance or major applied research activities of the HFS Project. In these cases, the SAR contributes to the technical guidance provided to clients, or adds to the body of knowledge on topics of health financing and economics.

As with all HFS research, drafts of small applied research reports are reviewed by HFS staff. Drafts are then evaluated by external technical reviewers selected on the basis of area of substantive and/or geographic expertise.

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EXECUTIVE SUMMARY

Economic analysis of the demand for medical care in developing countries has largely been concerned with the impact of price or income on utilization. The role of qualitative differences in health care environments has long been recognized as important in policy discussions, but has only recently been a subject of investigation by economists. Previous research on the role of quality suffers from several problems. First, studies that are based only on data from households are restrictive because facility attributes that influence quality are unobserved. Second, studies that are based only on facility data contain no information on potentially important individual determinants of demand. Third, studies that use discrete choice methods to analyze choice of facility typically use arbitrary definitions of choice sets. Finally, studies that use data that come from two-stage sample surveys do not correct for this design effect when estimating standard errors. As a result, the standard errors used in testing for the significance of quality can have a substantial downward bias.

In this paper, a mixed multinomial logit model is used to estimate the effects of quality, price, distance, and individual characteristics on the choice of obstetric care provider in a developing country. The analysis is based on data collected from both households and health care facilities in Cebu, Philippines. The availability of both types of data makes this one of only a handful of demand for health care studies that includes detailed information on both individual characteristics and facility attributes of all relevant alternatives. The developing country setting provides substantial variation in the type of alternative chosen, ranging from home delivery aided only by friends and relatives, to modern, private hospitals. The alternatives vary greatly in quality and price, making this an ideal context for examining the role of these variables in facility choice. The reduced-form model specifications that are estimated contain price, travel time, and different combinations of quality measures, including the availability of medical supplies, practitioner training, service availability, facility size, and crowdedness, and their interaction with individual characteristics. In addition, the sensitivity of the results to different choice-set definitions is analyzed. In particular, models that use conventional choice set definitions based only on nominal status are compared to models that attempt to classify facilities into relatively homogeneous groups based on price and quality.

Estimation results, which correct for the two-stage design of the household survey, indicate that facility crowding and practitioner training are significant determinants of consumer choice. The results also indicate that individual characteristics, such as education of the woman, interact in important ways with quality in influencing choice. For example, the availability of drugs is a significant determinant of facility choice for well-educated women, but not for others. In addition, the results support the hypothesis that poor households are more sensitive to increased user fees than other households. The model is used to conduct policy simulations designed to be informative to public officials interested in the effect of cost recovery schemes on utilization patterns. The simulations indicate that when public facilities simultaneously increase user fees and the aspects of quality over

which policymakers can exercise control in the short run, the mean probability of using public facilities increases for both poor and non-poor households.

1.0 INTRODUCTION

Economic analysis of the demand for medical care has largely been concerned with the impact of price and cost-sharing on utilization [Phelps (1992) and Gertler (1990)]. The role of qualitative differences in health care environments has long been recognized as important in policy discussions, but has only recently been a subject of investigation by economists. This type of research has particularly important policy implications for developing countries, where it is common for the public health sector to offer free care. Policymakers interested in the implementation of effective financing schemes need to know how cost recovery policies that simultaneously increase quality and user fees would affect utilization patterns. For example, it is possible that the positive effects of increasing various dimensions of health care quality on utilization patterns might offset any negative effects of price increases. It is also possible that higher quality public facilities that charge user fees may be better able to generate the amount of revenue required to purchase expensive inputs that can substantially improve the quality of the services delivered.

Although a number of health care demand (HCD) studies have found both indirect and direct evidence on the importance of quality in household decision making, this previous work suffers from a number of problems, the most serious of which concerns the type of data that is used. The most prevalent type of HCD study uses household data to determine the effect of individual characteristics, such as severity of illness or income, on choosing alternatives that are designated by the researcher as being of different quality.[1] These studies are likely to produce biased coefficient estimates because facility attributes that influence quality are unobserved. For example, estimates of price effects may actually combine negative price effects and positive quality effects (Feldstein, 1981, p. 158).[2] On the other extreme, a small number of recent studies, which use hospital data to estimate the impact of facility attributes, such as case-mix adjusted mortality rates and drug availability on facility choice, are restrictive because potentially important individual determinants of demand are unobserved.[3] In addition, because these studies are based only on persons who chose to receive medical treatment, the coefficient estimates may be biased because of sample selectivity.

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[1]Studies which are based only on household data include Gertler et al. (1990, 1987), Marquis (1985), Heller (1982), and Sloan (1978).

[2]This type of effect is evident in a study by Guilkey et al. (1989), which included only limited attribute information from health providers. In their model of the number of prenatal visits in urban Cebu, Philippines, the authors found that as the price of private facilities increases, the number of public visits declines and private visits increase. The explanation of this result offered by the authors is that private facilities tend to be of higher quality in ways they cannot control.

[3]Studies which are based only on supplier information include Burns and Wholey (1992), Luft et al. (1990), and Garnick et al. (1989).

The small number of HCD studies that are based on information from both consumers and providers remedies these data limitations, but is hampered by two problems that concern choice set definition and hypothesis testing.[4] First, choice sets are usually defined by classifying providers on the basis of nominal status, such as whether the facility is private or public and whether the care provided is traditional or modern. However, health care providers within a given alternative, such as the group of private modern facilities, may be characterized by a high degree of heterogeneity in both prices and quality attributes. The effect on inferences of aggregating potentially quite diverse facilities has not been investigated. Second, most of these studies use data that come from cluster sampling techniques, in which communities are randomly selected from a population and all eligible households within those communities are then interviewed. These studies, however, do not correct for this design effect when estimating standard errors. Ignoring this sample design effect can result in a substantial upward bias when testing for the significance of facility-specific variables such as price and quality attributes. This occurs because the characteristics associated with the alternatives available to the sample population varies only across and not within communities. As a result, the effective sample size for such variables is equal to the number of clusters that were sampled. To adjust for the sample design effect, estimates of standard errors must account for an error term that represents unobserved community effects as well as an error term that is specific to the individual (Guilkey, 1992).

In addition to these problems, studies based on data from consumers and suppliers have not investigated whether individual characteristics interact with provider attributes in determining demand. For example, a possible explanation for the relationship between mother's education and child health that is frequently found by social scientists is that mothers with higher education may purchase for their children preventative and curative care from higher quality alternatives. However, the importance of interactions between specific attributes of the health care practitioner and individual characteristics such as education is a topic that has not been pursued in previous HCD studies.

In this paper, an empirical analysis of the role of quality in the demand for health care in a developing country is provided. In particular, a discrete choice model is used to estimate the effects of provider attributes, price, distance, and individual characteristics on the demand for obstetric care. The study utilizes a rich data source from Cebu, Philippines that contains information from both pregnant women and health care providers. Schwartz et al. (1988) also analyzed this topic using the same data set.

This study extends the analysis of Schwartz et al. in a number of respects. First, a structural model that explains the role of health care quality in consumer behavior is proposed. In the theory, households choose a bundle of provider attributes to maximize utility subject to time, budget, and

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[4]Studies which are based on both consumer and supplier information include Akin et al. (1986), Schwartz et al. (1988), Denton et al. (1991), and Lavy and Germain (1993).

health production constraints. Second, additional survey data from Cebu, which were not available to Schwartz et al., are used to more accurately define the available delivery alternatives and investigate the sensitivity of the model results to different choice set definitions.[5] Third, the cluster-based design of the Cebu survey will be taken into account by using an appropriate technique to estimate the standard errors of the coefficient estimates. The effect of this adjustment on hypotheses testing will be a subject of investigation. Fourth, the model specification allows for interaction between facility attributes and individual characteristics such as education in influencing the choice of health care provider. And fifth, the impact of various policy scenarios on the utilization patterns will be investigated by conducting simulations designed to be informative to public policymakers interested in the effect of cost recovery schemes on utilization. In particular, the simulation exercises will address whether the positive effects of increasing various dimensions of health care quality on utilization offset any negative effects of price increases for both poor and non-poor households.

This paper is organized in the following way: Section 2 presents the structural model of consumer behavior; Section 3 presents the econometric model and justifies the selection of the statistical technique used in the analysis; Section 4 discusses the data set and defines the variables included in the model; Section 5 presents estimation results and policy simulations; and Section 6 concludes the paper.

[5]This information includes the name of the facility that each woman utilized for obstetric care and the distance between every sample woman's home and every health facility.

2.0 THEORY

Previous research on the demand for health care in developing countries has usually focused on price and income effects. As a result, the theoretical models that underlie these studies have not included an adequate treatment of the role of quality. In this section, a structural model that incorporates quality into consumer decision making is proposed. The model features a health production function and a hedonic price function in which health care services are valued in terms of the structural attributes that can influence the process and outcome of health care. Comparative statics analysis is then used to determine whether the model yields testable hypotheses.

2.1 MODEL OF THE DEMAND FOR HEALTH CARE

A woman receives utility from her own health as well as the health of her baby (H), a composite commodity good (C), and leisure time (L) according to the function:

$$U = U\ (H,\ G,\ L,\ \mu,\ \epsilon_1)(1)$$

where μ is an error term reflecting differences in preferences, and ϵ_1 is an error term reflecting stochastic shocks. The model notation suppresses the subscripts i and t, indicating the i'th woman and the t'th time period respectively, except where noted. Health is produced by the woman via the following health production function:

$$H = H\ (\mathbf{Y},\ \mathbf{Z},\ \mathbf{E},\ T,\ H_{t-1},\ \delta,\ \epsilon_2)(2)$$

The inputs to health production include a vector of structural attributes of the health care provider (Y), a vector of non-health care inputs (Z) of which food is an important component, time (T), and the health status of the previous period (H_{t-1}), which is predetermined. In addition, a vector of environmental factors (E), such as family characteristics and sanitary conditions, can affect health production. The remaining inputs are δ, which is an unobserved health endowment, and ϵ_2, which is an error term reflecting stochastic shocks to health.

A key assumption of the model is that the provider of any given health care service has many structural attributes. These include the attributes of material resources (such as drugs, equipment, and money), human resources (such as the number and qualifications of the personnel), and organizational structure (such as medical staff organization and methods of reimbursement). These characteristics, along with the process followed by the practitioner and the actual health outcome, have been recognized as the important categories of information from which inferences can be drawn about the quality of care (Donabedian, 1988). This classification of the technical aspects of quality is possible because "good structure increases the likelihood of good process, and good process increases the likelihood of good outcome" (Donabedian, 1988). However, while a particular attribute of a provider may be important in influencing the process and outcome of care, the possibility that it may not valued by the consumer is recognized.

The woman faces the following time constraint:

$$T + L + R = 1 \quad (3)$$

where R is the hours of market work, and the total amount of time is normalized to equal one. An element of time input is the travel time necessary to receive medical care. The woman also faces a budget constraint:

$$WR + A = G + P + QZ \quad (4)$$

where W is the wage rate, A is the level of assets, P is the total health care fee, and Q is the price of Z. The price of the composite commodity is the numeraire. By combining the two constraints into a full-budget constraint, it is obvious that the cost of health production is the monetary price of health care inputs and non-medical inputs and the opportunity cost of the time used to produce health.

The fee associated with using a health care service is determined by the following hedonic price function:

$$P = P\ (Y\ ;\ \alpha) \quad (5)$$

where α is a exogenous shift term. This function emerges from the interaction between consumers and providers of health care in a perfectly competitive market. In equilibrium, consumers and suppliers are perfectly matched when the consumer's bid function, which represents the willingness to pay for different combinations of attributes, and the supplier's offer function, which represents the price that a provider is willing to accept for different combinations of attributes at a constant profit, are tangent with one another.[6] The implicit price of any given attribute is represented by P_y and observed by consumers and providers but not by the researcher.

In addition to perfect competition, two important assumptions underlie hedonic price theory. First, consumers are assumed to have perfect information regarding the level of each structural attribute in any given health care service. For example, one consumer cannot perceive that the practitioner has training in modern midwifery, while another consumer perceives that the practitioner has only traditional training. Second, the continuous availability of any given attribute is assumed. A necessary and sufficient condition for continuous availability is that there is a large number of health care alternatives such that consumers can identify the producer that offers the utility maximizing bundle of attributes. The appropriateness of applying these assumptions to health care in the Philippines will be discussed in Section 3.

The shift term in the hedonic price function reflects the positive effect that results from residing in a market with a higher price structure and the negative effect that results from having pregnancy-related insurance. As a result, the shift term can be viewed as an exogenous factor that affects the

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[6]See Rosen (1974) for the theoretical framework for generating the hedonic price function.

money price of health care faced by the consumer. The total expenditures of a health care service can be derived by summing the costs of using the bundle of attributes embodied in the service.

The consumer maximizes a utility function subject to a health production function and a full-budget constraint. The choice variables in the model are the attributes of a health care service, the non-health care inputs to health production, time used for health production, leisure time, and the composite commodity. Exogenous variables are the price of non-medical inputs, wage rate, non-earned income, and the shift term in the price function. The following are the Lagrangian function and first-order conditions:

$$\text{Max } S = U [H (Y, Z, E, T, H_{t-1}, \delta, \epsilon_2), G, L, \mu, \epsilon_1] \quad (6)$$
$$+ \lambda [W (1 - T - L) + A - G - P(Y; \alpha) - QZ]$$

$$\partial S/\partial Y: \quad U_1 H_1 - \lambda P_1 = 0 \quad (7)$$
$$\partial S/\partial Z \quad U_1 H_2 - \lambda Q = 0 \quad (8)$$
$$\partial S/\partial T: \quad U_1 H_4 - \lambda W = 0 \quad (9)$$
$$\partial S/\partial G: \quad U_2 - \lambda = 0 \quad (10)$$
$$\partial S/\partial L: \quad U_3 - \lambda W = 0 \quad (11)$$
$$\partial S/\partial \lambda: \quad W (1 - T - L) + A - G - P(Y; \alpha) - QZ = 0 \quad (12)$$

The optimum condition of inputs in the production of health is determined by the familiar condition that the technical rate of substitution is equal to the input price ratio:

$$\frac{H_1}{H_4} = \frac{P_1}{W}$$

$$\frac{H_2}{H_4} = \frac{Q}{W}$$

In addition, the marginal rate of substitution between leisure and health is equal to the marginal product of quality times, input price ratio of wages and quality, and marginal rate of substitution between the composite commodity and health is equal to the marginal product of quality times the input price ratio of the composite commodity and quality.

$$\frac{U_3}{U_1} = H_1 \frac{W}{P_1}$$

$$\frac{U_2}{U_1} = H_1 \frac{1}{P_1}$$

2.2 COMPARATIVE STATICS ANALYSIS

Comparative statics analysis was undertaken to determine whether the model yields predictions on the effect of changes in prices, wages, and non-earned income on consumer choices of medical inputs, non-medical inputs, and time allocated to health production. In addition, the effects of changes in environmental conditions and health status in the previous period were also investigated.

Assumptions used in the comparative statics analysis follow. It is assumed that both utility and health production functions are additively separable. To ensure that the consumers choices of time allocation and purchases are optimal, it is also assumed that second-order conditions are satisfied. Finally, it is assumed that non-earned income effects are positive. This means that all goods are normal. The mathematical implications of these assumptions are discussed in the Appendix.

The results of the comparative statics analysis are contained in Exhibit 10. The following hypotheses emerge:

1. Increases in non-earned income should increase the level of health care attributes demanded, level of non-medical inputs demanded, and amount of time allocated to health production.

2. Increases in the cash price of health care inputs should decrease the level of quality demanded. Increases in the cash price of non-health care inputs should decrease the amount of non-health care inputs demanded.

3. Having health insurance should increase the level of quality demanded and the quantity of non-health care inputs demanded.

4. Increases in the price of any one of the three endogenous inputs to health production results in a positive substitution effect on the remaining two inputs. In other words, medical inputs and non-medical inputs are net substitutes, medical inputs and health time are net substitutes, and non-medical inputs and health time are net substitutes.

5. Increases in the wage rate results in ambiguous substitution effects on the amounts of health and leisure time. One would expect the sign of these effects to be negative. The results probably occur because of the

assumption that a consumer can use her time in three different ways. For example, a wage increase could have a zero substitution effect on health time and a negative substitution effect on leisure (or vice versa).

6. Increases in the wage rate are expected to increase the amount of purchased inputs to health production because the income and substitution effects are positive. Other models of the demand for health care yield a negative substitution effect because a higher wage increases the opportunity cost of travel time, making it possible for consumers to shift away from purchasing medical care. The result obtained in this analysis appears to be due to the assumption that health time can be used not only for traveling to receive care, but also for other activities that sustain health.

7. Increases in environmental conditions and health status in the previous period have ambiguous effects on the choice variables in the health production function.

The comparative statics results regarding income effects and own price substitution effects are robust to the relaxation of the separability assumptions. These results only depend on the assumptions that all goods are normal and consumers make optimal choices. Results concerning the positive substitution effects between health care attributes, food, and time for health production, however, are not robust to non-separability. This is because imposing the separability of preferences in the utility function and the separability of technology in the production function place severe restrictions on the mechanisms in which a price change of one type of input can affect the demand for another. If the assumptions of separability are relaxed, cross-substitution effects cannot be signed.

Perhaps the most important restriction in this analysis concerns the substitution effects of a change in the wage rate. If the utility function is weakly separable, then the allocation of time for leisure is independent from the production of health, of which time is an input. It might be interesting to investigate the implications of relaxing these assumptions on time allocation.

3.0 ECONOMETRICS

One important criterion of selecting an econometric technique is that it be well-suited to the nature of the endogenous variables in the model. In this study, the endogenous variables of concern are the attributes of health care services. It is important to understand whether the availability of these attributes can be characterized as being continuous or discrete in nature. If the health care market offered a continuous availability of each of the attributes of obstetric care, each woman could select the utility-maximizing bundle of attributes, and then go to the provider that offered that particular bundle. Methods such as ordinary least squares could then be applied to test the hypothesis.

The Cebu data come from a developing country in which this continuous choice assumption is not realistic. The obvious example is the stark difference in the quality of care available from the traditional and modern care sectors. The type of practitioner training and response to delivery complications within the traditional and modern care sectors have little in common. Even within the modern sector, the quality of care available in the heavily subsidized public sector is quite different than that of the fee-based private sector. For example, inadequate resources available to the public sector result both in shorter periods of interaction between patients and practitioners and in lower drug supplies.

Because the quality attributes come only in discrete bundles, a discrete choice method is appropriate to estimate the demand for various delivery arrangements. The econometric model used to estimate the demand for obstetric care is the mixed multinomial logit model, which is a random utility model.[7] It is assumed that individuals make choices that are based on the comparison of the following alternative-specific indirect utility functions.

$$U_{ij0} = X_{j0}\beta + Z_{ij}\alpha_0 + X_{j0}Z_{ij}\gamma + u_j + \epsilon_0$$

$$U_{ij1} = X_{j1}\beta + Z_{ij}\alpha_1 + X_{j1}Z_{ij}\gamma + u_j + \epsilon_1$$

$$\vdots$$

$$U_{ijK} = X_{jK}\beta + Z_{ij}\alpha_K + X_{jK}Z_{ij}\gamma + u_j + \epsilon_K$$

where U_{ijk} represents the utility that individual i (i=1,2,...,N) of community j (j=1,2,...M) will enjoy if alternative k (k=0,1,2,...,K) is chosen. The individual chooses the alternative that yields the highest level of utility. Each woman has the choice of K+1 types of obstetric care alternatives: K alternatives which involve the assistance of either a modern or traditional practitioner and a self-care alternative involving the assistance of only

[7]The approach is mixed in that it combines a multinomial model where individual specific characteristics determine the consumer's choice with a conditional model where alternative specific variables determine choice.

friends and relatives. The set of obstetric care alternatives available to the sample women will be precisely defined later.

The vector X consists of three groups of characteristics that vary by alternative: provider attributes, price, and travel time. It is important to note that no a priori predictions are made regarding which provider attributes are significant determinants of the woman's choice. This is an empirical issue that will be resolved by estimating the discrete choice model.

The vector Z consists of exogenous characteristics of individuals or households that do not vary by alternative, such as age and educational attainment. In developing countries such as the Philippines, demographic characteristics such as educational attainment and family composition are important factors associated with health status.

Also notice that the indirect utility function includes interactions between provider characteristics and household characteristics. An interaction of price and household assets is included to test whether poor households are more responsive to price changes than non-poor households. The interaction of facility attributes and education is included to test whether women with higher levels of education are better able to convert certain attributes into health.

The coefficient vectors, β and γ, do not vary by alternative and represent the weight of provider characteristics on the individual's indirect utility function. The coefficient vector, α, varies by alternative and represents the impact of the vector of unconditional variables on the probability of choosing that alternative relative to another designated alternative.

The error term ϵ represents structural attributes of providers not captured by the data set. For example, there may be unobserved characteristics that are common to delivery alternatives away from home that affect the decision process. As a result, ϵ_k may be correlated across alternatives. The error term μ represents unobserved community factors that can affect the choice of health care provider.

The main disadvantage of using a multinomial logit model concerns the structure of the error terms. The logit model restricts the correlation between the error terms of the indirect utility functions to equal zero. This assumption is called the Independence of Irrelevant Alternatives (IIA), and in this research, means that the relative probabilities of choosing any two delivery options are unaffected by the addition of an option or the elimination of an option. This restriction could cause biased estimates of parameters if there is significant correlation between the error terms among alternatives away from home.[8] A nested multinomial logit (NML) model can partially address

[8]A specification test proposed by Hausman and McFadden (1984) can be used to determine the importance of the IIA problem. The test involves reestimation of the model after eliminating a particular delivery option to see whether coefficients estimated by each model are the same. If the coefficients are stable, than this is an indication that the IIA problem is not affecting the coefficient estimates.

the limitations of the IIA restriction by allowing the errors of the indirect utility functions of specified groupings to be correlated.[9]

Although the IIA restriction is a severe problem theoretically, there is a small but growing body of evidence that suggests that estimates generated from logit models are very similar to those of probit models, where error terms are allowed to be correlated across alternatives without restriction. In a Monte Carlo experiment that compares two forms of a mixed probit model with a mixed logit model, Chen (1987) showed that, if correctly specified, the logit model can legitimately be used. The Monte Carlo experiment tested the effect of various error structures on the estimates. The results suggest that the logit and probit estimators are very similar in terms of the magnitudes of both their mean square errors and bias. In a demand for health care study using Nigerian data, Denton et al. (1991) estimated models using both the mixed logit and mixed probit methods. The coefficient estimates generated by the probit model were very similar to those of the logit estimates. Both studies indicate that the importance of IIA is diminished if the choices available to the consumer are carefully defined. Choices must be distinguished by more than their nominal status; they must differ by the attributes that are provided and prices that consumers are charged.

To simplify the notation, each woman's utility of choosing alternative k can be partitioned in the following way:

$$U_{ijk} = V_{ijk} + \epsilon_k$$

where

$$V_{ijk} = X_{jk}\beta + Z_{ij}\alpha_k + X_{jk}Z_{ij}\gamma + \mu_j$$

Utility is divided between two components: one consisting of both observed utility and unobserved community characteristics and one that represents unobserved characteristics of provider k.

If each ϵ_{ijk} for each individual and alternative is distributed independently and identically in accordance with the extreme value distribution, then the model implies that the probability that individual i of community j will choose the k'th alternative is the following:

$$P_{ijk} = \frac{e^{V_{ijk}}}{\sum_{l=0}^{K} e^{V_{ijl}}}$$

Defining each probability as a function of both the observed component of utility and the unobserved community component enables the application of the

[9]This is discussed in Denton, et. al, 1991.

Huber-White technique, which adjusts the covariance matrix for the two-stage design of the sample. This adjustment is discussed in the Appendix.

The probabilities are then used to construct the following log likelihood function, which is maximized with respect to the unknown coefficients.

$$LOG\ L = \sum_{j=1}^{J} \sum_{i=1}^{N_j} \sum_{k=0}^{K} D_{ijk}\ LOG\ P_{ijk}$$

where

D_{ijk} = 1 *if individual i of community j chose alternative k*

= 0 *otherwise*

4.0 DATA

This analysis is based on both household and provider data from the Cebu Longitudinal Health and Nutrition Study. The survey population live in Metropolitan Cebu, Philippines, which consists of the city of Cebu and surrounding rural areas. A random sample of 17 urban and 16 rural *barangays*, or neighborhoods, in the metropolitan Cebu area was selected. To be eligible for the survey, a woman had to be a permanent resident of the sample *barangays* and had to give birth to a single live child between May 1, 1983 and April 30, 1984. The baseline data set consists of 3,327 women. The women were reinterviewed following their delivery and every two months through the first two years of the infants' lives. The household surveys collected information on income, assets, time allocation, health status, and health-related behavior. The household surveys are supplemented with surveys of health facilities and health personnel and community surveys of wages and food prices. The facility data set includes 82 facilities utilized by the sample population for health care, consisting of public hospitals and clinics, and private hospitals and clinics. Facility surveys collected information on the range of services that are offered, prices, facility size, staff personnel, hours of operation, drug availability, and waiting time. In addition to information from surveys, maps of households and health facilities were constructed and used to determine the distance between each health facility and 49 points that represent household clusters.

These data are well-suited to studying the demand for health care because of the availability of information from suppliers as well as consumers. Information on alternatives actually utilized by women as well as on the alternatives foregone allows the construction of choice sets using alternate criterion.[10] Data sets that include both types of information are rare. As a result, this research is one of only a handful of HCD studies that include detailed supply-side data on all relevant choices.

4.1 VARIABLE SPECIFICATION

This section defines the variables included in the mixed multinomial logit model.

4.1.1 Dependent Variable: Choice of Delivery Alternative

A number of choice set definitions were used in the analysis. Each definition provides an alternate characterization of the options available to the sample population and is based on the following two components: a classification scheme that aggregates providers into groups that represent the available health care options and a technique of matching each woman with the attributes of a provider that represent each alternative.

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[10]Although the household survey includes questions on many types of health care, the actual name of the facilities utilized by women is only available for obstetric care. This makes it possible to match women who delivered away from home to the prices and attributes of the facilities actually utilized. For other types of health care services, information is available only on the types of facility and practitioner utilized. For this reason, obstetric care was chosen as the service to be analyzed.

In most HCD studies that use discrete choice models, the convention is to classify alternatives on the basis of nominal status, such as private/public and traditional/modern status. This study uses choice-sets based on nominal status, but also considers other definitions that attempt to reduce the heterogeneity in provider attributes and prices within any given grouping. For example, when all private alternatives were grouped into one category, the standard deviations of price and facility attributes were considerably higher than those of the other groupings. This occurs because this particular definition does not allow the researcher to distinguish between private hospitals on the basis of price and provider attributes when matching women with the attributes of the closest facility. To test whether other characterizations of the choices available to women affect the results of the model, information on facility attributes was used to construct two other choice set definitions. The first divides private facilities into a private hospital and maternity hospital alternative. The second further divides the remaining private hospitals into a high price-high quality option and a low price-low quality option on the basis of a ranking of the hospitals by price and quality attributes. This latter definition classifies delivery alternatives into the following eight types:

1. Type 1 private hospital (high price/high quality) away from home;
2. Type 2 private hospital (lower price/lower quality) away from home;
3. Maternity hospital/clinic away from home;
4. Public hospital away from home;
5. Private practitioner at home;
6. Public practitioner at home;
7. Traditional practitioner at home, and
8. Friends and relatives at home.

In addition to reducing the standard deviations of prices and structural attributes within categories, this classification eliminates the possibility of assigning a woman a high price-high quality hospital when she actually chose a lower price-lower quality hospital, or vice versa.[11] More importantly, the definition may be a better portrayal of the actual choice set if women differentiate between private hospitals on the basis of price and quality. Sensitivity analysis will be used to determine the impact of alternate definitions on the estimation results.

The following technique was used to match each woman with the characteristics of a provider representing each alternative. If the alternative was modern, each woman was assigned the attributes and price of the closest facility used by at least one woman in her *barangay*, regardless of

[11]This classification differs from the one defined by Schwartz, et al. (1988) in three ways. First, because deliveries away from home almost always took place in hospitals, clinics are never used to represent the away alternatives. Second, private hospitals have been divided into more narrowly defined subgroups. Third, maternity hospitals are treated as a separate category rather than as a type of public facility. The de jure status of maternity hospitals is private, but they do receive government subsidies. The justification for treating them as a separate group is that they offer only maternal and infant care, and the attributes offered and prices charged by maternity hospitals differ from either public or private hospitals.

whether that alternative was chosen or foregone.[12] If the alternative was traditional, it was assumed that the woman was charged the average price of that alternative within her *barangay* and that the delivery was carried out with minimal crowding (zero), and was assisted by a person who did not have modern training nor had access to the type of drugs used in modern deliveries. These provider attributes will be precisely defined later in this section.

Exhibit 1 shows the percentage distribution of women by delivery alternative and by urban/rural status. Over 38 percent of the sample women delivered their babies in hospitals, while 62 percent delivered in their home. Public hospitals were the most frequently chosen alternative away from home and traditional practitioners were the most common home alternative. Rural women were much less likely to have their babies delivered in a hospital than urban women, and were almost three times as likely to be assisted only by a traditional practitioner at home.

4.1.2 Independent Variables: Facility Characteristics

Quality attributes included in the model are crowding, drug availability, and practitioner training.[13] Crowding may affect the woman's psychological well-being prior to delivery and can be a determinant of the level of sanitation within a facility, which affects the risk of morbidity. The level of crowding is of particular relevance in Cebu where it is common for two, three, or four women to share one bed in a public hospital obstetric ward. Unfortunately, a question on crowding within delivery wards was not included in the survey. As a result, crowding is defined as the waiting time in minutes for child out-patient care. It is assumed that there is a high correlation between waiting time for out-patient care and such unobserved measures as the ratio of staff to patients or the average number of women per hospital bed.

The availability of drugs may also have an important influence on the choice of provider. A number of drugs are commonly utilized by practitioners of modern obstetric care. *Oxytocin* and *pitocin* are used for the induction and augmentation of labor, while *chloroprocaine*, *tetracaine*, and *lidocaine* are used as analgesic and anesthetic techniques (Hacker and Moore, 1992). Because the facility questionnaire did not include specific questions on the availability of drugs for obstetric care, drug availability is defined as the number of drugs that the facility has in stock to treat diarrhea. Diarrhea was selected because all facilities treat persons with diarrhea.

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[12]Another way of matching women with facilities that was considered is to use this method only for the foregone alternatives and use the actual facility for the chosen alternative. This would eliminate the possibility of incorrectly assigning the attributes of a facility not chosen by the woman. Unfortunately, information on the facility actually chosen by women was only available for delivery options away from home. As a result, each woman was assigned the closest facility regardless of whether the alternative was chosen or foregone. Not only does this ensure the application of only one rule of assigning facilities that represent the alternatives actually chosen, it is also consistent with the choice set definitions used by every previous HCD researcher.

[13]The facility attributes associated with the choice of prenatal care might also be determinants of the choice of obstetric care provider. However, these factors are not considered in this analysis because of their endogeneity.

Practitioner training is important because the methods used during the delivery can have a substantial impact on the health of both the mother and her child. The handling of the umbilical cord, use of drugs, advice on infant feeding, and response to delivery complications are important factors in determining infant morbidity and mortality (Akin et al., 1984). Two dummy variables on practitioner training were created, and indicate whether the usual delivery practitioner is a medical doctor or a midwife with modern training.

Prices: Ideally, price information should come from providers and not consumers. In this way, price is a characteristic to which the consumer responds, "not a variable whose value is partly or wholly determined by the behavior of the health care demander" (Denton, et al., 1991). Although the Cebu survey of health facilities included questions on prices, this information could not be used because of the prevalence of missing values. As a result, prices of the alternatives were determined in the following way. For the alternatives that were used to deliver away from home, the average cost of delivery for each private, maternity, and public facility was computed using information provided in the household survey by the women who used a given facility. For the alternatives in which women delivered in the home, *barangay*-specific average costs were computed.[14] The endogeneity of this variable is minimized by including in the calculation of average costs only those women who purchased similar services. Specifically, a woman was included in the calculation if her delivery was not caesarian, had no complications, was drug-free, and her hospital stay was less than seven days.

As Exhibit 2 indicates, there is substantial variation in prices and facility attributes across alternatives. For example, private hospitals charge over twice as much for a birth delivery, have a better stock of drugs, and have more highly trained practitioners than type 2 private hospitals.

Time: The opportunity cost of the travel time necessary to use health care is an important cost of health care, and its relative importance could be higher in developing countries such as the Philippines given that the public sector often charges a very low or no fee. Placing a value on the time of women, however, is difficult for two reasons. First, a large proportion of sample women are not formally employed. Heckman's two-step procedure could be used to estimate predicted wages. This is not a satisfactory solution to the problem, however, because the value of time for women out of the work force is greater than their market wage. Second. because women included in the analysis are about to deliver, it is highly likely that the value of their time is different than what it would be under normal conditions.

Because there is no satisfactory method of valuing the time of women under these conditions, this study estimates and compares models that use both time and time weighted by the woman's predicted market wage. Time for the four alternatives away from home is defined as the distance in meters to each alternative. Implicit in this operationalization is the assumption that the

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[14]Schwartz, Akin and Popkin (1988) state that it is a common cultural practice in the Philippines to pay a gratuity to friends or relatives when they assist in the birth delivery.

straight line distance between the household and health facility is a good proxy for travel time.[15] For each of the four home alternatives, the assigned time is zero. Other time price variables were generated by interacting distance with the predicted wages of the pregnant woman and her spouse. The equations used to predict wages were corrected for sample selection.[16] The estimation results are included in Exhibits 11 through 14.

4.1.3 Independent Variables: Individual Characteristics

Assets are defined as the deflated value of the house, land, transportation vehicles, livestock, machinery or equipment, furniture, and appliances. Assets enter the model in two ways: as an interaction with price to test the hypotheses that poor households are more responsive to price than non-poor households and as an unconditional variable.

Household structure: Four household structure variables are included: the number of children below three, number of children between three and five, number of female relatives over 17 years of age, and a dummy indicating the presence of the spouse in the household. These variables were created to test whether various dimensions of household structure can affect the choice decision. For example, demand for home deliveries may be greater for those women who have young children or who have older daughters and other women in the households who have some experience in caring for women in delivery. The presence of the spouse in the household may also affect a woman's preference for modern care vs. traditional care.

Educational attainment of both the pregnant woman and her spouse are included to test the hypothesis that the demand for away alternatives increases with higher levels of schooling. Educational attainment is also interacted with certain attributes to test the hypothesis that women with more education are either better able to use certain attributes to produce health or have different preferences for particular attributes.

Food prices: The deflated price of cereal per kilogram is included in the model to indirectly test the hypothesis that food and quality are substitutes.

Health insurance is not common in Cebu. Most households that do have insurance are covered by the social security plan that is part of the benefit package provided to some formal sector workers (such as government employees). A dummy variable is included to indicate whether the household is partially or

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[15]The baseline survey included questions on the travel time to the closest public, private, and traditional practitioners. This information was not used in this study because of the inability to match the facilities the respondent had in mind when answering these questions to the facilities that were surveyed. It is likely that these travel times more often refer to clinics, which were rarely used by women for deliveries away from home.

[16]The specification of the labor force participation model and the wage model relied heavily on that used by Blau, Guilkey and Popkin (1993).

fully insured for prenatal and obstetric-related expenses. It is hypothesized that having such insurance increases the demand for higher quality care.

5.0 RESULTS

Many versions of the model were estimated to identify specifications which fit the data well. These versions included different combinations of conditional and unconditional variables as well as alternate definitions of the dependent variable. The estimates in Exhibit 3 contain provider and household characteristics, their interactions, insurance coverage, and food prices. This section presents the estimation results and discusses both the effect of using alternative choice set definitions and the effect of adjusting standard errors for the cluster-based design of the survey on the results. In addition, the results of a number of simulations that are of interest to policymakers are reported.

5.1 ESTIMATION RESULTS

The results in Exhibit 3 indicate that structural attributes of providers have a significant impact on choices. For example, crowding and having doctors perform deliveries both have the expected signs and are significant determinants of choice. Schwartz, et al. (1988) found that mothers prefer deliveries where midwives are the only practitioner, whether they are formally trained or not, to deliveries by other combinations of practitioners. This variable was included in many of the specifications that were estimated, but was never significant.

Findings also suggest that facility attributes can interact in important ways with individual characteristics, such as education, in influencing the choice of provider.[17] For example, drug availability is a significant determinant of choice for well-educated women,[18] but not for others. Lavy and Germain (1993) and Denton et al. (1991) also found drug availability to be a significant determinant of choice, but did not include in their specifications interactions between facility and individual characteristics.

Other provider attributes found to be statistically significant determinants of choice in previous HCD studies were entered in many specifications. For example, the number of services offered by the facility[19] and the number of facility personnel included in Lavy and Germain (1993) were never significant. The number of hours per week that the facility is open (Schwartz et al., 1988) and the presence of an operating room (Lavy and Germain, 1993) were not included here because the hospitals which perform deliveries away from home were open 24 hours per day and had operating rooms. Facility-specific measures of the outcome of health care services that were included in Luft et al. (1990) and Burns and Wholely (1992) were not available in Cebu data set.

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[17]Because the model is a reduced form, there is no way of knowing whether various dimensions of quality are chosen due to their role in health production or due to tastes and preferences of the consumer.

[18]Well-educated woman are defined as being in the top 50 percent of educational attainment.

[19]The variable equals the number of the following services available from the facility: out-patient services, immunizations, well-baby care, house calls for postnatal services, and house calls for well-baby care.

Price effects for both poor and non-poor households[20] are negative, but only the former is statistically significant. The results offer support to the findings of many researchers that increasing user fees with constant levels of quality would reduce the use of modern care by poor households.[21] However, the results of this model, as well as those of every other specification that was tested, do not offer any indication that the utilization patterns of better-off households would change with the implementation of user fees.

Distance to the health facility has a negative and highly significant effect on facility choice.[22] It is likely that the distance measure confounds two different effects: the opportunity cost of time and the cost of transportation. Although these effects cannot be disentangled here, findings suggest that the probability of using modern facilities would increase if health facilities were more conveniently located. This strong role of distance in the demand for health care is consistent with the findings of most HCD studies using data from both developed and developing countries.[23]

The coefficients of the unconditional variables included in the model indicate that demographic factors have an important impact on delivery choices. Individuals with more education prefer obstetric care alternatives that are associated with higher quality. Moreover, older women are more likely to choose private hospitals than younger women, *ceribus paribus*.

Households with children under three years of age are more likely to choose alternatives in the home. It is possible that the need for child care may have an important influence on choices. Moreover, the presence of the spouse in the household increases the probability of choosing the traditional alternative.

Having health insurance significantly increases the likelihood of choosing alternatives that are associated with higher levels of quality. For example, those households with some type of pregnancy-related insurance are more likely to choose private hospitals than any other alternative.[24]

Models that used other choice set definitions were estimated and indicate that the specification of delivery alternatives available to the consumer can have a substantial impact on the estimates of the conditional coefficients.

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[20]Non-poor households are defined as being in the top 75 percent of household assets.

[21]See Lavy and Germain (1993), Denton et al. (1991), Gertler et al. (1990, 1987) for examples.

[22]Similar results emerge from a specification that included an interaction between distance and the predicted wage of the mother.

[23]See Lavy and Germain (1993), Burns and Wholely (1992), Luft et al. (1990), and Schwartz et al. (1988) for examples.

[24]Some might argue that the presence of young children and health insurance are endogenous variables. However, the simulation results from a model that excluded these variables from the specification are identical to those reported in the Exhibits.

For example, when the private delivery alternatives away from home were aggregated into one group, coefficients of the attribute variables were not significant. When the private alternative was divided into two groups, private hospitals and maternity hospitals, coefficient estimates became significant and very similar to the model reported, in which three private alternatives were defined. The results of the latter model are reported because they are based on a choice set definition that is believed to most accurately measure the actual choices available to Cebu women.[25]

Sensitivity analysis was also conducted on the effect of accounting for the two-stage sample design on the estimation of standard errors. Exhibit 4 shows that the effect of the Huber-White adjustment on the coefficient estimates of the conditional variables is to increase the standard errors and reduce the T-statistics. In fact, the coefficients of two conditional variables become insignificant with the adjustment. On the other hand, the adjustment does not have much effect on the coefficients of the unconditional variables. The substantial impact on the conditional variables, such as price and facility attributes, is due to the fact that these variables have no variation within a given community. As a result, the ratio of the community error term to the sum of the two error terms is one, which means that the effective sample size is equal to the number of communities (Guilkey, 1992).

5.2 SIMULATION RESULTS

To aid in the interpretation of the results of the logit model, simulations were conducted to predict the effect of changes in the characteristics of health care choices on utilization patterns.[26] Exhibit 5, 6, and 7 present simulation results for all households, households in the bottom asset quartile, and those in the top three asset quartiles, respectively. Because the focus of this research is on the impact of various policy scenarios, the following discussion only considers those simulations which are based on changing the prices and structural attributes of public facilities.

If the price of deliveries in public hospitals were doubled, the average probability of choosing that alternative would fall 3.7 percentage points for poor households, and 1.6 percentage points for other households.[27] These results suggest that the implementation of price increases alone would not

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[25]Choice sets with even more alternatives were not created because it became impossible to rank health facilities on the basis of both price and quality attributes.

[26]The simulations were based on two steps. First, the baseline probabilities of choosing each type of alternative were calculated for each individual by using the actual values of the independent variables. The probabilities were then averaged over the sample. Second, the effect of various changes in choice or household characteristics are examined by altering the value of one or more variables at a time, recalculating and averaging the probabilities, and then comparing them to the baseline values.

[27]The simulations that vary the price paid by non-poor households are based on a coefficient that is not significant.

cause huge effects on utilization, but would hurt the poor more than other households.

Improving each of the quality attributes of public hospitals results in increased utilization. For example, if the level of crowding was reduced to zero, the probability of choosing public hospitals would increase 3.8 percentage points for poor households and 3.3 percentage points for other households. In addition, if the availability of drugs in public hospitals was doubled, the probability of choosing public hospitals would increase by 2.4 percentage points for poor households and 2.9 points for other households. On the other hand, ensuring that only doctors deliver in public hospitals has only a marginal effect on the choice probabilities. This result most likely occurs because the level of practitioner training, according to this dummy indicator, is already quite high in public hospitals (88 percent). Taken together, these simulations of alternative attribute improvements indicate that improving the quality of public facilities will increase the demand for care not only for non-poor households, but poor households as well. The effect of quality improvements, however, can vary greatly by the attribute that is being considered.

The final set of simulations considers the impact of simultaneously implementing user fees and quality improvements. For example, if the price of away deliveries was doubled to 270 pesos, level of crowding was reduced to zero, and availability of drugs was doubled to 4, the probability of choosing a public hospital would actually increase by 1.8 percentage points for poor households and 4.4 percentage points for non-poor households. This suggests that the effects of quality improvements can offset the effects of price increases even without altering the qualifications of facility personnel, which is an aspect of quality over which public policymakers have very little control in the short run. Moreover, the results suggest that, even for the poorest quartile of the sample, quality improvements can play a large role in mitigating any negative welfare effects of increased user fees.

5.3 ELASTICITIES

Another way to evaluate the magnitude of price effects on demand is to derive elasticities using the choice probabilities.[28] Exhibit 8 reports mean price elasticities of demand for both poor and non-poor households.[29] Here, only the effects for poor households are discussed, since price was not found to be a statistically significant determinant of choice for other households. The poor's average response to price is inelastic for the lower price-lower quality private alternatives and for public facilities, and is elastic only for the high price-high quality private hospitals which few of the poor would be

[28]An elasticity represents the percentage change in the dependent variable caused by a one percent change in the explanatory variable.

[29]The price elasticity for any given alternative k is a function of the probability of an individual choosing alternative k, the price of using alternative k, and the price coefficient which does not vary across alternatives. As a result, elasticities differ across choices only because of variation in probabilities and prices.

expected to use anyway.[30] These results suggest that increased user fees in public hospitals will reduce utilization very little.[31] It should be remembered, however, that these elasticities measure effects of small increases in price. Moreover, results suggest that the effects of price become larger as the price associated with using an alternative become higher.

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[30]Other model specifications allowed the effect of price to vary by asset decile. The only group of households in which the elasticity of demand with respect to private hospitals was elastic (1.05) were those in the lowest decile.

[31]Schwartz, Akin, and Popkin (1988) report elasticities of demand with respect to public price that are in the same general range as the ones reported here. However, exact comparisons are not possible because price effects in this study are allowed to differ by household wealth.

6.0 CONCLUSION

Previous research on the demand for medical care has rarely accounted for the heterogeneity of particular types of services. The quality of care that differentiates providers, however, is a potentially important determinant of demand, particularly in those developing countries where consumers can choose to receive free care from public facilities. In this study, a structural model which incorporates the role of provider attributes into consumer behavior is proposed and used to guide the econometric analysis. The model assumes that consumers maximize welfare subject to health production and budget constraints, and that the cost of using a given health care service is determined by a hedonic price function.

Because one of the assumptions that underlie the hedonic pricing model, that of continuous availability of provider attributes, was not deemed to be a realistic characterization of the Philippine health care market, the hedonic price function was not estimated. Nevertheless, the model was valuable in guiding the discrete choice specification of the indirect utility function. Most importantly, the model provides a theoretical basis for including as choice variables the structural attributes that can influence both the health care process as well as the actual health outcome.

This research is one of only a handful of empirical studies of the demand for medical care that includes information on provider attributes as well as on individual characteristics. Empirical results suggest that facility attributes that influence the quality of care, such as crowding, practitioner training, and drug availability, are significant determinants of the choice of obstetric care provider. Moreover, results indicate that certain provider attributes interact in important ways with individual characteristics, such as educational attainment. For example, drug availability has a significant influence on choice for well-educated women, but not for others. This finding is important because it provides evidence of a specific pathway that is at work in a relationship commonly found by social scientists — that between maternal education and child health.

Results also indicate that the interaction between price and household wealth has an important effect on choice. In particular, the findings suggest that price is a statistically significant determinant of the demand for health care for poor households, but not for others. Moreover, the price elasticity of demand falls as household wealth rises. However, the average response to price among the poor is inelastic for all alternatives except that of high price private hospitals.

Of considerable interest to policymakers in developing countries is the net impact of cost recovery schemes that are based on increased user fees as well as on improvements in the quality of care. Policy simulations based on the demand model indicate that when public facilities simultaneously increase user fees and the aspects of quality over which policymakers can exercise control in the short run, the mean probability of using public facilities increases for both poor and non-poor households. While these results indicate that policies that implement an appropriate mix of user fees and quality

improvements can result in welfare gains, government programs that ensure health care for those not able to pay should also be seriously considered.

The findings regarding the impact of alternate choice set definitions on the results are of considerable methodological interest. For example, facility attributes were not found to be significant determinants of choice when the choice set grouped all of the private hospital delivery alternatives into one category. Models that used more disaggregated choice set definitions that more accurately portrayed available alternatives, however, found provider attributes have statistically significant effects. Thus, the sensitivity of the model results to alternative choice set definitions should indicate to future researchers the importance of investigating whether broadly defined alternatives with substantial heterogeneity in provider characteristics and price could be disaggregated further.

There are a number of ways that future research could contribute to the literature on the role of quality in the demand for health care. Models of the demand for services other than birth delivery could incorporate health outcomes to identify those provider attributes that are valued for their health production effects. In addition, such models could be used to investigate whether the role of facility attributes differs by health care service, such as child vs. adult care or preventative vs. curative care.

Future surveys of health providers could include questions on the aspects of quality that have been found to be significant by other researchers in the field. Possible candidates include other structural attributes, such as physician characteristics (Burns and Wholely, 1992), expenditure per person, the physical condition of the facility (Denton et al. 1991), more detailed measures of schooling and qualifications of health care practitioners, and health outcome measures, such as complication rates and mortality rates adjusted for case mix (Luft et al., 1990). Finally, data sets that come from health care markets with a continuous availability of quality attributes could be used to estimate a hedonic price function, which is included in the structural model proposed in this research. As a result, implicit prices and demand functions for specific structural attributes offered by the health care provider could be estimated. This type of information would be valuable to policymakers because it could be used to implement government subsidization programs to ensure quality in the health care market.

EXHIBITS

Exhibit 1. Percent Distribution of Sample Women by Choice of Delivery Arrangement and Urban-Rural Status

Choice	Total N	Total Percent	Urban N	Urban Percent	Rural N	Rural Percent
Away Deliveries						
Private Hospital/ High Quality	101	3.24	97	4.07	4	0.54
Private Hospital/ Lower Quality	208	6.67	196	8.23	12	1.63
Maternity Hospital	400	12.83	380	15.96	20	2.71
Public Hospital	476	15.27	439	18.44	37	5.02
Home Deliveries						
Private Practitioner	220	7.06	205	8.61	15	2.04
Public Practitioner	482	15.46	371	15.58	111	15.06
Traditional Practitioner	1,020	32.71	555	23.31	465	63.09
Friends and Relatives	211	6.77	138	5.80	73	9.91
Total	3,118	100.00	2,381	100.00	737	100.00

Exhibit 2. Descriptive Statistics for Variables in Multinomial Logit Model for All Households (Sample Size = 3,118)

Variable	Mean	Standard Deviation
urban	0.7636	0.4249
number of children 0-2	0.6254	0.6086
number of children 3-5	0.5901	0.7196
number of females 18 or older	0.3409	0.7456
male spouse present	0.9432	0.2314
education of spouse	7.3570	4.2219
education of mother	7.5459	3.7212
age of mother	26.0629	5.9995
insurance	0.1090	0.3117
cereal price (pesos per kilo)	360.9254	58.8005
assets (thousands of pesos)	12.1490	48.3252
Price (in pesos)		
Private Hospital 1	905.8946	66.7284
Private Hospital 2	399.1354	105.0936
Maternity Hospital	355.1991	88.6105
Public Hospital	134.6185	24.2828
Private Pract at Home	59.5915	16.0803
Public Pract at Home	46.8600	11.4602
Traditional Practitioner	53.2348	15.7797
Friends and Relatives	37.6873	13.5656
Crowding		
Private Hospital 1	5.9718	4.9054
Private Hospital 2	4.2415	9.1424
Maternity Hospital	15.1924	14.9046
Public Hospital	21.3534	10.7966
Private Pract at Home	5.9750	9.3969
Public Pract at Home	7.9355	8.1789
Traditional Practitioner	0.0000	0.0000
Friends and Relatives	0.0000	0.0000
Facility Size		
Private Hospital	104.0173	89.6202
Maternity Hospital	43.0311	34.3921
Public Hospital	230.4817	126.6384
Private Pract at Home	15.0026	21.0179
Public Pract at Home	40.3788	85.3549
Traditional Practitioner	1.0000	0.0000
Friends and Relatives	1.0000	0.0000

Exhibit 2 (Continued)

Variable	Mean	Standard Deviation
Drug Availability		
Private Hospital 1	5.0000	0.0000
Private Hospital 2	4.3066	1.3166
Maternity Hospital	1.8810	0.7264
Public Hospital	2.1841	1.8973
Private Pract at Home	1.1052	0.8810
Public Pract at Home	0.4775	1.0435
Traditional Practitioner	0.0000	0.0000
Friends and Relatives	0.0000	0.0000
Only Doctors Deliver		
Private Hospital 1	1.0000	0.0000
Private Hospital 2	0.7091	0.4542
Maternity Hospital	0.5853	0.4927
Public Hospital	0.8775	0.3279
Private Pract at Home	0.0000	0.0000
Public Pract at Home	0.0000	0.0000
Traditional Practitioner	0.0000	0.0000
Friends and Relatives	0.0000	0.0000
Distance (in meters)		
Private Hospital 1	6,870.8695	5,707.5169
Private Hospital 2	5,346.5443	5,758.0082
Maternity Hospital	5,095.6180	5,716.8529
Public Hospital	4,820.7826	4,059.6860
Private Pract at Home	0.0000	0.0000
Public Pract at Home	0.0000	0.0000
Traditional Practitioner	0.0000	0.0000
Friends and Relatives	0.0000	0.0000

Exhibit 3. Multinomial Logit Model of Obstetric Provider Choice with Adjusted T-statisti

Variable	Low Price Private Hospital versus High Price Private Hospital Coeff	t-stat	Maternity Hospital versus High Price Private Hospital Coeff	t-stat	Public Hospital versus High Price Private Hospital Coeff	t-stat
Conditional Variables						
price*low asset dummy	-0.0024	-2.8653***	-0.0024	-2.8653***	-0.0024	-2.8653***
price*high asset dummy	-0.0010	-1.1594	-0.0010	-1.1594	-0.0010	-1.1594
distance	-0.0002	-6.9922***	-0.0002	-6.9922***	-0.0002	-6.9922***
crowding	-0.0122	-1.9124**	-0.0122	-1.9124**	-0.0122	-1.9124**
drug availability* low education dummy	0.0926	1.2742	0.0926	1.2742	0.0926	1.2742
drug availability* high education dummy	0.1117	2.2920**	0.1117	2.2920**	0.1117	2.2920**
only doctors deliver in facility	0.7801	3.4899***	0.7801	3.4899***	0.7801	3.4899***
Unconditional Variables						
constant	2.9341	2.1505**	3.6815	2.1578**	3.9886	2.2470**
urban	-0.0853	-0.1384	0.0806	0.1419	0.3387	0.6360
cereal price	0.0005	0.3157	0.0015	0.8312	0.0031	1.7343*
age of mother	-0.0268	-1.1969	-0.0416	-1.7581*	-0.0662	-3.0370***
education of mother	-0.1944	-3.9574***	-0.1881	-4.2682***	-0.2690	-6.2768***
education of father	-0.0378	-0.7528	-0.1110	-2.3127**	-0.1592	-2.8452***
spouse present	0.6074	0.7620	1.6251	2.1442**	2.0450	2.4622**
children 0-2	-0.1534	-0.5433	-0.0121	-0.0691	0.0589	0.3433
children 3-5	0.5925	4.1623***	0.5803	4.1239***	0.6796	4.0026***
females 18+	0.0469	0.2489	0.0219	0.1319	0.1372	0.7431
insurance	-0.6871	-2.2909**	-0.9399	-3.3324***	-1.4569	-5.5383***
assets	-0.0006	-0.6925	-0.0026	-2.1726**	-0.0053	-2.5126**

Note: ***, **, and * indicates parameter estimate is significant at the 1%, 5%, and 10% level, respectivel

Exhibit 3 (Continued)

Variable	Private Practitioner versus High Price Private Hospital Coeff	t-stat	Public Practitioner versus High Price Private Hospital Coeff	t-stat	Traditional Practitioner versus High Price Private Hospital Coeff	t-stat	Friends and Relatives versus High Price Private Hospital Coeff	t-stat
Conditional Variables								
price*low asset dummy	-0.0024	-2.8653***	-0.0024	-2.8653***	-0.0024	-2.8653***	-0.0024	-2.8653***
price*high asset dummy	-0.0010	-1.1594	-0.0010	-1.1594	-0.0010	-1.1594	-0.0010	-1.1594
distance	-0.0002	-6.9922***	-0.0002	-6.9922***	-0.0002	-6.9922***	-0.0002	-6.9922***
crowding	-0.0122	-1.9124**	-0.0122	-1.9124**	-0.0122	-1.9124**	-0.0122	-1.9124**
drug availability* low education dummy	0.0926	1.2742	0.0926	1.2742	0.0926	1.2742	0.0926	1.2742
drug availability* high education dummy	0.1117	2.2920**	0.1117	2.2920**	0.1117	2.2920**	0.1117	2.2920**
only doctors deliver in facility	0.7801	3.4899***	0.7801	3.4899***	0.7801	3.4899***	0.7801	3.4899***
Unconditional Variables								
constant	0.2391	0.1287	4.0696	1.9246**	4.8132	2.7426***	4.8584	2.1231**
urban	1.9946	2.7025***	0.6708	0.7289	-0.2494	-0.4391	0.2053	0.3040
cereal price	0.0068	4.0309***	0.0025	1.2790	0.0043	2.2982**	0.0003	0.0872
age of mother	-0.0589	-2.3777**	-0.0692	-2.6452***	-0.0715	-2.9315***	-0.0768	-2.5722**
education of mother	-0.3493	-7.8102***	-0.3211	-6.2515***	-0.3900	-7.9700***	-0.4067	-7.2092***
education of father	-0.2177	-3.6251***	-0.2231	-3.9005***	-0.2473	-3.9434***	-0.2313	-3.7092***
spouse present	2.5985	3.4119***	2.5828	3.1112***	3.0340	3.4175***	2.5954	3.0206***
children 0-2	0.5711	2.8855***	0.3098	1.6231	0.3918	2.3075**	0.6663	3.8869***
children 3-5	0.6058	3.1112***	0.6634	4.1669***	0.8161	5.2094***	0.7424	4.1636***
females 18+	0.0488	0.2214	0.1245	0.9330	0.0247	0.1867	-0.0382	-0.1554
insurance	-1.3005	-4.4102***	-1.4744	-4.8010***	-1.2577	-5.3511***	-1.3271	-3.9007***
assets	-0.0132	-2.4286**	-0.0054	-1.8066*	-0.0059	-1.7491*	-0.0113	-1.8499*

N = 3,118 Psuedo R Square = 0.44 Percent Predicted Correctly = 0.41

Exhibit 4. **Multinomial Logit Model of Obstetric Provider Choice, Comparison of Adjusted and Unadjusted Results for Conditional Variables**

Variable	Coefficient	Adjusted S.E.	Adjusted t-stat	Unadjusted S.E.	Unadjusted t-stat
Price*Low Asset Dummy	-0.0024	0.0008	-2.8653***	0.0006	-3.7946***
Price*High Asset Dummy	-0.0010	0.0009	-1.1594	0.0005	-1.8989*
Distance	-0.0002	0.0003	-6.9922***	0.0001	-12.4309***
Crowding	-0.0122	0.0064	-1.9124**	0.0035	-3.4509***
Drug Availability* Low Education Dummy	0.0926	0.0727	1.2742	0.0447	2.0740**
Drug Availability* High Education Dummy	0.1117	0.0487	2.2920**	0.0259	4.3135***
Only Doctors Deliver in Facility	0.7801	0.2235	3.4899***	0.1119	6.9715***

Note: ***, **, and * indicates parameter estimate is significant at the 1%, 5%, and 10% level, respectively.

Exhibit 5. Mean Simulated Probabilities of Choosing Delivery Alternatives — All Households

	Private Hospital Type 1	Private Hospital Type 2	Private Maternity Hospital	Public Hospital	Private Pract. Home	Public Pract. Home	Trad Home	Relatives Home
Baseline	.032	.069	.127	.151	.071	.158	.323	.069
Double All Public Prices Away Price=270 Home=54	.033	.071	.131	.131	.073	.160	.332	.070
Double Away Public Prices Away Price=270	.033	.071	.131	.130	.073	.162	.330	.071
Lower Public Hospital Crowding Wait=10 minutes	.031	.066	.123	.169	.069	.155	.318	.068
Lower Public Hospital Crowding Wait=0 minutes	.031	.064	.120	.185	.068	.152	.313	.067
Double Public Hospital Drug Availability Drug Number=4	.031	.065	.121	.179	.068	.153	.315	.067
Only Doctors Deliver in Public Hospitals Doctor=1	.032	.068	.126	.158	.070	.157	.320	.068
Double Prices for Public Hospitals, Reduce Crowding to 10, Double Drug Availability Away Delivery=270 Crowding=0 Minutes Drug Number=4	.030	.064	.119	.189	.068	.151	.313	.067
Double Prices for Public Hospitals, Reduce Crowding to 0, Double Drug Availability Away Delivery=270 Crowding=10 Minutes Drug Number=4	.031	.065	.122	.172	.069	.154	.318	.068

Exhibit 6. Mean Simulated Probabilities of Choosing Delivery Alternatives — HHs in Bottom Asset Quartile

	Private Hospital Type 1	Private Hospital Type 2	Private Maternity Hospital	Public Hospital	Private Pract. Home	Public Pract. Home	Traditional Home	Relatives Home
Baseline	.006	.040	.088	.159	.091	.177	.356	.083
Double All Public Prices Away Price=270 Home Price= 54	.007	.042	.095	.122	.095	.182	.370	.087
Double Away Public Prices Away Price=270	.007	.042	.095	.122	.095	.185	.368	.086
Lower Public Hospital Crowding Wait=10 Minutes	.006	.038	.085	.180	.088	.172	.349	.082
Lower Public Hospital Crowding Wait=0 Minutes	.006	.037	.082	.197	.086	.168	.343	.080
Double Public Hospital Drug Availability Drug Number=4	.006	.038	.085	.183	.088	.171	.348	.081
Only Doctors Deliver in Public Hospitals Doctor=1	.006	.040	.088	.162	.090	.176	.354	.083
Double Prices for Public Hospitals, Reduce Crowding to 10, Double Drug Availability Away Delivery=270 Crowding=10 Minutes Drug Number=4	.006	.039	.088	.161	.090	.176	.355	.083
Double Prices for Public Hospitals, Reduce Crowding to 0, Double Drug Availability Away Delivery=270 Crowding=0 Minutes Drug Number=4	.006	.038	.086	.177	.088	.173	.350	.082

Exhibit 7. Mean Simulated Probabilities of Choosing Delivery Alternatives — HHs in Top 3 Asset Quartiles

	Private Hospital Type 1	Private Hospital Type 2	Private Maternity Hospital	Public Hospital	Private Pract. Home	Public Pract. Home	Traditional Home	Relatives Home
Baseline	.041	.078	.139	.149	.064	.152	.312	.064
Double All Public Prices Away Price=270 Home Price=54	.041	.080	.143	.133	.066	.154	.317	.065
Double Away Public Prices Away Price=270	.041	.080	.143	.133	.066	.155	.317	.065
Lower Public Hospital Crowding Wait=10 Minutes	.040	.076	.136	.166	.063	.149	.308	.063
Lower Public Hospital Crowding Wait=0 Minutes	.039	.074	.132	.182	.062	.146	.304	.062
Double Public Hospital Drug Availability Drug Number=4	.039	.075	.133	.178	.062	.147	.304	.062
Only Doctors Deliver in Public Hospitals Doctor=1	.041	.078	.139	.157	.064	.150	.308	.064
Double Prices for Public Hospitals, Reduce Crowding to 10, Double Drug Availability Away Delivery=270 Crowding=10 Minutes Drug Number=4	.039	.074	.133	.176	.062	.147	.305	.063
Double Prices for Public Hospitals, Reduce Crowding to 0, Double Drug Availability Away Delivery=270 Crowding=0 Minutes Drug Number=4	.038	.072	.130	.193	.061	.144	.301	.062

Exhibit 8. Demand Elasticitites with Respect to Own Price

	Bottom Asset Quartile	Top Three Asset Quartiles
Away Delivery		
Private Hospital Type 1	-2.16	-0.85
Private Hospital Type 2	-0.92	-0.36
Maternity Hospital	-0.76	-0.30
Public Hospital	-0.27	-0.11
Home Delivery		
Private	-0.13	-0.05
Public	-0.09	-0.04

Exhibit 9. Assumptions Concerning the Determinants of Matrices Used in Comparative Statics Analysis

Result	Assumed or Calculated
$D < 0$	assumed
$D_{11} > 0$	assumed
$D_{21} < 0$	calculated
$D_{31} < 0$	calculated
$D_{51} < 0$	calculated
$D_{61} > 0$	assumed
$D_{12} < 0$	calculated
$D_{22} > 0$	assumed
$D_{32} < 0$	calculated
$D_{52} < 0$	calculated
$D_{62} > 0$	assumed
$D_{13} < 0$	calculated
$D_{23} < 0$	calculated
$D_{33} > 0$	assumed
$D_{53} < 0$	calculated
$D_{63} > 0$	assumed
$D_{35} < 0$	calculated
$D_{55} > 0$	assumed
$D_{65} > 0$	assumed

Exhibit 10. Results of the Comparative Statics Analysis

Total Effect =	Income Effect	+	Substitution Effect
Health Care Attributes			
$\partial Y/\partial A =$	$(-1)*D_{61}/D$ (+)		
$\partial Y/\partial W =$	$(-1)*(1-T-L)*D_{61}/D$ (+)	+	$\lambda*(D_{31}+D_{51})/D$ (+)
$\partial Y/\partial \alpha =$	$P_{1n}*D_{61}/D$ (-)	+	$\lambda*P_{1n}*D_{11}/D$ (-)
$\partial Y/\partial Q =$	$Z*D_{61}/D$ (-)	+	$\lambda*D_{21}/D$ (+)
Non-Health Care Inputs			
$\partial Z/\partial A =$	$(-1)*D_{62}/D$ (+)		
$\partial Z/\partial W =$	$(-1)*(1-T-L)*D_{62}/D$ (+)	+	$\lambda*(D_{32}+D_{52})/D$ (+)
$\partial Z/\partial \alpha =$	$P_{1n}*D_{62}/D$ (-)	+	$\lambda*P_{1n}*D_{12}/D$ (+)
$\partial Z/\partial Q =$	$Z*D_{62}/D$ (-)	+	$\lambda*D_{22}/D$ (-)
Time for Health Production			
$\partial T/\partial A =$	$(-1)*D_{63}/D$ (+)		
$\partial T/\partial W =$	$(-1)*(1-T-L)*D_{63}/D$ (+)	+	$\lambda*(D_{33}+D_{53})/D$ (?)
$\partial T/\partial \alpha =$	$P_{1n}*D_{63}/D$ (-)	+	$\lambda*P_{1n}*D_{13}/D$ (+)
$\partial T/\partial Q =$	$Z*D_{63}/D$ (-)	+	$\lambda*D_{23}/D$ (+)
Leisure			
$\partial L/\partial W =$	$(-1)*(1-T-L)*D_{63}/D$ (+)	+	$\lambda*(D_{33}+D_{53})/D$ (?)

Exhibit 11. Probit of Labor Force Participation of Women with Huber Standard Errors

Variable	Coef	S.E.	t	P>|t|
Education of Spouse	-.0092698	.0065883	-1.407	0.160
Age	.0188484	.0060658	3.107	0.002
Interview date	.0003032	.0002021	1.500	0.134
Education				
6-7 years	-.1325988	.0704751	-1.881	0.060
8-10 years	-.1428485	.0818205	-1.746	0.081
11 years	-.0049219	.0800381	-0.061	0.951
12-14 years	-.0702026	.0933914	-0.752	0.452
15-16 years	.3268464	.108505	3.012	0.003
17+ years	.6445513	.3663254	1.760	0.079
Spouse	.3655336	.1876255	1.948	0.051
Age of Spouse	-.0114435	.0046509	-2.461	0.014
Grandmother	-.0006128	.097294	-0.006	0.995
Grandfather	-.107278	.1307323	-0.821	0.412
Number of Children				
Ages 0-2	-.1409714	.0444829	-3.169	0.002
Ages 3-5	-.0588863	.0334879	-1.758	0.079
Ages 6-10	-.0111781	.0326156	-0.343	0.732
Ages 12-16	.0625884	.0484298	1.292	0.196
Other Relatives				
Ages 0-5	-.0439262	.0496694	-0.884	0.377
Ages 6-11, male	.1488954	.0542635	2.744	0.006
Ages 6-11, fem	.1486312	.0556149	2.673	0.008
Ages 12-17, ma	-.0541528	.0660514	-0.820	0.412
Ages 12-17, fe	-.0178159	.0351424	-0.507	0.612
Ages 18+, mal	-.1264747	.0383428	-3.299	0.001
Ages 18+, fem	-.0407559	.0455349	-0.895	0.371
Non-relative 0-17	.2591078	.0777731	3.332	0.000
Mother born in barangay	-.3352879	.141649	-2.367	0.018
Fraction of life lived in baran	.6046699	.1730989	3.493	0.000
distance to road	-.0000662	.0000576	-1.150	0.250
Barangay Dummy Variables				
dbrgy2	-.0153673	.0233211	-0.659	0.510
dbrgy3	.0218317	.0244003	0.895	0.371
dbrgy4	.5993293	.0151208	39.636	0.000
dbrgy5	.3815395	.0339437	11.240	0.000
dbrgy6	.3437697	.0201448	17.065	0.000
dbrgy7	.1013934	.0172528	5.877	0.000
dbrgy8	.2148648	.0202944	10.587	0.000
dbrgy9	.2702385	.0159689	16.923	0.000

dbrgy10	-.1685738	.0217121	-7.764	0.000
dbrgy11	.2712143	.0181810	14.917	0.000
dbrgy12	.0974196	.0260737	3.736	0.000
dbrgy13	.0902207	.0185730	4.858	0.000
dbrgy14	.4309981	.0178013	24.212	0.000
dbrgy15	.1717111	.0193322	8.882	0.000
dbrgy16	.1797906	.0153717	11.696	0.000
dbrgy17	-.1050225	.0227305	-4.620	0.000
dbrgy18	-.2329124	.1404827	-1.658	0.097
dbrgy19	.3295959	.0281111	11.725	0.000
dbrgy20	-.751629	.0389325	-19.306	0.000
dbrgy21	.527633	.0646394	8.163	0.000
dbrgy22	.7889106	.0348104	22.663	0.000
dbrgy23	-.122842	.1114621	-1.102	0.271
dbrgy24	.2986353	.0444941	6.712	0.000
dbrgy25	.3308692	.0322924	10.246	0.000
dbrgy26	-.0367172	.0612940	-0.599	0.549
dbrgy27	.5684856	.0722993	7.863	0.000
dbrgy28	.0576392	.0230395	2.502	0.012
dbrgy29	-.4202287	.0412370	-10.191	0.000
dbrgy30	.292831	.0299518	9.777	0.000
dbrgy31	-.5197276	.1281938	-4.054	0.000
dbrgy32	1.222811	.0475935	25.693	0.000
dbrgy33	.0773462	.0422062	1.833	0.067
_cons	-.8508107	.1791898	-4.748	0.000

N = 3327
Log Likelihood = -2107.4962
Pseudo R2 = 0.0635

Exhibit 12. Regression of Log Wages of Women with Huber Standard Errors

Variable	Coef	S.E.	t	P>|t|
Age	.0119164	.0048794	2.442	0.015
Interview date	-.0005282	.0002855	-1.850	0.065
Education				
6-7 years	.0465241	.0673763	0.691	0.490
8-10 years	.2719200	.0929969	2.924	0.004
11 years	.2900366	.0669804	4.330	0.000
12-14 years	.3597083	.0781908	4.600	0.000
15-16 years	1.0368190	.0688889	15.051	0.000
17 years	.9547082	.2095027	4.557	0.000
Inverse Mills Ratio	-.0302397	.2215277	-0.137	0.891
Barnagay Dummy Variables				
dbrgy2	.4837198	.0200929	24.074	0.000
dbrgy3	.303278	.0211522	14.338	0.000
dbrgy4	-.2918538	.0924534	-3.157	0.002
dbrgy5	.4844048	.0880563	5.501	0.000
dbrgy6	.2495711	.0593047	4.208	0.000
dbrgy7	.1990777	.0210988	9.435	0.000
dbrgy8	.3520951	.0349199	10.083	0.000
dbrgy9	.0717449	.0505733	1.419	0.156
dbrgy10	.5064914	.0219841	23.039	0.000
dbrgy11	.2222156	.0445226	4.991	0.000
dbrgy12	.5398447	.0347001	15.557	0.000
dbrgy13	.4080513	.0149195	27.350	0.000
dbrgy14	.1653725	.058965	2.805	0.005
dbrgy15	.0991567	.0331709	2.989	0.003
dbrgy16	.1738571	.029992	5.797	0.000
dbrgy17	.401322	.0145117	27.655	0.000
dbrgy18	.6079093	.0533364	11.398	0.000
dbrgy19	.2377191	.0576349	4.125	0.000
dbrgy20	1.116521	.1153229	9.682	0.000
dbrgy21	.1603648	.0824804	1.944	0.052
dbrgy22	.0391931	.120062	0.326	0.744
dbrgy23	.333705	.042398	7.871	0.000
dbrgy24	.4513508	.0620111	7.279	0.000
dbrgy25	-.1141154	.0576206	-1.980	0.048
dbrgy26	.1637456	.0249662	6.559	0.000
dbrgy27	.8934953	.0861817	10.368	0.000
dbrgy28	-.07339	.0117858	-6.227	0.000
dbrgy29	.0588125	.0524405	1.122	0.262
dbrgy30	.1398263	.0624955	2.237	0.025
dbrgy31	1.28621	.0875883	14.685	0.000
dbrgy32	-.1943206	.1554136	-1.250	0.211
dbrgy33	.9976664	.0467975	21.319	0.000

Exhibit 12 (continued)

_cons	-.1451752	.2945348	-0.493	0.622

N	=	1,344
R-square	=	0.1946
Adj R-square	=	0.1693

Exhibit 13. **Probit of Labor Force Participation of Spouses with Huber Standard Errors**

Variable	Coef	S.E.	t	P>|t|
Education	.0145608	.0210989	0.690	0.490
Age	.0681349	.0282862	2.409	0.016
Age Square	-.0010963	.0003970	-2.761	0.006
Interview Date	.0000353	.0004461	0.079	0.937
Education				
6-7 Years	.2091154	.1240941	1.685	0.092
8-10 Years	-.1171447	.1134122	-1.033	0.302
11 Years	-.3171264	.1530138	-2.073	0.038
12-14 Years	-.4666159	.2027102	-2.302	0.021
15-16 Years	-.1660236	.2800956	-0.593	0.553
17 Years	-.8723779	.4951906	-1.762	0.078
Grandmother	-.0429939	.1499932	-0.287	0.774
Grandfather	-.420638	.1784989	-2.357	0.019
Number of Children				
Ages 0-2	.1670327	.0507331	3.292	0.001
Ages 3-5	.0845026	.0635776	1.329	0.184
Ages 6-11	.0550949	.0362358	1.520	0.129
Ages 12-16	-.1220875	.0578289	-2.111	0.035
Other Relatives				
Ages 0_5	.0017412	.0761798	0.023	0.982
Ages 6_11, ma	-.2067118	.1027904	-2.011	0.044
Ages 6-11, fe	.1775586	.0890691	1.993	0.046
Ages 12-17, ma	-.2444094	.0669648	-3.650	0.000
Ages 12-17, fe	-.0317056	.0479694	-0.661	0.509
Ages 18+, m	-.2229877	.0696985	-3.199	0.001
Ages 18+, f	-.1461768	.055232	-2.647	0.008
Non Relatives				
Ages 0-17	-.1204586	.1253954	-0.961	0.337
Distance to Road	-.0000567	.0000488	-1.161	0.246
Barangay Dummy Variables				
dbrgy2	.2296465	.0414351	5.542	0.000
dbrgy3	-.5849237	.042982	-13.609	0.000
dbrgy4	-.1894796	.0267346	-7.087	0.000
dbrgy5	-.3709921	.0966774	-3.837	0.000
dbrgy6	-.3959802	.0326785	-12.117	0.000
dbrgy7	-.4101034	.0329744	-12.437	0.000
dbrgy8	-.4872181	.0353476	-13.784	0.000
dbrgy9	-.0731836	.030896	-2.369	0.018
dbrgy10	-.436689	.042069	-10.380	0.000
dbrgy11	-.3134144	.0447045	-7.011	0.000

dbrgy12	-.674006	.0365539	-18.439	0.000
dbrgy13	-.1099395	.0376699	-2.919	0.004
dbrgy14	-.2374284	.0346546	-6.851	0.000
dbrgy15	-.6249577	.0227756	-27.440	0.000
dbrgy16	.1242862	.0615012	2.021	0.043
dbrgy17	-.3946811	.0273799	-14.415	0.000
dbrgy18	-2.062204	.116163	-17.753	0.000
dbrgy19	-1.322197	.0432418	-30.577	0.000
dbrgy20	-1.57682	.0412508	-38.225	0.000
dbrgy21	0	.	.	.
dbrgy22	0	.	.	.
dbrgy23	-1.708849	.0972874	-17.565	0.000
dbrgy24	0	.	.	.
dbrgy25	-1.023377	.0413529	-24.747	0.000
dbrgy26	-.5386437	.0413776	-13.018	0.000
dbrgy27	-1.39919	.0538518	-25.982	0.000
dbrgy28	.1747009	.0273824	6.380	0.000
dbrgy29	-.5128846	.0367088	-13.972	0.000
dbrgy30	-.2295957	.0699459	-3.282	0.001
dbrgy31	-2.001113	.0940042	-21.287	0.000
dbrgy32	-.3884146	.0384506	-10.102	0.000
dbrgy33	-.084489	.1028863	-0.821	0.412
_cons	.8809449	.5028316	1.752	0.080

N = 3,084
Log Likelihood = -784.39447
Pseudo R2 = 0.2169

Exhibit 14. Regression of Log Wages of Spouses with Huber Standard Errors

Variable	Coef	S.E.	t	P>|t|
Age	.0333636	.0127676	2.613	0.009
Age Squared	-.0004096	.0002148	-1.907	0.057
Interview Date	-.0002765	.0001674	-1.652	0.099
Education				
6-7 Years	.0489955	.0325430	1.506	0.132
8-10 Years	.1595971	.0453848	3.517	0.000
11 Years	.3120085	.0365881	8.528	0.000
12-14 Years	.4201326	.0560249	7.499	0.000
15-16 Years	.6270648	.0722663	8.677	0.000
17 Years	.9567097	.1778697	5.379	0.000
Inverse Mills Ratio	-.0058549	.124282	-0.047	0.962
Barangay Dummy Variables				
dbrgy2	.0361064	.009982	3.617	0.000
dbrgy3	-.0848006	.014162	-5.988	0.000
dbrgy4	-.0268750	.0075082	-3.579	0.000
dbrgy5	.0284871	.0188214	1.514	0.130
dbrgy6	-.0514272	.0083608	-6.151	0.000
dbrgy7	.1078410	.0117476	9.180	0.000
dbrgy8	.0449661	.016435	2.736	0.006
dbrgy9	.0005047	.0038456	0.131	0.896
dbrgy10	.0336369	.0124494	2.702	0.007
dbrgy11	-.0875425	.0076957	-11.375	0.000
dbrgy12	.1152606	.024223	4.758	0.000
dbrgy13	-.0058893	.0076008	-0.775	0.439
dbrgy14	.1024060	.0078693	13.013	0.000
dbrgy15	.0230919	.0129119	1.788	0.074
dbrgy16	.0610409	.0076575	7.971	0.000
dbrgy17	.1674221	.0136344	12.279	0.000
dbrgy18	.0457813	.099977	0.458	0.647
dbrgy19	-.2665372	.05032	-5.297	0.000
dbrgy20	.0788998	.0613968	1.285	0.199
dbrgy21	-.2335091	.0108057	-21.610	0.000
dbrgy22	-.7702398	.0078925	-97.592	0.000
dbrgy23	-.2050233	.0677517	-3.026	0.003
dbrgy24	.3965228	.0379833	10.439	0.000
dbrgy25	-.5130108	.0298744	-17.172	0.000
dbrgy26	.0129238	.0169963	0.760	0.447
dbrgy27	.0350387	.0479193	0.731	0.465
dbrgy28	-.1778527	.0041627	-42.726	0.000
dbrgy29	-.0447696	.0119296	-3.753	0.000
dbrgy30	.1140535	.0086928	13.120	0.000
dbrgy31	.4171078	.0888517	4.694	0.000
dbrgy32	-.2915765	.0154219	-18.907	0.000
dbrgy33	.4640856	.0264005	17.579	0.000

Exhibit 14 (continued)

_cons	.2382774	.1903528	1.252	0.211

Number of obs = 2,720
R-square = 0.1161
Adj R-square = 0.1022

APPENDIX

MATHEMATICAL ASSUMPTIONS USED IN COMPARATIVE STATICS ANALYSIS

The bordered Hessian matrix, denoted by D, used in the comparative statics analysis is the following:

$D =$

$$\begin{vmatrix} U_{11}H_1H_1 + U_1H_{11} - \lambda P_{11} & U_{11}H_2H_1 & U_{11}H_4H_1 & 0 & 0 & -P_1 \\ U_{11}H_1H_2 & U_{11}H_2H_2 + U_1H_{22} & U_{11}H_4H_2 & 0 & 0 & -Q \\ U_{11}H_1H_4 & U_{11}H_2H_4 & U_{11}H_4H_4 + U_1H_{44} & 0 & 0 & -W \\ 0 & 0 & 0 & U_{22} & 0 & -1 \\ 0 & 0 & 0 & 0 & U_{33} & -W \\ -P_1 & -Q & -W & -1 & -W & 0 \end{vmatrix}$$

The assumption that consumers make optimal choices implies that the determinant of D must be negative and the cofactors along the main diagonal must be positive. (Subscripts used in the elements of D indicate partial derivatives.) The signs of the remaining cofactors were calculated and are listed in Exhibit 9. D_{ij} denotes the cofactor of the ith row and the jth column. Results of the comparative statics analyis are listed in Exhibit 10.

HUBER-WHITE ADJUSTMENT OF STANDARD ERRORS

Standard errors are adjusted using the following Huber-White technique, which corrects for the design of the sample. Both adjusted and unadjusted models are estimated using a Fortran program written by David Guilkey. If the sample contains j=1, ..., M clusters with i=1,..., N_j individuals in each cluster, the adjusted covariance matrix is the following (Guilkey, 1992):

$$cov(\hat{\beta}) = I(\hat{\beta})^{-1} M(\hat{\beta}) I(\hat{\beta})^{-1}$$

where

$$I(\hat{\beta}) = \textit{the information matr}$$

$$M_j(\hat{\beta}) = \sum_{i=1}^{N_j} \frac{\partial L_{ij}}{\partial \hat{\beta}}$$

$$M(\hat{\beta}) = \sum_{j=1}^{M} M_j(\hat{\beta}) M_j(\hat{\beta})$$

The matrix accounts for the fact that the error term in a cluster-based sample consists of a term that represents unobserved community variables and a term that represents unobserved individual-specific variables. As a result, the error term between observations within a sample cluster are correlated. This type of error structure is also found in random effects models, where the error term consists of a time-invariant component and an individual component.

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