An Econometric Analysis of the Asymmetric Information, Regulator-Utility Interaction

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ABSTRACT. – This paper presents procedures for estimating the parameters of a regulated firm's production function which explicitly model the impact of the private information possessed by utility in the regulatory process. The paper derives the optimal regulatory outcome for two cases: (1) the utility's private information is observable by the regulator and (2) only the distribution of the private information is observable by the regulator. Given a parametric form for the utility's production function, these optimal regulatory outcomes yield structural econometric models which can be estimated to recover the parameters of the regulated firm's production function. These models are estimated for the Class A California water utility industry, and the parameter estimates obtained are compared to those obtained from applying conventional cost-function estimation procedures. This estimation procedure recovers the parameters of the utility's production function as well as an estimate of the distribution function of the utility's private information parameter. Using a non-nested hypothesis testing procedure we find that the second private information model provides a superior description of the observed level of costs and output. The estimates from these models are then used to compute the increased production costs and output reduction which result from the utility's superior private information about its production process. We find noticeable, but not overwhelming, percentage cost increases introduced by this private information in the regulatory process. The major effect is the welfare loss to consumers from the reduction in output produced under asymmetric information versus symmetric information.

Une analyse économétrique avec information asymétrique de l'équilibre entre régulateur et utilité publique

RÉSUMÉ. – Dans cet article, il s'agit de méthodes pour estimer les paramètres de la fonction de production d'une entreprise réglementée; ces méthodes expliquent les effets dans le processus réglementé d'information privée possédé par une utilité publique. Cet article dérive le résultat optimum de la régulation pour deux structures d'information : (1) où l'information privée de l'utilité publique peut être observé par le régulateur (le modèle avec information symétrique), et (2) où seulement la distribution de cette information privée peut être observé par le régulateur (le modèle avec information asymétrique). Etant donné des formes paramétriques pour la fonction de production et pour la fonction de commandes de l'utilité publique, ces résultats optimum de régulation produisent des modèles économétriques structuraux; ces modèles peuvent être estimer de sorte que l'on puisse récupérer les paramètres de la fonction de production de l'entreprise réglementée ainsi que la distribution d'information privée. Ils sont estimés pour la classe A des utilités publiques d'eau en Californie; cette industrie consiste en un ensemble d'entreprises qui livrent l'eau aux clients dans les centres métropolitains de la Californie.

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1 Introduction

This paper presents procedures for estimating the parameters of a regulated firm's production function which explicitly model the impact of the regulatory process on firm behavior. As emphasized by Joskow [1976], the major goal of public utility regulation is price-setting. One of the most common causes of disputes in determining these prices is over the regulated firm's true minimum-cost of production. The regulated firm has private information, not known by the regulator, concerning its true production technology. In most instances, the utility also has very little incentive to reveal this private information to the regulator. Moreover, because it is a privately-owned company that must answer to its shareholders, the utility should use this private information to maximize its profits subject to the constraints imposed on it by the regulatory process.

Economic theorists have been sympathetic to this asymmetric information problem faced by regulators and have addressed it by modeling the regulatory process as a revelation game where the regulator announces, for example, a price schedule giving the amount the utility is allowed to charge for its output as a function of its reported private information. A utility faced with this price schedule finds it in its best interest to truthfully report its private information. The regulator's price schedule is chosen to maximize some measure of welfare (for example, consumer surplus), subject to the constraints that each utility earns nonnegative profits and truthfully reports its private information. Although these theoretical models utilize stylized views of the regulatory process under asymmetric information, they do compute the optimal "second-best" regulator-utility equilibrium for this information structure. Important examples of this work include Baron and Myerson [1982], Baron and Besanko [1984, 1987] and Besanko [1984]. Laffont and Tirole [1986] have derived an alternative class of models where an *ex post* audit of the utility's costs is used, in addition to the *ex ante* price schedule, to obtain higher levels of welfare for the regulato r.

Applied economists have largely ignored the impact of this private information on both utility and regulator behavior when attempting to recover the parameters of the utility's production function. The standard approach assumes: (1) a regulatory outcome where the utility minimizes total production costs for each level of output, and (2) that all economic magnitudes relevant to the utility and regulator, up to additive disturbances, are observable by the econometrician. Consequently, standard results from microeconomic duality theory can be applied and a cost function and system of factor demand functions are estimated which impose the restrictions implied by cost-minimizing behavior. Representative of works along these lines are Christensen and Greene [1976] for electric utilities, and Mann and Mikesell [1976], Morgan [1977], Crain and Zardhooki [1978], Bruggink [1982], Feigenbaum and Teeples [1983], and Teeples and Glyer [1987] for water utilities.

Our approach differs from the standard approach in four basic respects. First it acknowledges and models the impact of the utility's private

information on the (not necessarily minimum) cost function estimated to recover the parameters of the production function. Second, we recover an estimate of the distribution of this private information or unobservable (to the econometrician) source of heterogeneity across firms. A third way in which our analysis deviates from the standard approach is in explicitly modeling the impact of the demand and cost uncertainty faced by the utility on the observed regulatory outcome. Finally, our econometric model allows for the possibility that, from the viewpoint of the econometrician, both firms and regulators may not satisfy first-order conditions for optimizing behavior exactly each time period. In other words, from the perspective of the econometrician (but not from the perspective of the regulator or utility), first-order conditions are satisfied only in expectation; so that our model does not require that a firm purchase the same input mix when it is faced with the same set of input prices and demand, but in a different time period [1].

This paper posits two behavioral models of regulator-utility interaction under private information and estimates the parameters of the production function for urban water delivery in California under the assumptions of each model [2]. This analysis uses data from a sample of Class A California water utilities for the period 1980 to 1988. The first model assumes private information on the part of the utility, but somehow, through information gathering, the regulator is able to completely learn the parameter. Consequently, the regulator can impose what we call the symmetric (or full) information regulatory outcome. Unfortunately, the econometrician is unable to observe this private information parameter and so must take into account its effect on utility behavior in specifying and estimating the cost function used to recover the parameters of the utility's production function. The second model assumes that the utility possesses private information, but the regulator is unable to completely learn this parameter through its information gathering efforts. However, the regulator does learn the distribution of this private information for each utility, and regulates using this incomplete information optimally. We assume that the regulator imposes the asymmetric information optimal "second-best" regulatory outcome, which maximizes the regulator's objectives subject to this informational asymmetry, without using *ex post* cost observations to reward or punish the utility. In this case, as well, the econometrician is unable to observe the utility's private information (or even its distribution), but must account for this assumed utility-regulator interaction when estimating the parameters of the utility's production function. We compare the estimates of the utility's production technology obtained from these two information structures. We also constrast these estimates with those obtained from standard minimum-cost function estimation procedures.

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1. McElroy [1987] points out the importance of modeling sources of error in econometric models of producer behavior in a manner consistent with economic theory.

2. Feinstein and Wolak [1991] show that the interaction of the regulatory process with both the utility's desire to maximize profits and its superior knowledge of the production technology can invalidate the usual result that profit maximization implies cost minimization. They give instances when the structure of the regulatory process can cause a profit-maximizing utility to choose an input mix that is substantially different from the cost minimizing one, implying that empirical models of regulated firm behavior which assume cost minimization by the utility are misspecified.

Our theoretical model of the private information regulator-utility interaction is closer in spirit to the BARON and MYERSON [1982] model rather than the LAFFONT and TIROLE [1986] model because we do not allow the regulator to use *ex post* cost information to regulate the firm. We provide some justification for this assumption and other modeling assumptions when we describe the actual regulatory process faced by California water utilities. Nevertheless, in future research we plan to explore the empirical implications to the LAFFONT and TIROLE [1986] regulatory framework using this sample of utilities.

We find that modeling the presence of private information in the regulatory process yields substantially different estimates for the structure of the production technology of a regulated utility. The major difference between conventional estimation techniques and those which account for the presence of private information is in the scale economies estimates obtained. Conventional procedures estimate substantial increasing returns to scale, whereas procedures which control for private information recover slight decreasing returns to scale. The major difference in estimation results across the two private information estimation procedures is in the distribution of unobserved efficiency recovered. The asymmetric information model finds far higher level of average efficiency than does the symmetric information model. The asymmetric information model also finds a smaller dispersion in the distribution of unobserved efficiency. In a non-nested test of the explanatory power of the symmetric versus asymmetric information models, we find that the asymmetric information model provides a statistically superior description of the observed regulator-utility equilibrium. We also quantify the extent of the regulatory distortions introduced into the asymmetric versus symmetric information equilibrium. Using our structural model parameter estimates we compute the increased cost of production to the utility of operating in an asymmetric versus symmetric information environment. We find that at its mean efficiency level, the average utility must spend about 8 percent more on production costs in the asymmetric information versus symmetric information environment to produce the same level of output due to the costs of signaling to the regulator its unobserved efficiency level. To assess the welfare loss to consumers, we compute an estimate of the output reduction due to asymmetric information. We find that at its mean efficiency level, the average utility produces about 25 percent less under asymmetric versus symmetric information.

The remainder of the paper explains the methodology used to obtain these results. The next section first describes the Class A California water utility industry and the regulatory process faced by these utilities. This section then specifies the utility's production process, the demand function it faces, and our model of the regulatory process. Section 3 derives the optimal capital stock and rate schedules for both private information models of the regulatory process. Section 4 derives the likelihood function necessary to estimate each of the models. Section 5 describes our data sources and the process used to transform the raw data into the magnitudes used in the estimation procedure. Section 6 presents the results of our estimation. Section 7 concludes and discusses some of the caveats associated with our results. The paper contains two appendices, Appendix A, which presents

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derivations of the results presented in the text, and Appendix B, which describes the details of the data construction process.

2 Economic Environment and Model Development

This section describes the Class A California water utility industry and the regulatory process faced by these firms. This discussion motivates both our use of the BARON and MYERSON [1982] conception of the private information regulatory process and our assumption about the source of the utility's private information. We then describe the production and demand conditions faced by the utility. We then present our theoretical model's conception of the process through which a utility files for a rate increase and the regulatory commission sets rates for our two models of commission information and behavior.

2.1. California Water Utility Industry

The Class A water utility industry is composed of all large privately-owned water utilities delivering water to customers in California. These utilities primarily service medium-sized urban areas. The large cities such as San Francisco and Los Angeles are served by municipal water agencies. However, three out of the top five largest local water agencies in California are investor-owned (ASKARI [1988]). History appears to play a crucial role in determining whether a city is served by a municipal or private water company. Nevertheless, the trend toward municipal supply of water cited in BAIN, CAVES and MARGOLIS [1966] does not appear to be present in our sample period.

For the purposes of regulation, the larger of these utilities are divided into districts and regulated on that basis by the California Public Utilities Commission (CPUC). The CPUC treats each district as a separate entity. As part of the regulatory process, each year all water districts must submit a copy of their annual report to the CPUC. For both of these reasons, we treat the CPUC districts as the unit of observation for the purposes of our study.

The CPUC is composed of a five member commission appointed by the Governor of California for staggered six-year terms. The commission is backed by a staff of over 900 civil servants (CPUC [1987]). After a utility applies for a rate increase it must provide convincing evidence for reasonableness of their request during the rate case proceedings. The primary role of the staff in these proceedings is to protect the interests of consumers by challenging any statement or claim made by the utility they do not believe to be accurate or justified. The CPUC staff may present evidence

on all relevant factors to the case. Members of the public may also present their own views and may offer testimony by their own expert witnesses. All of this evidence then becomes the basis for the decision by the five commissioners.

General rate cases are by far the most common mechanism for a utility to obtain a rate increase. When a utility files an application for a general rate increase, it prospectively chooses a *test year* level of demand for a future year (usually the next year) on which to base its financial projections in determining its *revenue requirements* for that test year. The first step of this prospective process is to establish the utility's rate base–the value of the utility's plant and equipment devoted to public use (CPUC [1987]). Generally, the rate base is calculated by adding up the original cost of all capital equipment purchased by the utility and then substracting the accumulated depreciation on this equipment to date. The next step is the determination of the utility's rate of return, expressed as a percentage of the rate base. The commission then determines the estimated operating expenses for the utility in this prospective test year. The sum of the utility's operating costs and the return on its rate base is its *revenue requirements*. The final step involves taking the total revenue requirements and test year demand level and computing a price structure for the utility which sets total revenues equal to total costs at this test year demand level. As emphasized in many CPUC documents, the utility is not guaranteed to earn the rate of return on its rate base that was used to construct its test year revenue requirements. Consider, for instance, the following statement,

> Does this mean the utility is guaranteed a profit? No, it only means that the company is entitled through prudent management and efficiency, to recover the approved revenues and to try to earn the authorized rate of return (CPUC, 1987, p. 9).

This prospective nature of the regulatory process and the fact that it is concerned with setting prices, with no guarantee to the utility that it will receive the CPUC authorized rate of return, favor the BARON and MYERSON [1982] view of price regulation which only uses prospective information to set prices for the utility. However, this is not say that the LAFFONT and TIROLE [1986] view which also uses *ex post* cost observations does not have some support. In certain extraordinary circumstances, the CPUC can issue Orders Intituting Investigations (OIIs) which can result in rate revisions because of new information not available at the time of the regulatory proceedings. However, these rate revisions occur because of such events as unexpected energy input price increases or unexpected increases in the technological efficiency of production by the utility, and hence primarily occur in the electric utility and telecommunications sector. Because water delivery is low rate of productivity change production technology which is not very energy intensive, these rate revisions rarely occur in the water utility industry. In fact, none occurred during our sample period. Nevertheless, because of the possibility of OIIs, exploring the empirical implications of the LAFFONT and TIROLE [1986] view of the regulatory process is a worthwhile topic for future research.

We are now in a position to discuss our reasons for choosing labor efficiency as the source of the utility's private information. The difficulty in

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assigning a dollar measure to the utility's capital stock points to using it as the source of unobserved heterogeneity. However, from our reading of the rate cases and discussions with both the staff of the CPUC and management of several water utilities, it appears that both sides in the utility versus regulator interaction are equally puzzled as to how to properly put a dollar value on the physical assets used to deliver water and how to charge off the costs associated with maintaining these assets over time. Nevertheless, both sides are extremely familar with the technological parameters associated with each piece of physical capital and concerned with ensuring that the utility undertakes the amount of investment necessary to service its customers properly. The CPUC staff makes several site visits to the plant to inspect the capital equipment and compares this equipment with that available at other plants. A major source of conflict in most of these rate hearings is over the necessity of investing in new capital. Here all of the economic and technological merits of the proposed investment are debated in great detail before it can be given the CPUC's Certificate of Public Convenience and Necessity (CPCN) as a "prudent" investment. Consequently, although both sides have extreme difficulty assigning a single dollar magnitude to the utility's capital stock (because several of the assumptions necessary for the perpetual inventory method of capital accumulation may in fact not be valid), its appears that both sides are equally informed about the physical size and technological capabilities of the utility's capital stock. Consequently, there appears to be little justification for the utility's capital stock to be the source of its private information advantage relative to the regulator.

On the other hand there is considerable heterogeneity in the quality of labor employed in the California water utility industry. A major reason is the sheer size of the state. This leads to substantial climatic and geographic diversity within the state. There is also a large amount of variability in the funding devoted to education and other local services. One would expect the utility and its management to have a more intimate knowledge of these local conditions than the regulator. Consequently, we select the utility's labor as the source of its private information advantage.

2.2. Description of Production and Cost Technologies

The water delivery production process can be classified into four stages: (1) withdrawal, (2) pumping, (3) treatment, and (4) transmission and distribution [3]. Withdrawal is the catch-all for the process of finding the necessary water to deliver to the utility's final customers. Pumping expenses are incurred both in transporting the water from the source to the treatment plant and from the treatment plant to the final customers. Treatment refers to the process of filtering out impurities in the water before the final stage of distributing it to the utility's customers. There are four primary inputs to the water delivery process: (1) capital, (2) labor, (3) electricity (to power the water pumps) and (4) a source of water. For the purposes of this paper we consider the utility's source of water to be a part of its capital stock. All of the utilities in our sample own a substantial portion, if not all, of their

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3. DZURIK [1990] provides a useful introduction to the water delivery production process.

water sources in the form of wells or reservoirs and these water sources are listed on their balance sheet as part of their capital stock. However, a small number buy a portion of their water from other sources, such as local, state, or federal water agencies. In these instances the assumption implicit in our model is that the price charged for this water yields the owner of the resource the current rate of return on capital for the utility purchasing the water. For the purposes of our modeling effort, we represent the production function for utility i as

$$(1) \qquad Q_i = f\left(K_i, L_i^*, E_i, \varepsilon_q\left(i\right) \mid \beta\right),$$

where K_i denotes capital (physical plant and water sources), L_i^* labor, and E_i electricity. The variable $\varepsilon_q\left(i\right)$ is a stochastic disturbance to the ith utility's production process which is realized after the utility makes its capital stock selection for the period but before it produces. The utility knows the distribution of $\varepsilon_q\left(i\right)$, which is independently and identically distributed over time and across utilities. Finally, β is a parameter vector describing the technical coefficients of production. It is known to both the regulator and utility, but is unknown to the econometrician. Consistently estimating this parameter vector is the goal of our analysis.

One aspect of this production function deserves special mention; that is the source of the utility's private information. To this end we make the distinction between, L_i^*, the amount of labor actually used in the production process, and L_i, the observed physical quantity of labor input which is implied by the utility's total labor costs. These two magnitudes are related by the equation $L_i^* = L_i/d\left(\theta_i\right)$, where $d\left(\theta\right)$ is a known increasing function of θ, and θ_i is what we define as utility i's labor efficiency parameter. Higher values of θ imply more inefficiency. The econometrician and regulator observe the utility using the quantity of labor L_i, but the actual amount of "standardized" labor available in the production process is L_i^*.

The utility's observed costs are

$$(2) \qquad w_i\,L_i + r_i\,K_i + pe_i\,E_i,$$

where w_i is the wage rate, r_i is the price of capital, and pe_i is the price of electricity. As discussed above, the variable L_i included in the utility's costs is not the same as the $L_i^* = L_i/d\left(\theta_i\right)$ entering into the production function.

From the viewpoint of the econometrician, θ_i is an unobservable random variable in the same sense as, for example, $\varepsilon_q\left(i\right)$. Nonetheless, θ_i plays a central role in the model development to follow because it is the source of the potential asymmetry of information between the utility and the regulator. In particular, we distinguish between two cases. In the first, the symmetric information model (S), the regulator is assumed to observe θ_i together with the utility. In the second model the regulator only knows its distribution, $F\left(\theta\right)$ which has compact support on the interval $[\theta_{\text{low}}, \theta_{\text{high}}]$. We call this the asymmetric information model (A). As we show below, these two information structures between the utility and regulator lead to different rate structures and input choice decisions. For both models the econometrician must estimate $F\left(\theta\right)$. We also assume that conditional on all

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observable characteristics of the utility and its customers the distribution of θ_i is independent of the other stochastic disturbances included in the model. This assumption embodies the intuition that the utility's labor efficiency parameter is independent of any shocks to the regulatory environment.

2.3. **Assumptions Underlying Utility Behavior**

For both models, we assume the utility chooses its input mix to maximize expected profits (because of demand and production uncertainty) given its private information [4]. Each utility faces a demand function $Q_i(p_i) \varepsilon_d(i)$ for its product, where $\varepsilon_d(i)$ is a positive, mean one stochastic shock to the utility's demand which independently and identically distributed across time and utilities. Once p is set, the demand shock for the period is realized and output produced is determined from this demand function which we assume is known both to the regulator and the utility, up to the stochastic disturbance $\varepsilon_d(i)$.

Because its price (equivalently, its total revenue and output) and capital stock are set before the utility produces each period, for both models A and S, the utility's desire to maximize expected profits will lead it to minimize total operating costs for a fixed level of output and capital stock. This minimum operating cost mix of variable inputs for a type θ utility is the solution to:

$$(3) \qquad \min_{L, E} w\,L + pe\,E \text{ subject to } Q = f(K, L, E, \theta, \varepsilon_q \mid \beta).$$

Optimization problem (3) yields the minimum variable cost factor demand functions for E and L conditional on K and Q. Because ε_q is known by the time the utility chooses L and E, it enters into both input demand functions. Substituting both of the variable factor demand functions back into the expression for total operating costs yields the conditional (on K) variable cost function $CVC(pe, w, \theta, K, Q, \varepsilon_q, \eta_L, \eta_E \mid \beta)$, where η_L and η_E are mean one disturbances introduced into the model to allow, from the viewpoint of the econometrician (but not the regulator or utility), the first-order conditions for the optimal choice of L and E to hold only in expectation [5]. Note that the utility's private information θ enters into this variable cost function. Using this expression for variable costs, we can re-write utility i's total observed costs as:

$$(4) \qquad TC = CVC(pe, w, \theta, K, Q, \varepsilon_q, \eta_L, \eta_E \mid \beta) + r_i\,K_i.$$

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4. These utilities are privately-owned companies that must be concerned with earning the highest return possible on their equity in order to attract shareholders so that the assumption of profit maximization seems reasonable.

5. In Appendix A we derive the parametric form of the unconditional variable cost function, including where the structural disturbances enter, for the functional forms used in our empirical analysis. We also discuss the necessity of including these disturbances in our econometric model.

2.4. Description of Models of Regulation with Private Information

We now present our conception of the regulatory process for the two models of regulator-utility interaction with private information. Both models of the regulatory process involve the following steps. First, the utility chooses its capital stock for the coming period. After observing the utility's choice, the regulatory commission mandates rates for the coming period. The commission sets two rates. One is the fixed charge each consumer must pay to access the system, assuming that N, the number of consumers desiring access is known. In the aggregate, this becomes a known transfer from consumers to the utility, which we denote $T = Nt$, where t is the access fee each consumer must pay [6]. The second rate is the marginal price p each consumer must pay for an additional unit of the utility's service. Finally, the utility satisfies all demand forthcoming at these rates.

Our approach attempts to parallel the following two aspects the actual regulatory process. First, the utility is required by law to produce all that is demanded at the regulated prices. Second, the CPUC exercises a large degree of control over the utility's capital stock, although it does not explicitly set the level. Generally, in order to make any increment to the capital stock a utility must apply for and obtain a Certificate of Public Convenience and Necessity. Although, as described above, both sides of process have considerable difficulty summarizing the utility's capital stock with a single dollar magnitude, they are both very familar with capabilities of all of the utility's capital equipment and any additions to this stock are highly scrutinized. For these reasons, capital appears to serve as a screening variable in the actual regulatory price setting process as well, in that more efficient firms are allowed to invest more. For these reasons, we use capital as a screening variable in our theoretical model.

For the symmetric information case, the regulator is assumed to know utility i's private information, its labor efficiency parameter θ_i. Given this information, the regulator sets prices to maximize some measure of expected total welfare (in our case consumer surplus) subject to the constraint that the utility earns zero expected economic profit. The utility is aware of the regulator's objective function and therefore knows the price and fee the regulator will implement, so that it chooses a capital stock consistent with minimizing the total cost of producing the welfare maximizing output level. The regulator could wait until the utility sets its capital stock before setting rates. However, in this symmetric information model, both agents have access to the same amount of information about the utility's production function and this is common knowledge to both agents, so the utility's capital stock selection does not convey any information to the regulator. In this case, the timing of the regulatory process described above is unimportant to its success.

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6. Because we allow for the presence of fixed transfers, this model can be extended to case in which this fixed charged excludes some consumers and thus has a social cost as discussed in LAFFONT and TIROLE [1983], Chapter 2.

For the asymmetric information case, the timing of the process is crucial to its success. Here, the regulator does not know the utility's private information parameter, only the distribution $F(\theta)$ of possible values it can take on. Consequently, the regulator announces price and fee schedules as a function of the utility's capital stock selection. These schedules are chosen to maximize expected total welfare, in our case consumer surplus (where the expectation is taken with respect to the distribution of θ as well as with respect to the distribution of the production and demand shocks facing the utility), subject to the constraints that the expected profits for all possible utility types are nonnegative and that all types of utilities (indexed by θ) find it in their best interest to truthfully reveal to the regulator their private information through their capital stock selection.

These two models differ in what the regulator knows about the utility's labor efficiency in production, as measured by θ, and how it incorporates this knowledge into the rate-setting process. The asymmetric information model (A) assumes that the regulator does not observe θ and cannot verify the utility's reported θ. However, the regulator is aware that the utility has an incentive to misreport its θ value, understating its efficiency (overstating θ). Therefore, the regulator designs incentive-compatible capital and rate schedules which cause a profit-maximizing utility to reveal its θ value through its capital stock selection. Because the regulator only knows the distribution of this private information θ and not its true value, for all but the least efficient utilities there are informational rents that must be paid to induce them to truthfully report. This results in welfare losses relative to the symmetric information regulatory outcome [7]. At the opposite extreme, the symmetric information model (S) assumes that the regulator can observe θ, so that the regulator can choose the utility's rates as a function of its θ, and therefore implement the first-best welfare maximizing optimum.

Our description of the regulatory process has a number of features which deserve comment. First, consider our assumption that the regulator maximizes consumer surplus. It is possible that regulators have a concern for more than just aggregate consumer surplus; they may also be concerned about producer welfare, and, among consumers, may distinguish between different consumer groups. In addition, the regulatory body's preferences among these groups may depend on political factors, such as which political party currently controls the branch of the state government exercising control over the regulatory body. BARON [1989] discusses many of these issues. Our model can be modified to allow for these kinds of considerations in the regulator's preference function. All that is required to implement our modeling framework is that the regulator possesses a stable preference function that it is known to the utilities it regulates.

However, one may also question whether regulatory commissions maximize any specific objective function. Traditionally, these bodies have spoken in terms of guaranteeing utilities a "fair rate of return" on their rate base–hence the widespread popularity of the AVERCH and JOHNSON [1962] model (see also BAUMOL and KLEVORICK [1970]. This suggests

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7. FEINSTEIN and WOLAK [1991] describe aspects of the regulatory environment which determine the magnitude of these losses.

that a mechanical fair rate of return guaranteeing regulator may be a more appropriate model of regulator behavior. However, JOSKOW [1976] very persuasively argues that the Averch and Johnson model has caused economists to place an excessive emphasis on the rate of return model of regulation. He presents evidence supporting the view that although regulators are concerned about guaranteeing utilities a "fair" rate of return on their capital stock, the setting of this rate of return is only an intermediate step in the final goal of setting nominal rates for the utility's output. As shown above, this view is consistent with the behavior of the CPUC in regards to the California water utilities we study.

Another shortcoming of our approach is that it does not explicitly model the various steps which occur in an actual regulatory review—in particular, the utility's submission of its proposed rates, the CPUC staff's proposed rates which respond to the utility's proposed rates, expert testimony and testimony from other interested parties, and then the commission's final decision [8]. For this reason we view the equilibria arising from our models in the same manner as a standard Walrasian market equilibrium: a reasonable description of the prices and quantities observed which provides, at best, a stylized model of how these magnitudes are arrived at.

Furthermore, once we acknowledge the existence of asymmetric information between the regulator and the utility there are many possible equilibria between these two agents that could arise from this interaction which satisfy individual rationality (the participation constraint that the utility expects to earn nonnegative economic profits). Our model A has the attractive property of being the optimal second-best regulator-utility equilibrium for the regulator objective function we have specified. The widespread belief in the existence of informational asymmetries between the utility and regulator and its second-best optimality properties makes the model A equilibrium a logical first choice for empirical implementation and for comparison with estimates of model S, which assumes the full-information regulator-utility equilibrium.

Because our theoretical model is explicitly static, we focus our econometric modeling efforts on utilizing the across-firm differences in observable variables to identify the parameters of economic interest while allowing for some dependence over time in economic magnitudes from the same utility. Favoring this approach is the fact that our dataset is primarily cross-sectional in nature, with many more utilities than time periods. Nevertheless, we do have multiple observations on the same utility, although in most cases these observations are not contiguous in time. Consequently, the dynamics of the regulatory interaction is one aspect of the data generation process that our theoretical and empirical modeling framework fails to address. LAFFONT and TIROLE [1988] present a two-period model of the regulatory interaction with private information. This is a topic we hope to pursue in future research.

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8. JOSKOW [1972, 1973] are the most prominent examples of models of the actual rate-setting process. JOSKOW and SCHMALENSEE [1986] surveys much of the recent work studying the regulatory process.

3 Derivation of Model Solutions

In this section we derive the equations which define the solution to each of the models described in Section 2. First we consider the symmetric information model, then the asymmetric information model.

3.1. The Symmetric Information Model

In this case the regulator observes each utility's true θ and sets the fee (T) and price (p) to maximize expected consumer surplus subject to the constraint that the utility's expected profits (with respect to the distributions of ε_q and ε_d) equal zero, knowing that the utility will choose its inputs to maximize profits. This implies that the regulator will solve for the p, T, and K which maximize expected consumer surplus for the utility's consumers in deciding the optimal p, K and T for that utility. Although the regulator does not explicitly set K, it will set prices so that the utility finds it in its profit-maximizing interest to choose the capital stock which arises from the solution to the regulator's welfare maximization problem.

Let $S_i(p) = E_d(\varepsilon_d(i)) \int_p^\infty Q_i(s) \, ds$ denote expected consumer surplus for the ith utility, where $E_d(\cdot)$ denotes the expectation with respect to the distribution of ε_d. In terms of our notation, the regulator solves:

(5)
$$\max_{p, \text{T}, \text{K}} S_i[p(\theta_i)] - \text{T}(\theta_i) \text{ subject to}$$

$$
\begin{aligned}
E_{q,d}(\pi(\theta_i)) = &E_{q,d}[p(\theta_i) Q[p(\theta_i)]\varepsilon_d(i) + \text{T}(\theta_i) \\
&- \text{CVC}(pe, w, \theta_i, \text{K}(\theta_i), Q(\theta_i)\varepsilon_d(i), \varepsilon_q(i), \eta(i) \mid \beta)] \\
&+ r_i \text{K}(\theta_i) = 0.
\end{aligned}
$$

where $E_{q,d}(\cdot)$ is the expectation with respect to the distribution of both ε_p and ε_d and $\eta(i) = (\eta_L(i), \eta_E(i))'$ is the vector of optimization errors from the conditional variable cost function problem (3). The first-order conditions for this problem imply:

(6) $\quad p_i = \dfrac{\partial E_{q,d}[\text{CVC}(pe, w, \theta_i, \text{K}(\theta_i), Q(\theta_i)\varepsilon_d(i), \varepsilon_q(i), \eta(i) \mid \beta)]}{\partial Q}$,

(7) $\quad r_i = -\dfrac{\partial E_{q,d}[\text{CVC}(pe, w, \theta_i, \text{K}(\theta_i), Q(\theta_i)\varepsilon_d(i), \varepsilon_q(i), \eta(i) \mid \beta)]}{\partial K}$.

Note that equations (6) and (7) are completely deterministic given $\eta(i)$, so that if we selected the correct functional form for both the utility's demand and production function, using the observed p_i, K_i and T_i these equations should hold as identities. To allow for the fact that (6) and (7) will not hold

exactly for any empirical dataset or functional form we might select, we add a mean one, positive, multiplicative disturbance, η_K and η_p respectively, to each of the first-order conditions. Equations (6) and (7) become:

$$(8) \quad p_i = \frac{\partial E_{q,d}\left[\mathrm{CVC}\left(pe,\ w,\ \theta_i,\ \mathrm{K}\left(\theta_i\right), \mathrm{Q}\left(\theta_i\right) \varepsilon_d\left(i\right),\ \varepsilon_q\left(i\right),\ \eta\left(i\right)\mid \beta\right)\right]}{\partial \mathrm{Q}}\ \eta_p\left(i\right)$$

$$(9) \quad r_i = -\frac{\partial E_{q,d}\left[\mathrm{CVC}\left(pe, w, \theta_i, \mathrm{K}\left(\theta_i\right), \mathrm{Q}\left(\theta_i\right) \varepsilon_d\left(i\right), \varepsilon_q\left(i\right), \eta\left(i\right)\mid \beta\right)\right]}{\partial \mathrm{K}}\ \eta_K\left(i\right),$$

where these disturbances are independent and identically distributed over time and utilities. Consequently, (8) and (9) hold only in expectation because $E\left(\eta_p\left(i\right)\right) = 1$ and $E\left(\eta_K\left(i\right)\right) = 1$.

The fixed fee, $T\left(\theta_i\right)$ is set so that expected profits are zero at the $K\left(\theta_i\right)$ and $p\left(\theta_i\right)$ which solve (8) and (9). The final equation needed to solve for the equilibrium magnitudes is $Q_i\left(p_i\right) \varepsilon_d$, the demand function. The observed input demands for E_i and L_i can be derived from the factor demand functions arising from the solution of the minimum variable cost problem (3).

3.2. The Asymmetric Information Model

Our asymmetric information model (A) takes as a starting point the theoretical models of regulator-utility interaction described above, in particular, BESANKO [1985]. In Besanko's model, the utility possesses private information about its labor efficiency which directly affects production costs, and indirectly, the utility's optimal mix of inputs. Under our conception of the asymmetric information problem, the regulator cannot observe θ directly and must condition the utility's rates on its capital stock choice. The regulator recognizes that the utility may have an incentive to misreport θ as higher than it really is (the utility claims to be less efficient than it really is). Consequently, the regulator constructs incentive-compatible rate schedules (as a function of θ) such that given these schedules, the utility truthfully reports its private information θ through its K selection. Hence, in this model, expected (with respect to the distributions of θ, ε_d, and ε_q) consumer surplus is maximized subject to the incentive-compatibility constraint that the utility truthfully reports, and the constraint that expected profits are nonnegative for all types of efficiencies, as indexed by θ, that a firm can have.

To derive our model A equilibrium, we follow the approach in BARON [1989]. First, we follow his four-step procedure for characterizing the set of feasible mechanisms. We then solve for the optimal regulator-utility equilibrium subject to differentiable local incentive compatibility constraints. Finally, we verify that the solution to this local problem lies in the set of feasible mechanisms so that it is an optimal second-best equilibrium.

The first step is to derive the global truth-telling constraints in terms of the profit function. Note that a utility with true parameter θ_i which reports θ_j

earns expected profit

(10) $\quad E_{q,d}[\pi(\theta_j, \theta_i)]$
$$= E_{q,d}[p(\theta_j) Q(p(\theta_j)) \varepsilon_d - CVC(\theta_i, K(\theta_j), Q(\theta_j))]$$
$$- r K(\theta_j) + T(\theta_j),$$

where we suppress the dependence of the minimum variable cost function (CVC) on pe, w, ε_q, ε_d, η and β. Consequently, for any two arbitrary values θ might take for a given utility, say θ_x and θ_y, incentive compatibility requires $E_{q,d}[\pi(\theta_x, \theta_x)] \geq E_{q,d}[\pi(\theta_y, \theta_x)]$. The usual approach is to first specify a local approximation to this global constraint, which in the present case is:

(11) $$\frac{dE_{q,d}[\pi(\theta)]}{d\theta} = -\frac{\partial E_{q,d}[CVC(\theta, K(\theta), Q(\theta))]}{\partial \theta},$$

for all θ. Equation (11) is a local incentive compatibility condition which quantifies how rapidly the regulator must raise the expected profits of a utility as its true θ value falls (the utility becomes more efficient) in order to encourage truthful revelation. The second step of the process involves integrating (11) to obtain the expected profit function. This allows us to show that the expected profit function is locally decreasing in θ so that the individual rationality constraint which requires the firm to earn nonnegative expected profits for all values of θ, can be replaced by the single constraint that $E_{q,d}[\pi(\theta_{high})] \geq 0$.

The third step involves demonstrating that the price function $p(\theta)$ can be implemented by choosing a fixed charge function $T(\theta)$ which induces truth-telling by the utility. Step four involves deriving conditions on the price, capital stock and fixed fee functions which guarantee a globally incentive compatible equilibrium. We derive these conditions in Appendix A. If the solution to the regulator's problem yields price, capital stock, and fee schedules which satisfy these restrictions then this solution is the optimal, second-best regulator-utility equilibrium under this asymmetric information structure.

In light of our four-step process of characterizing the set of feasible mechanisms, the regulator's optimization problem is

(12) $$\max_{K(\theta), p(\theta), T(\theta)} \int_{\theta_{low}}^{\theta_{high}} [S_i[p(\theta)] - T(\theta)] f(\theta) d\theta \text{ subject to}$$
$$E_{q,d}[\pi(\theta)]$$
$$= E_{q,d}[p(\theta) Q(p(\theta)) - CVC(\theta, K(\theta), Q(\theta)) - r K(\theta) + T(\theta)]$$
$$\frac{dE_{q,d}[\pi(\theta)]}{d\theta} = -\frac{\partial E_{q,d}[CVC(\theta, K(\theta), Q(\theta))]}{\partial \theta},$$
$$E_{q,d}[\pi(\theta_{high})] \geq 0.$$

Although we do not explicitly include the restrictions implied by the global truth-telling constraints, in Appendix A we derive restrictions on the regulatory environment and distribution of θ necessary for the price, capital, and fixed fee functions to satisfy the constraints derived in step 4 for our parametric econometric model of (12).

Note that the formulation in (12) refers specifically to the ith utility-regulator pair. Because the regulator does not know utility i's efficiency parameter, he must set rates over the entire support of θ for each utility. Consequently, the regulator must solve this problem for each utility that it regulates.

To determine the regulator's rate and fee schedules, we form the Hamiltonian

$$
\begin{aligned}
(13) \qquad H =\; & S\left[p\left(\theta\right)\right] f\left(\theta\right) - T\left(\theta\right) f\left(\theta\right) \\
& - \mu\left(\theta\right) \frac{\partial E_{q,d}\left[\text{CVC}\left(\theta,\, K\left(\theta\right),\, Q\left(\theta\right)\right)\right]}{\partial \theta} \\
& + \rho\left(\theta\right)\left(E_{q,d}\left\{\pi\left(\theta\right)\right\} - \left[E_{q,d}\left\{p\left(\theta\right) Q\left(p\left(\theta\right)\right)\varepsilon_d\right.\right. \\
& \left.\left. - \text{CVC}\left(\theta,\, K\left(\theta\right),\, Q\left(\theta\right)\right)\right\} - r\,K\left(\theta\right) + T\left(\theta\right)\right]\right),
\end{aligned}
$$

where $\mu\left(\theta\right)$ is the costate variable associated with the incentive compatibility constraint, and $\rho\left(\theta\right)$ is the multiplier associated with the expected profit constraint.

The first-order conditions associated with equation (13) are:

$$
\begin{aligned}
(14) \qquad H_p = 0 =\; & \frac{\partial S\left(p\left(\theta\right)\right)}{\partial p} f\left(\theta\right) \\
& - \mu\left(\theta\right) \frac{\partial^2 E_{q,d}\left[\text{CVC}\left(\theta,\, K\left(\theta\right),\, Q\left(\theta\right)\right)\right]}{\partial\theta\,\partial Q}\,\frac{\partial Q}{\partial p} \\
& - \rho\left(\theta\right)\left[\left\{p\left(\theta\right)\frac{\partial Q}{\partial p} + Q\left(p\left(\theta\right)\right)\right\}E_d\left(\varepsilon_d\right)\right. \\
& \left. - \frac{\partial E_{q,d}\left[\text{CVC}\left(\theta,\, K\left(\theta\right),\, Q\left(\theta\right)\right)\right]}{\partial Q}\,\frac{\partial Q}{\partial p}\right].
\end{aligned}
$$

$$
\begin{aligned}
(15) \qquad H_K = 0 =\; & -\mu\left(\theta\right)\frac{\partial^2\,\text{CVC}\left(\theta,\, K\left(\theta\right),\, Q\left(\theta\right)\right)}{\partial\theta\,\partial K} \\
& + \rho\left(\theta\right)\left[\frac{\partial E_{q,d}\left[\text{CVC}\left(\theta,\, K\left(\theta\right),\, Q\left(\theta\right)\right)\right]}{\partial K} + r\right]
\end{aligned}
$$

$$
(16) \qquad H_T = 0 = -f\left(\theta\right) - \rho\left(\theta\right)
$$

$$
(17) \qquad -H_{E_{q,d}\left[\pi\right]} = -\rho\left(\theta\right) = \mu'\left(\theta\right),
$$

where H_Z denotes partial differentiation of the Hamiltonian with respect to Z. Although we do not explicitly include it in the Hamiltonian, we must

also impose the constraint that $E_{q,d}[\pi(\theta_{\text{high}})] \geq 0$ in order to complete our characterization of the solution.

From equation (16) we deduce that $p(\theta) = -f(\theta)$. Using this equation and equation (17), we have $\mu(\theta) = F(\theta)$. Because $\partial S / \partial p = -Q(p(\theta)) E_d(\varepsilon_d)$, we can simplify the first and second equations to:

$$(18) \qquad p(\theta) = \left[\frac{\partial E_{q,d}[\text{CVC}(\theta, K(\theta), Q(\theta))]}{\partial Q} \right.$$
$$\left. + \frac{F(\theta)}{f(\theta)} \frac{\partial^2 E_{q,d}[\text{CVC}(\theta, K(\theta), Q(\theta))]}{\partial \theta \, \partial Q} \right] \eta_p$$

$$(19) \qquad r = - \left[\frac{\partial E_{q,d}[\text{CVC}(\theta, K(\theta), Q(\theta))]}{\partial K} \right.$$
$$\left. + \frac{F(\theta)}{f(\theta)} \frac{\partial^2 E_{q,d}[\text{CVC}(\theta, K(\theta), Q(\theta))]}{\partial \theta \, \partial K} \right] \eta_K.$$

where η_p and η_K are the mean one multiplicative disturbances defined above and added for same reasons as given in the discussion of the model S solution. These two equations determine the amount of capital stock $K(\theta)$ a utility of type θ will purchase, and the price $p(\theta)$ it will be directed to charge.

The demand function $Q_i(p)$ and equations (18) and (19) determine the two regulatory variables $K(\theta)$ and $p(\theta)$. The access charge $T(\theta)$ is given by

$$(20) \qquad T(\theta^*) = E_{q,d}[\pi(\theta^*)] - E_{q,d}[p(\theta^*) Q(p(\theta^*)) \varepsilon_d$$
$$+ \text{CVC}(\theta^*, K(\theta^*), Q(\theta^*))] + r K(\theta^*)$$

for a utility of type θ^*. Once a utility's K is chosen and its p and T are set, its demands for L and E can be determined from the solution to the minimum operating cost problem (3).

Although these rate schedules are functions of the utility's labor efficiency parameter θ, as mentioned above, the regulator can transform these rate schedules to depend on the utility's capital stock selection. The logic for constructing these schedules proceeds as follows. As shown in Appendix A, one of the restrictions required for feasability of the price and capital mechanisms is that $K(\theta)$ is increasing in θ. Therefore we can construct the inverse function $\psi(K) = \theta$ which gives the utility's true θ as a function of the capital stock arising from the regulator's expected welfare maximization problem (12). Substituting $\theta = \psi(K)$ into $p(\theta)$ and $T(\theta)$ yields $p(K^0)$ and $T(K^0)$, where K^0 is the utility's observed capital stock selection. By construction, when faced with these rate and fee schedules (which depend on its capital stock selection), a utility with private information θ^* will find it in its best interest to choose the capital stock $K(\theta^*)$. Its rates will then be $p(\theta^*)$ and $T(\theta^*)$, where $\theta^* = \psi(K^0)$ and $K^0 = K(\theta^*)$. Therefore, under the

assumptions of our econometric modeling framework given in Appendix A the rate setting process can be thought of as based on either: (1) the utility's capital stock selection or (2) its private information announcement.

In closing this section we note that both of these models reduce to the conventional minimum cost function with no private information on the part of the utility in the special case that θ_i and all of the η_j ($j = $ L, E, K, p) are identically equal to one for all utilities, and this is known to the regulator and utility, as well as the econometrician. Under this assumption both models lead to the regulator setting rates to maximize expected consumer surplus, subject to the constraint that the utility earns zero expected-profit. The utility will produce its output in an expected total cost minimizing fashion so that conventional simultaneous equations cost function estimation techniques which result from the application of duality theory yield consistent estimates of the parameters of the utility's production function.

4 Econometric Modeling Framework

In this section we specify the functional form for our production function $Q_i = f(K_i, L_i^*, E_i, \varepsilon_q(i) \mid \beta)$ and derive the corresponding cost function which we use to recover an estimate of the parameter vector β. We then specify distributions for the structural disturbances introduced into the model and derive the implied likelihood function we maximize to compute our parameter estimates. There are three types of disturbances to our econometric model: (1) shocks which the agents optimize against (ε_q and ε_d), (2) optimization errors which allow agents' first-order conditions to only be satisfied in expectation (η_j, $j = $ L, E, K, p), and (3) the utility's private information θ. Each of the composite errors to our estimating equations are functions of these structural disturbances.

Because our focus is on estimating these models accounting for the utility's private information, we choose a fairly simple functional form for our production function. This functional form still has sufficient flexibility to illustrate several important empirical distinctions between model S, model A, and conventional estimation procedures. We choose the Cobb-Douglas production function

$$(21) \qquad Q = \beta_0 \, K^{\beta_K} \, (L/d(\theta))^{\beta_L} \, E^{\beta_E} \, \varepsilon_q,$$

where $d(\theta) = \theta^{(\beta_L + \beta_E)/\beta_L}$. The demand function for the utility's output is

$$Q_d = \begin{cases} \exp(Z'b) \, p^{-\kappa} \, \varepsilon_d & \text{if} \quad p \leq p_{\max} \\ 0 & \text{if} \quad p > p_{\max} \end{cases}$$

where Z is a vector of utility service area characteristics assumed to shift demand, b is a parameter vector associated with Z, κ is the elasticity of

demand for water, and $p_{\max}$ is the price beyond which demand for the firm's output is zero[9]. This form of the demand function simplifies the imposition of the regularity conditions required for our theoretical model and allows us to simplify a computationally intensive estimation problem. Appendix A presents the derivations of all of the results described in this section.

Solving the minimum operating cost problem (2.3) for this production function yields the following (conditional on K) variable cost function:

(22) $\mathrm{CVC}\,(pe,\,w,\,\mathrm{K},\mathrm{Q},\,\theta,\,\varepsilon\mid\beta)$

$$= \theta\beta_0^{-\frac{1}{\beta_L+\beta_E}}\,\mathrm{K}^{-\frac{\beta_K}{\beta_L+\beta_E}}\left[\left(\frac{\beta_L}{\beta_E}\right)^{\frac{\beta_E}{\beta_L+\beta_E}}+\left(\frac{\beta_L}{\beta_E}\right)^{-\frac{\beta_L}{\beta_L+\beta_E}}\right]$$

$$\times w^{\frac{\beta_L}{\beta_L+\beta_E}}\,pe^{\frac{\beta_E}{\beta_L+\beta_E}}\,\mathrm{Q}^{\frac{1}{\beta_L+\beta_E}}\,u\,\varepsilon_d^{-\frac{1}{\beta_L+\beta_E}},$$

where u takes the form given in equation (A.4) in Appendix A in terms of our previously defined disturbances η_L and η_E and parameter vector β. Recall that the disturbances η_L and η_E are multiplicative disturbances to the conditional factor demand functions arising from the conditional minimum variable cost problem (3), which imply that the first-order conditions for the minimum cost L and E selection are satisfied only in expectation.

Taking the partial derivative of the expected value $(\mathrm{E}_{q,d}\,[\mathrm{CVC}])$ of this cost function with respect to K and inserting it into the first-order condition for the symmetric information regulatory outcome with respect to K [equation (9)] yields the following unconditional variable cost (VC) function:

(23) $\mathrm{VC}\,(\mathrm{S}) = \mathrm{D}^*\,r^\alpha\,w^\gamma\,\theta^{(1-\alpha)}\,pe^{(1-\alpha-\gamma)}\,\mathrm{Q}_d^\delta\,\nu.$

Expressions for D^* and ν in terms of the underlying parameters of the model are given Appendix A. The parameters α, γ and δ are defined as follows:

(24) $\begin{cases} \alpha = \dfrac{\beta_K}{\beta_K+\beta_L+\beta_E}, \qquad \gamma = \dfrac{\beta_L}{\beta_K+\beta_L+\beta_E}, \\[2mm] \qquad\quad \delta = \dfrac{1}{\beta_K+\beta_L+\beta_E}\,. \end{cases}$

The only difference between this unconditional variable cost function and the usual Cobb-Douglas unconditional variable cost function is the presence of the utility's private information, the efficiency parameter θ. Consequently, setting θ equal to one for all utilities implies that our symmetric information

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9. We assume the existence of this maximum price, so that consumer surplus is a well-defined concept for this constant elasticity demand function. Because there are substitutes for residential water service–backyard wells or bottled water–it is reasonable (as well as essential to the mathematics) to assume the existence of a very high price which induces zero demand. This price can be set to any positive finite number so that economically this assumption should be of little consequence.

regulatory outcome gives rise to the standard unconditional minimum variable cost Cobb-Douglas cost function.

We should emphasize that because it excludes capital costs, (23) is the utility's unconditional minimum *variable* cost function conditional on θ, not the minimum *total* cost function. Although it is straghtforward to derive the utility's minimum total cost function from the first-order conditions given in (9), for the following reason, we depart from the tradition of estimating a total cost function. Operating or variable costs are measured with little if any error, whereas, capital cost (the missing ingredient necessary to compute total production costs) is extremely poorly measured. Rather than complicate our analysis with potentially substantial measurement error, we instead use the unconditional variable cost function given in (23) to estimate the same parameters of the utility's production function that can be recovered by estimating a total cost function.

To derive the asymmetric information cost function, we substitute the partial derivative of the expected value of the variable cost function $(E_{q,d}(\text{CVC}))$ with respect to K into the first-order condition for the optimal capital stock given in equation (19). Simplifying this expression gives the following cost function:

(25) $\qquad \text{VC}(\text{A}) = \text{D}^* \, \text{H}(\theta)^{-\alpha} \, \theta \, r^\alpha \, w^\gamma \, pe^{(1-\alpha-\gamma)} \, \text{Q}_d^\delta \, \nu,$

where $\text{H}(\theta) = \left[\theta + \dfrac{\text{F}(\theta)}{f(\theta)}\right]$. The parameters α, γ and δ are as defined above.

We now specify distributions for all of the stochastic shocks to our econometric model. This is necessary to derive the likelihood function for the variable cost functions under the two information structures. We require that ν be lognormally distributed with $\ln(\nu_{it}) \sim \text{N}(\mu_\nu, \sigma_\nu^2)$ independent across time and utilities. In Appendix A, we give distributional assumptions for η_L, η_E, η_p, η_K, ε_q, and ε_d sufficient for these results to hold for ν. Taking the natural logarithm of both sides of (23) gives the following symmetric information logarithm-of-operating-cost equation:

(26) $\quad \ln(\text{VC}(\text{S})) = \xi^* + (1-\alpha)\ln(\theta) + \gamma\ln(w)$
$\qquad\qquad\qquad + \alpha\ln(r) + (1-\alpha-\gamma)\ln(pe) + \delta\ln(\text{Q}_d) + \zeta$

where $\xi^* = \ln(\text{D}^*) + \mu_\nu$ and $\zeta = \ln(\nu) - \mu_\nu$. Therefore, ζ is $\text{N}(0, \sigma_\zeta^2)$, where $\sigma_\zeta^2 \equiv \sigma_\nu^2$. Repeating this procedure for equation (25) yields the asymmetric information log of variable costs equation:

(27) $\quad \ln(\text{VC}(\text{A})) = \xi^* - \alpha\ln(\text{H}(\theta)) + \gamma\ln(w) + \alpha\ln(r)$
$\qquad\qquad\qquad + (1-\alpha-\gamma)\ln(pe) + \delta\ln(\text{Q}_d) + \ln(\theta) + \zeta.$

We now proceed to define the likelihood function for each information structure. First we define notation which simplifies the presentation. Let $\Gamma^* = (\xi^*, \alpha, \gamma, \delta)'$. Define $\text{X} = (\ln(r), \ln(w), \ln(pe))'$, $q = \ln(\text{Q}_d)$, and $\text{Y} = \ln(\text{VC})$. In this notation we can abbreviate equations (26) and (27) as:

(28) $\qquad\qquad \text{Y} = \Omega_\text{Y}(\text{X}, q, \Gamma^*, \theta) + \zeta$

and

(29)
$$Y = \Psi_Y(X, q, \Gamma^*, \theta) + \zeta$$

where $\Omega_Y(X, q, \Gamma^*, \theta)$ is the right hand side of (26) excluding ζ and $\Psi_Y(X, q, \Gamma^*, \theta)$ is the right hand side of (27) excluding ζ. We now derive the likelihood function and discuss our estimation procedure for the case of model S. Following this discussion, we describe the additional complications introduced by model A.

In Appendix A we solve the first-order condition for the optimal price given in (8) to obtain an expression for this price in terms of X and Q_d. Using the market demand function, we then solve for Q_d as a function of X and Z and the disturbances to the model. This yields the following equation for q under model S:

(30)
$$q = (Z', X', \ln(\theta)) \Lambda^* + \psi$$

where Λ^* is the vector of coefficients associated with $(Z', X', \ln(\theta))$ and ψ is the composite disturbance defined in Appendix A. Comparing the expressions for ψ and ζ in terms of the structural disturbances given in Appendix A shows that q is correlated with ζ and hence a single equation estimation technique for (28) will not yield consistent structural parameter estimates. Under our distributional assumptions, ψ is $N(0, \sigma_\psi^2)$. Let $\rho_{\zeta, \psi}$ denote the correlation between ζ and ψ. Finally, define $\Lambda = (\Lambda^{*\prime}, \sigma_\psi^2, \rho_{\zeta, \psi})'$. Conditional on the value of θ, equations (28) and (30) make up a triangular system of simultaneous equations. The Jacobian of the transformation from $(\zeta, \psi)'$ to $(Y, q)'$ is one, so that the joint density of $(Y, q)'$ conditional on θ, X and Z is:

(31)
$$h_S(Y, q \mid \ln(\theta), \Gamma, \Lambda) = \frac{1}{2\pi\sigma_\zeta^2 \sigma_\psi^2 (1 - \rho_{\zeta, \psi}^2)^{1/2}}$$
$$\times \exp\left\{ -\frac{1}{2(1 - \rho_{\zeta, \psi}^2)} \left[(\psi/\sigma_\psi)^2 \right] \right.$$
$$\left. - 2\rho_{\zeta, \psi}(\psi\zeta)/(\sigma_\psi \sigma_\zeta) + (\zeta/\sigma_\zeta)^2 \right] \right\},$$

where $\Gamma = (\Gamma^*, \sigma_\zeta)'$. Note that θ enters both (26) and (30) only through $\ln(\theta)$ so that without loss of generality we can express $h_S(\cdot, \cdot)$ as a function of $\ln(\theta)$.

Because θ is unobservable, to construct the likelihood function in terms of the observable variables, we must compute the density of (Y, q) given X and Z only. To obtain this density we integrate the conditional density (31) with respect to the density of θ. Rather than assume that θ_{it} is independently and identically distributed across utilities (i) and time (t), we assume following distribution for θ_{it}

(32)
$$\theta_{it}(a_{it}) = B(rw_{it})^{a_{it}},$$

where B > 0 is a constant scale factor, a_{it} is independently and identically distributed across time and utilities, $rw_{it} = \dfrac{w_{it}}{cpi_t}$, w_{it} is the nominal wage paid to labor at utility i in year t, and cpi_t is the consumer price index for year t. The ratio $\dfrac{w_{it}}{cpi_t}$ is the real wage received by employees of utility i in year t.

This specification for θ has the attractive feature of allowing for temporal dependence into the values of θ_{it} for firm i based on observable characteristics of the utility. Each draw of θ_{it} is independent of the value of θ_{is} for $s \neq t$ conditional on the values of rw_{it} and rw_{is}. Because rw_{it} and rw_{is} are not independent (real wages are correlated over time), θ_{it} and θ_{is} should be unconditionally dependent. This specification also embodies the notion that differences in labor efficiencies across utilities and time should be partially reflected in different real wages paid to labor. This form of θ_{it} makes a_{it} the elasticity of θ with respect to the real wage. We expect a_{it} to take on values less than zero, or at least that its mean should be negative, because small values of θ_{it} imply greater efficiency. We could allow the distribution of θ to depend on other characteristics of the utility. Experimentation with other variables determining differences in the distribution of θ_{it}, such as observable physical characteristics of the utility's service area (e.g., number of meters or number of miles of pipe), resulted in little change in the structural parameter estimates [10]. Because of its intuitive appeal we settled on the specification given in (32).

Substituting the logarithm of (32) into (26) yields

$$(33) \quad \ln(VC(S)) = \xi + a(1-\alpha)\ln(rw) + \gamma\ln(w) \\ + \alpha\ln(r) + (1-\alpha-\gamma)\ln(pe) + \delta\ln(Q_d) + \zeta,$$

where $\xi = \xi^* + (1-\alpha)\ln(B)$. Note that ξ^* and B are not separately identified. Later we will show this result holds for model A as well. Therefore, we must choose a normalization for θ in order to separately identify these two parameters. Because it is an efficiency parameter, we choose B such that $E(\theta) = 1$ for the model A parameter estimates and rw_{it} set equal to its sample mean.

Conditional on rw_{it}, variability in the unobserved source of heterogeneity depends solely on a_{it}. Integrating (31) with respect to $\dfrac{dM(a)}{da} \equiv m(a)$, the density of a, yields:

$$(34) \quad g(Y, q | X, Z, \Gamma, \Lambda, M) \\ = \int_{a_{low}}^{a_{high}} h_S(Y, q \mid X, Z, \ln(B(rw))^a, \Gamma) \, dM(a),$$

---

10. Our description of the regulator-utility interaction in the California Water utility industry in section 2 describes our reasons for selecting labor as the source of unobserved heterogeneity in the regulatory process.

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where $a_k = \ln(\theta_k/\mathrm{B})/rw$ for $k = $ high, low. The density $g(\mathrm{Y}, q | \mathrm{X}, \mathrm{Z}, \Gamma, \Lambda, \mathrm{M})$ is a member of the general class of mixture distribution models. The major complication in estimating these types of models is that the parameter space is infinite dimensional. In particular, the likelihood function depends on $\mathrm{M}(a)$, the distribution function of a. Equivalently, the a_{it} are nuisance parameters whose numbers grow with the sample size. Within the context of these models, $\mathrm{M}(a)$ is called the mixing distribution. These models have a long history in both econometrics and statistics beginning with NEYMAN and SCOTT [1948] and KIEFER and WOLFOWITZ [1956]. The latter paper proved the consistency of the maximum likelihood estimates of Γ and $\mathrm{M}(a)$ for the case that X and rw_{it} do not appear in $h_S(\mathrm{Y}|\mathrm{X}, \ln(\mathrm{B}(rw_{it}))^a, \Gamma)$ and Γ is a scalar.

In a series of recent papers, LINDSAY [1981, 1983a, 1983b and 1983c) considers more general forms of the mixture models and derives large-sample results for classes of models not considered by KIEFER and WOLFOWITZ [1956]. In addition, extending the work of LAIRD [1978], he derives an algorithm for nonparametrically estimating the mixing distribution M [11]. Lindsay's procedure for estimating $\mathrm{M}(\theta)$ involves approximating it by a step function, with no more steps than the number of distinct observations. However, our theoretical models are derived under the assumption that θ is a continuously distributed random variable, rather than a discrete random variable (as is implicit in Lindsay's estimation procedure for any finite sample size). Consequently, his estimation procedure does not yield an estimate of $\mathrm{M}(a)$ that is consistent with our theoretical models for any sample size. Consequently, we choose a procedure for estimating $\mathrm{F}(\theta)$ that explicitly acknowledges that θ is continuously distributed. We utilize a kernel estimator of $m(a)$, the density of a_{it}. The generic form for the kernel density estimator is

$$(35) \qquad m_\mathrm{J}(t) = \sum_{j=1}^{\mathrm{J}} \left[\frac{w_j}{h_j} \mathrm{K}\left(\frac{t - \tau_j}{h_j} \right) \right]$$

where the parameters of this density are $\tau = (\tau_1, \ldots, \tau_\mathrm{J})'$, $h = (h_1, \ldots, h_\mathrm{J})'$, $w = (w_1, \ldots, w_\mathrm{J})'$, $\left(\sum_{k=1}^{\mathrm{J}} w_k = 1 \right)$ and J. The function $\mathrm{K}(z)$ is any kernel with compact support. The reason we must choose a kernel with compact support is that the assumption of our theoretical models require $\mathrm{F}(\theta)$ to have compact support. For our empirical application we choose the Epanechnikov kernel

$$(36) \qquad \mathrm{K}(z) = \frac{3}{4\sqrt{5}} \left(1 - \frac{1}{5} z^2 \right), \qquad |z| \leqslant \sqrt{5},$$

and is zero for all $|z| > \sqrt{5}$. Even for small J, the functional form given in (35) is extremely flexible, allowing a wide range of distributional shapes.

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11. HECKMAN and SINGER (1982 and 1984) have applied these nonparametric mixture distribution estimation methods to modeling individual heterogeneity in the analysis of duration data.

Substituting (35) for $d\mathrm{M}(a)/da$ in (34) gives the following integral

(37)
$$g\left(\mathrm{Y},\,q\mid\mathrm{X},\,\mathrm{Z},\,\Gamma,\,\Delta,\,\Lambda\right)$$
$$= \int_{a_{\mathrm{low}}}^{a_{\mathrm{high}}} h_{\mathrm{S}}\left(\mathrm{Y},\,q\mid\mathrm{X},\,\mathrm{Z},\,\ln\left(\mathrm{B}\left(rw\right)\right)^{s},\,\Gamma\right)$$
$$\times\left(\sum_{j=1}^{\mathrm{J}}\left(\frac{w_{j}}{h_{j}}\,\mathrm{K}\left(\frac{s-\tau_{j}}{h_{j}}\right)\right)ds\right)$$

where $\Delta=(\tau',\,h',\,w')'$. Equation (37) is the likelihood function value for a single observation. Selecting a value of J completes the specification of the likelihood function [12].

The log-likelihood function for N observations is:

(37)
$$\mathrm{L}\left(\Gamma,\,\Delta,\,\Lambda\right)=\sum_{i=1}^{\mathrm{N}}\ln\left(g\left(\mathrm{Y}_{i},\,q_{i}\mid\mathrm{X}_{i},\,\mathrm{Z}_{i},\,\Gamma,\,\Delta,\,\Lambda\right)\right).$$

Once maximum likelihood estimates of Γ, Δ and Λ have been obtained, the matrix of the sum of the outer products of first-partial derivatives of $\ln\left(g\left(\mathrm{Y}_{i},\,q_{i}\mid\mathrm{X}_{i},\,\mathrm{Z}_{i},\,\Gamma,\,\Delta,\,\Lambda\right)\right)$ evaluated at the ML parameter estimates of can be used to obtain consistent standard error estimates.

Given our ML estimate of $m_{\mathrm{J}}(a)$ we can transform this into an estimate of the distribution of θ_{it}, as follows:

(38)
$$f_{it}\left(\theta\right)=\frac{m_{\mathrm{J}}\left(\ln\left(\theta/\mathrm{B}\right)/rw_{it}\right)}{rw_{it}\,\theta}.$$

The construction of the likelihood function for the asymmetric information case proceeds in an analoguous fashion, with the major complication being the presence of $\mathrm{H}\left(\theta\right)$, which is a function of both $f\left(\theta\right)$ and $\mathrm{F}\left(\theta\right)$ in both regression equations. The conditional density of $(\mathrm{Y},\,q)'$ given θ, X and Z under model A takes the same form as for model S with equation (26) replaced by equation (27) and output equation (30) replaced by the following equation:

(39)
$$q=\left(\mathrm{X}',\,\mathrm{Z}',\,\ln\left(\theta\right),\,\ln\left(\mathrm{H}\left(\theta\right)\right)\right)\Phi+\psi,$$

where Φ is the vector of coefficients associated with $(\mathrm{X}',\,\mathrm{Z}',\,\ln\left(\theta\right),\,\ln\left(\mathrm{H}\left(\theta\right)\right)')$. Appendix A derives expressions for the elements of Φ in terms of our structural parameters. In Appendix A, we also show that restrictions of our structural model imply that $\ln\left(\theta\right)$ should not enter the output equation. We test this exclusion restriction in our empirical application.

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12. We perform our analysis conditional on the value of J. It is chosen to yield a sufficiently flexible mixing distribution relative to the amount of data at hand.

Under our specification of θ_{it}, the function $H(\theta)$ can be simplified as follows:

$$(40) \qquad H_{it}(\theta) \equiv \theta\, H_{it}^*(\theta) = \theta\left[1 + \frac{F_{it}(\theta)\, rw_{it}}{m_J\,(\ln(\theta/B)/rw_{it}}\right]$$

where $F_{it}(\theta) = \int_{\theta_{\text{low}}}^{\theta} f_{it}(s)\,ds$. Utilizing the logarithm of (32), we can express (27) in terms of $H^*(\theta)$ and θ as:

$$
\begin{aligned}
(41) \qquad \ln(\text{VC}(A)) =&\, \xi - \alpha \ln(H^*(\theta)) + \gamma \ln(w) + \alpha \ln(r) \\
&+ (1 - \alpha - \gamma) \ln(pe) + \delta \ln(Q_d) \\
&+ a(1 - \alpha) \ln(rw) + \zeta,
\end{aligned}
$$

where ξ is as defined earlier. Note that for model A we are also unable to separately identify ξ^* and B. Comparing (41) to (33), we can see that the only difference between the asymmetric and symmetric information variable costs is the term $-\alpha \ln(H^*(\theta))$.

The conditional distribution of Y and q given Z, X, and θ for this information structure, $h_A(Y, q \,|\, X, Z, \theta)$, depends on θ through both $\ln(\theta)$ and $\ln(H^*(\theta))$. To construct the likelihood in terms of only observables, we integrate this conditional density with respect to $f_{it}(\theta)$ over the interval $[\theta_{\text{low}}, \theta_{\text{high}}]$. We compute standard errors for these estimates in the same fashion as for the symmetric information estimates.

5 Data Sources

In this section we describe our dataset and the construction of the variables used in the empirical analysis. All of our cost data are obtained from the water district annual reports submitted annually to the CPUC. These reports break down the utility's costs by stages of production and by the three inputs used in the production process. The CPUC prepares a transcript of each of the rate hearings for each of the districts. Besides a summary of the proceedings, these transcripts list the rates set for the utility, and usually both the rate of return it is allowed to earn on its capital and the price it must pay for electricity.

We have collected annual reports and rate case transcripts for a sample of Class A water utilities for the period 1980 to 1988. From this data we have obtained the information necessary to estimate our cost functions for a sample of water utility districts. The only data not available from either of these sources is information on wages in the water industry. This information is derived from unpublished data provided by the California Employment

Development Department (EDD), Employment Data and Research Division. This agency collects information on wages at the county level for SIC Code 494 (Water Supply) on a quarterly basis. The annual average of the quarterly wages is used as our wage variable.

We now describe the variables used in our model. Total water delivered is our output measure. The price of capital is computed by a user cost of capital approach using ror_{it}, the rate of return on capital set by the CPUC in the rate hearing, as the rate of return for period t for utility i. Using equation (23) of JORGENSON [1989], the price of capital services for firm i in period t is given by:

$$r_{it} = p_{A, t-1} \, \text{ror}_{it} + \lambda \, p_{A, t} - (p_{A, t} - p_{A, t-1}),$$

where $p_{A, t}$ is the acquisition price of capital goods in time period t and λ is the annual rate of the depreciation for utility capital equipment as given in Table 1.2 of JORGENSON [1989]. For $p_{A, t}$ we utilize the Whitman, Requardt & Associates Index of utility construction costs for the Pacific region for year t. We assume a single type of labor. Ideally, we would like to divide the utility's labor force into two types of workers: (1) maintenance and (2) supervisory. However, we are unable to obtain wage data for the water industry at this level of job detail. Although wage differentials between maintenance and supervisory labor may vary across districts and over time, based on discussions with CPUC engineers it appears that the variations in these differentials are dominated by variations in the level of the average wage for all water industry workers over time and across districts. Hence our assumption of a single type of labor, although restrictive, should not seriously alter our results relative to a supervisory labor and maintenance labor model.

Because we focus our attention on estimating an operating cost function, rather than a total cost function in order recover the parameters of the utility's production function, we do not have to confront the question of properly measuring the utility's capital stock or capital service costs. The proper construction of these variables plagues all work estimating production or total cost functions. Because of the irregular availability of our annual report data for single districts, a time series of investment for each district is not available [13]. Even if all observations for the period 1980-1988 were available for each of the districts we would still have the problem that the vast majority of each district's capital stock was already in place by 1980. Our approach to estimating the parameters of the firm's technology concentrates on specifying a model in terms of variables that we are confident are measured with very little error, and hence avoids the problems inherent in constructing a single index representing the utility's capital stock [14].

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13. These annual reports were often in use by the CPUC staff or simply missing from the CPUC archives and therefore unavailable to our data collection efforts.

14. In Appendix B, we describe three approaches to estimating capital cost and capital stock using our data. These capital cost measures are used to estimate a total cost function under the standard cost-minimization, no private information assumptions.

6 Empirical Results for California Water Utility Industry

In this section first we present the results of the standard approach to estimating unconditional variable cost and total cost functions to recover the parameters of the utility's production function for three measures of capital service costs. Then we present our estimates of the symmetric and asymmetric information models. We compare these estimates to those obtained using conventional estimation techniques. We then explore several implications of the two private information models of the regulatory process. In particular, we compute an estimate of the expected change in both the variable and total costs of producing a given level of output under the symmetric information relative to the asymmetric information regulatory equilibrium.

As mentioned earlier, models A and S reduce to the standard minimum-cost full-information Cobb-Douglas cost function if $\theta = 1$ and $H(\theta) = 1$. Imposing these restrictions yields:

$$(42) \qquad \ln(TC) = \xi_{TC} + \gamma \ln(w) + \alpha \ln(r) \\ + (1 - \alpha - \gamma) \ln(pe) + \delta \ln(Q) + v,$$

as the utility's total cost function, with $E(v) = 0$ and $E(v^2) = \sigma_v^2$. For comparison, the model S and model A total cost functions are given in Appendix A in equations (A.17) and (A.18). In terms of the unconditional variable cost function, imposing these restrictions yields:

$$(43) \qquad \ln(VC) = \xi^* + \gamma \ln(w) + \alpha \ln(r) \\ + (1 - \alpha - \gamma) \ln(pe) + \delta \ln(Q) + \nu,$$

If θ and $H(\theta)$ are equal to one for all districts and time periods, the parameters of models (42) and (43) can be consistently estimated by ordinary least squares (OLS). For example, a Cobb-Douglas cost function with only capital and labor is estimated by OLS in CRAIN and ZARDKOOHI [1978] for a nationwide cross-section of public and private water utilities.

Table 1 contains the OLS estimates of (42) for our three definitions of capital service costs described in Appendix B. For all of the capital cost measures, there are several problems with these parameter estimates. First, these estimates imply a negative value of β_E in the water delivery production function, or equivalently a negative cost elasticity with respect to the price of electricity, i.e., increases in pe reduce the cost of water delivery. Second, the estimates imply an very small cost elasticity with respect to the price of labor. For two of the models, the point estimates imply elasticities less than 0.20, implying a 1 percent increase in the wage increases TC by no more that 0.2 percent.

TABLE 1

Ordinary Least Squares Estimates of Total Cost Function [a]
Number of Degrees of Freedom = 297, Number of Observations = 301
(No Time or District Dummies)

Model	REGC	UTILC	MPGC
Constant	−0.377	−1.189	−0.013
	(1.417)	(1.497)	(1.381)
Wage	0.191	0.290	0.170
	(0.154)	(0.162)	(0.150)
Price of Capital	0.236	0.214	0.251
	(0.229)	(0.056)	(0.051)
Price of Electricity	−0.552	−0.620	−0.495
	(0.197)	(0.208)	(0.191)
Output	0.751	0.729	0.755
	(0.028)	(0.029)	(0.027)
R^2	0.797	0.774	0.808

TABLE 2

Ordinary Least Squares Estimates of Total Cost Function [a]
Number of Degrees of Freedom = 289
(Time Dummies)

Model	REGC	UTILC	MPGC
Constant	0.957	1.630	1.246
	(2.046)	(2.151)	(1.993)
Wage	−0.097	−0.028	−0.083
	(0.169)	(0.178)	(0.165)
Price of Capital	0.443	0.035	0.376
	(0.415)	(0.434)	(0.401)
Price of Electricity	−0.880	−0.995	−0.818
	(0.212)	(0.223)	(0.206)
Output	0.777	0.756	0.777
	(0.028)	(0.029)	(0.027)
R^2	0.808	0.788	0.816

Definitions: REGC = Regulator's Definition of Captal Costs, UTILC = Utility's.
Definition of Capital Costs, and MPGC = Modified Pakes and Griliches (1984)
Definition of Capital Costs. See Appendix B for the details of the construction of these measures.
[a] Standard Error Estimates in Parentheses Below Coefficient Estimates.

The final problem is the large scale economies estimates embodied in the elasticity of cost with respect to output coefficient estimates. Transforming these output elasticity point estimates into the parameters of the Cobb-Douglas production function implies substantial scale economies. We define our scale economies estimates in terms of the Cobb-Douglas parameters as:

$$SCE = \beta_K + \beta_L + \beta_E = 1/\delta.$$

For the MPGC capital cost model, which yields the smallest scale economies estimate, a 10 percent increase in output leads to only a 7.55 percent increase in costs, or equivalently a 2.45 decrease in average costs. Nevertheless, these scale economies estimates are consistent with the results of CRAIN and ZARDKOOHI [1978]. We interpret this agreement of results as evidence that

our data is similar to that used by these authors, rather than as confirmation of the validity of the full-information, total-cost minimization estimation technique. Based on these estimates it would appear that many of the districts are operating quite far from the minimum efficient scale for water delivery.

In an attempt to salvage the full-information total cost-minimization model, we estimated the model with time dummies, a complete set of district dummies and both time and district dummies. The regression with time dummies is given in Table 2. Unfortunately, time dummies only seem to exacerbate the problem with the elasticity of cost with respect to the price of electricity. In addition, the elasticity of total cost with respect to the wage turns negative. However, the returns to scale estimates do become slightly smaller. Table 3 contains the model with district dummies. Here the labor elasticity is larger and the capital elasticity smaller than in the previous tables. All of the cost elasticity with respect to input price estimates are positive and not totally implausible. Unfortunately, the cost elasticities with respect to output become extremely small (implying unbelievably large scale economies estimates). Finally, for the case of time and district dummies, the input price elasticity estimates are positive (with one exception) but small in magnitude. In this case, the scale economies estimates are impossibly high.

Table 5 presents estimates of the unconditional minimum variable cost function (43) for the four estimation scenarios considered in Tables 1-4. In terms of the input price and output elasticity estimates, the results (in column 1) for the case of no time or district dummies are very similar to those from the total cost function estimates in Table 1. The impact of adding different fixed effects–time, district, and combination time and district–produce the same pattern of differences between the four columns of Table 5 as occur across the total cost function estimation scenarios in Tables 1-4.

Under the more general assumptions of our private information structural models of the regulatory process, models (42) and (43) are misspecified for two reasons. First, the presence of θ, the private information parameter, in the regulatory process implies that all equilibrium magnitudes including the output level of the utility, should depend on θ. However, θ is also part of the disturbance to the cost function when OLS is applied to either (42) or (43). For these equations, the disturbance and a regressor (q_{it}) are correlated so that OLS will lead to biased and inconsistent structural parameter estimates. Second, even if θ were not in the model, the presence of any unobservable (to the econometrician) variables in the firm's production function which both the utility and regulator condition their decisions on introduces correlation between q_{it} and the disturbance to the cost function. In our case, the vector of structural disturbances η and the structural disturbances to the production and demand functions, ε_q and ε_d, all enter into the disturbance to both the variable and total cost functions as well as into the determination of q_{it}. This induces correlation between q_{it} and the OLS disturbance to both cost functions despite the absence of θ from the model.

To provide an alternative metric for judging our parameter estimates, Table 6 gives the sample mean of the total input cost shares for our three capital cost measures. Under the assumption of full-information and cost-

minimizing behavior, by the logarithmic form of Shepard's Lemma, these cost shares should equal the elasticity of total cost with respect to input price for each of the inputs. The model with the district dummies comes closest to matching the sample means of these cost shares. Unfortunately, these models have the very unsatisfactory feature of yielding extremely large economies to scale estimates.

Given the unsatisfactory results obtained using the conventional full-information minimum cost estimation procedures, we now consider our private information cost function models. For both of the private information models estimated we set J, the number of kernels used to approximate the

TABLE 3

Ordinary Least Squares Estimates of Total Cost Function [a] Number of Degrees of Freedom = 247 (District Dummies)			
Model	REGC	UTILC	MPGC
Constant	0.366	2.496	−0.676
	(0.835)	(1.699)	(0.890)
Wage	0.774	0.877	0.661
	(0.063)	(0.128)	(0.067)
Price of Capital	0.087	0.067	0.115
	(0.012)	(0.025)	(0.013)
Price of Electricity	0.226	0.236	0.196
	(0.069)	(0.141)	(0.073)
Output	0.454	0.220	0.625
	(0.045)	(0.092)	(0.048)
R^2	0.995	0.982	0.995

TABLE 4

Ordinary Least Squares Estimates of Total Cost Function [a] Number of Degrees of Freedom = 239 (Time and District Dummies)			
Model	REGC	UTILC	MPGC
Constant	8.125	9.421	6.867
	(1.039)	(2.63)	(1.099)
Wage	0.111	0.313	0.148
	(0.087)	(0.221)	(0.092)
Price of Capital	0.212	0.186	0.083
	(0.070)	(0.178)	(0.091)
Price of Electricity	0.007	−0.097	0.002
	(0.058)	(0.149)	(0.062)
Output	0.294	0.024	0.403
	(0.038)	(0.098)	(0.040)
R^2	0.997	0.985	0.997

Definitions: REGC = Regulator's Definition of Captal Costs, UTILC = Utility's.
Definition of Capital Costs, and MPGC = Modified Pakes and Griliches (1984)
Definition of Capital Costs. See Appendix B for the details of the construction of these measures.
[a] Standard Error Estimates in Parentheses Below Coefficient Estimates.

TABLE 5

	Ordinary Least Squares Estimates of Variable Cost Function [a] Number of Observations = 301			
Model	NTDD	TD	DD	T & DD
Constant	−2.794	−1.394	−1.408	6.320
	(1.516)	(2.211)	(0.933)	(1.280)
Wage	0.422	0.185	0.794	0.161
	(0.164)	(0.183)	(0.071)	(0.108)
Price of Capital	0.181	0.242	0.091	0.139
	(0.056)	(0.446)	(0.013)	(0.086)
Price of Electricity	−0.359	−0.647	0.210	0.010
	(0.210)	(0.229)	(0.077)	(0.072)
Output	0.774	0.794	0.534	0.374
	(0.029)	(0.030)	(0.051)	(0.047)
R^2	0.793	0.800	0.995	0.997

Definitions: NTDD = No Time or District Dummies, TD = Time Dummies, DD = District Dummies, and T & DD = Time and District Dummies.

[a] Standard Error Estimates in Parentheses Below Coefficient Estimates.

TABLE 6

	Sample Averages of Input Cost Shares [a] Number of Observations = 301		
Input	REGC	UTILC	MPGC
Capital	0.341	0.318	0.414
	(0.005)	(0.007)	(0.005)
Labor	0.540	0.560	0.481
	(0.007)	(0.009)	(0.006)
Electricity	0.119	0.122	0.105
	(0.004)	(0.004)	(0.003)

[a] Sample Standard Errors in Parentheses Below Mean Shares.

density of θ, equal to two. Increasing the number of kernels led to very little change in the structural parameter estimates or the shape of the estimate of $f_{it}(\theta)$.

First we consider the symmetric information model. Table 7 contains the estimates of the model S unconditional variable cost function. These point estimates provide a drastically different picture of the water delivery production process than do those in Tables 1-5. All of the β_m, m = K, L, and E, implied by these parameter estimates are positive. Perhaps the most interesting aspect of these results is the large change in the scale economies estimate. The point estimate implies slight diseconomies to scale $(1/\delta < 1)$. In fact, based on the standard error estimate we can reject the hypothesis $H : \delta = 1$ in favor of the alternative $K : \delta > 1$, implying statistically significant, but economically small, diseconomies to scale.

These estimates imply that the districts are operating very close to the minimum efficient scale for the water delivery technology. These scale economies estimates appear far more consistent with the stylized facts regarding the current state of the California water delivery technology –that total costs of supply grow roughly in proportion to the expansion

TABLE 7

Parameter	Value	Standard Error
Symmetric Information Model Estimates Controlling for Unobserved Heterogeneity Unconstrained Estimates (301 Observations)		
Parameters of Variable Cost Function		
ξ	-5.413	0.698
Wage	0.457	0.123
Price of Capital	0.274	0.023
Price of Electricity	0.139	0.074
Output	1.051	0.018
σ_ζ	0.124	0.015
$\rho_{\zeta, \psi}$	0.949	0.015
Parameters of Reduced Form Output Equation		
Λ_1	4.140	1.129
Wage	0.866	0.153
Price of Capital	-0.268	0.040
Price of Electricity	-0.364	0.122
# of Meters in Service Area	0.231	0.028
Total Feet of Pipe	0.407	0.024
Meters * Pipe	-0.024	0.001
$\ln(\theta)$	-0.691	0.047
σ_ψ	0.328	0.018
Parameters of Mixing Distribution $t = \ln(\theta/\mathrm{B})/\ln(rw)$ $(\mathrm{J} = 2)$		
τ_1	-0.269	0.166
τ_2	-0.114	0.168
h_1	0.071	0.005
h_2	0.224	0.010
w_1	0.726	0.038
Likelihood Function Value	-375.456	

of output. A recent memorandum sent to all water utilities in California provides informal evidence for the close to proportionate increase in costs associated with expanding output. This memorandum describes the CPUC June 15, 1983 service improvement policy, which requires water companies to provide public notice of proposed plant additions. "If customer consensus is a desire to retain poor quality (but not unsafe) service rather than pay for improvements, the Commission may decide not to allow the proposed improvements in the rate base", (Public Utilities Commission Memorandum, November 30, 1983). While there are certainly other reasons why the CPUC would institute such a policy, one of the reasons, which is mentioned in this memorandum is the high cost of making these improvements and servicing the improved capital stock. These sorts of statements seem consistent with a technology that is characterized by constant or slight decreasing returns to scale, not one characterized by the large returns to scale implied by the estimates in Tables 1-5.

Table 8 presents the model S estimates imposing the restriction that the unconditional variable cost function is homogeneous of degree one in the input prices. Homogeneity implies the restriction that the sum of the input price elasticities equals one. This imposes one equality restriction. The Wald statistic (constructed from the Table 7 estimates) for this null hypothesis is 1.349. The likelihood ratio (LR) statistic (constructed from the likelihood function values given at the bottom of Tables 7 and 8) is

TABLE 8

Symmetric Information Model Estimates Controlling for Unobserved Heterogeneity
Constrained Estimates-Input Price Homogeneity Imposed (301 Observations)

Parameter	Value	Standard Error
Parameters of Variable Cost Function		
ξ	−6.380	0.384
Wage	0.582	0.048
Price of Capital	0.340	0.014
Output........................	1.080	0.011
σ_ζ	0.103	0.010
$\rho_{\zeta,\psi}$	0.965	0.009
Parameters of Reduced Form Output Equation		
Λ_1	4.891	1.132
Wage	0.737	0.141
Price of Capital	−0.322	0.041
Price of Electricity	−0.285	0.123
# of Meters in Service Area	0.226	0.026
Total Feet of Pipe	0.391	0.023
Meters * Pipe	−0.023	0.001
$\ln(\theta)$	−0.603	0.037
σ_ψ	0.336	0.015
Parameters of Mixing Distribution $t = \ln(\theta/\text{B})/\ln(rw)$ (J = 2)		
τ_1	−0.599	0.093
τ_2	−0.284	0.092
h_1	0.094	0.004
h_2	0.226	0.007
w_1	0.799	0.033
Likelihood Function Value	−376.065	

1.218. Both statistics possess a χ^2-distribution with 1 degree of freedom under the null hypothesis, so that for either test statistic the null hypothesis of homogeneity cannot be rejected at any reasonable level of significance. Imposition of this contraint leads to elasticity of cost with respect to input price estimates which are very close to the average factor shares given in Table 6. The output elasticity estimate still implies slight diseconomies to scale in the production technology.

Table 9 presents the model A estimates. The major difference between the model S and model A estimates are the larger cost elasticity with respect to labor and smaller cost elasticity with respect to capital for the model A estimates. In addition, the value of σ_ζ for model A is almost three times smaller than the corresponding estimate of σ_ζ for model S. This difference in magnitude of σ_ζ across the two models implies that model A attributes much of the variability in variable costs over time and across utilities to differences in the regulatory distortion function H (θ), defined in section 3. Both model A and model S allow costs to be affected by changes in θ. Only model A allows for variability in H (θ) to explain variable cost movements. As the relative magnitude of the σ_ζ across the two models shows, H (θ) possesses substantial explanatory power in the unconditional variable cost function. This increased explanatory power also shows up the substantially higher value of the likelihood function for model A relative to model S.

Table 10 presents estimates of model A under the assumption that the variable cost function is homogeneous of degree one in input prices. From

TABLE 9

Parameter	Value	Standard Error
Asymmetric Information Model Estimates Controlling for Unobserved Heterogeneity Unconstrained Estimates (301 Observations)		
Parameters of Variable Cost Function		
ξ	−3.945	0.450
Wage	0.653	0.088
Price of Capital	0.123	0.011
Price of Electricity	0.119	0.046
Output	1.052	0.012
σ_ζ	0.021	0.003
$\rho_{\zeta,\psi}$	0.236	0.415
Parameters of Reduced Form Output Equation		
Φ_1	2.274	1.479
Wage	1.010	0.153
Price of Capital	−0.164	0.049
Price of Electricity	−0.310	0.148
# of Meters in Service Area	0.237	0.031
Total Feet of Pipe	0.396	0.030
Meters * Pipe	−0.024	0.001
$\ln(H(\theta))$	−0.300	0.022
σ_ψ	0.413	0.021
Parameters of Mixing Distribution $t = \ln(\theta/\mathrm{B})/\ln(rw)$ (J = 2)		
τ_1	−0.841	0.115
τ_2	−0.549	0.118
h_1	0.073	0.003
h_2	0.172	0.004
w_1	0.855	0.022
Likelihood Function Value	−336.411	

the likelihood ratio function values given at the bottom of Table 9 and 10, likelihood ratio test statistic for homogeneity is 2.62. The Wald test based on the estimates in Table 9 is 2.15. Both test statistics imply that the null hypothesis of homogeneity cannot be rejected.

We also tested the model given in Table 10 against several less restrictive alternatives. The first was whether or not $\ln(\theta)$ should enter the reduced form output equation. As shown in Appendix A, under the assumptions of our structural model, θ should effect observed output of the utility only through $H(\theta)$. To test this hypothesis we estimated model A with homogeneity imposed, but included the term $\ln(\theta)$ in the reduced form output function. The Wald statistic for the null hypothesis that the coefficient on $\ln(\theta)$ is zero in the output equation is 1.93 and the likelihood ratio statistic is 1.6. Neither statistic leads to rejection of this exclusion restriction implied by our structural model. A second less restrictive model was considered which did not impose homogeneity of the variable cost function in the input prices or the constraint that $-\alpha$ equals the coefficient on $\ln(H(\theta))$ in the variable cost function but did not impose the above exclusion restriction on $\ln(\theta)$ in the output equation. The likelihood ratio statistic for this two-dimensional joint null hypothesis implied by our structural model is 4.34, which is smaller than 5.991, the $\alpha = 0.05$ critical value from a χ^2-random variable. Both of these hypothesis tests yield encouraging evidence in favor of the validity of the restrictions implied by model A.

TABLE 10

Parameter	Value	Standard Error
Asymmetric Information Model Estimates Controlling for Unobserved Heterogeneity Constrained Estimates-Input Price Homogeneity Imposed (301 Observations)		
Parameters of Variable Cost Function		
ξ	-4.204	0.493
Wage	0.746	0.073
Price of Capital	0.113	0.018
Output	1.044	0.021
σ_ζ	0.036	0.009
$\rho_{\zeta,\psi}$	0.680	0.120
Parameters of Reduced Form Output Equation		
Φ_1	2.238	1.448
Wage	0.988	0.148
Price of Capital	-0.162	0.049
Price of Electricity	-0.333	0.149
# of Meters in Service Area	0.237	0.031
Total Feet of Pipe	0.400	0.030
Meters * Pipe	-0.024	0.001
$\ln(H(\theta))$	-0.309	0.023
σ_ψ	0.397	0.020
Parameters of Mixing Distribution $t = \ln(\theta/B)/\ln(rw)$ $(J=2)$		
τ_1	-0.927	0.105
τ_2	-0.646	0.105
h_1	0.074	0.004
h_2	0.170	0.006
w_1	0.869	0.023
Likelihood Function Value	-337.722	

We should note here that both of our private information models determine the various cost elasticities controlling for the different unobserved efficiencies across observations, but each does this under a different assumed model of the regulator-utility interaction. Therefore, we can think of the cost elasticity estimates obtained from both the symmetric and asymmetric information models as determining the percentage increase in a utility's total production costs as a result of a 1 percent increase in the price of that input, given that model's assumed regulator-utility interaction. The cost elasticities differ across the symmetric and asymmetric information models precisely because the different models of utility-regulator interaction imply different responses by the utility to input price changes.

We now compare the implications of the two models of regulatory interaction with private information. All of the calculations presented below are based on the model S estimates in Table 8 and the model A estimates in Table 10 which impose all of the restrictions implied by our two structural models.

First we must address the issue of the scale of θ for models S and A. As shown in section 4, B, the constant determining the scale of θ in equation (32), cannot be separately identified from the constant in the variable cost function for either model A or S. In order recover an estimate of B, we must normalize θ in some manner. We normalize θ to have an expected value of one when evaluated at the sample mean of rw_{it} for the model A parameter estimates. We choose the same value of B for both models A

and S so that the efficiency levels [values of θ and $d(\theta)$] implied by the model A and model S parameter estimates are directly comparable. The sample mean of rw_{it} is 5.42, which implies a value of B of 81.18. For these values of rw_{it} and B, the mean of θ for model A is, by construction, one, and the mean of θ for model S is 9.84. Based only on a comparison of means of θ, model S implies a much greater average level of labor inefficiency than does model A. This occurs because model A allows an additional source of variability in variable costs, the differential regulatory distortion embodied in $\ln(H(\theta))$. On the other hand, model S must attribute all unexplainable variability in variable costs not accounted for by variability in ν_{it} to variability in θ_{it} alone, whereas model A has both θ_{it} and $H(\theta_{it})$ to explain movements in variable costs.

Figure 1 presents a plot of the density of θ implied by our model A and S estimates for the value of B we have selected and for rw_{it} set to it sample mean. Both the model A and S estimates of $f(\theta)$ exhibit substantial positive skewness, indicating that the vast majority of draws of θ for any observation (utility and time period) lie below the mean value of that observation. For example, for model A approximately 83 percent of the time θ lies below its mean value. However, θ takes on very large values with small probability so that the expectation of θ is one. For model S, the same general results hold, approximately 86 percent of the time θ lies below 9.84, the mean of θ under model S. A comparison of the two densities reinforces our above conclusions made based only on mean values. For every value of t, the probability that θ is less than t is greater for model A than for model S. In other words, because it allows for regulatory distortions, model A estimates each utility's absolute labor efficiency to be substantially higher than the estimate coming from model S.

Estimated Density of Theta
Models A and S
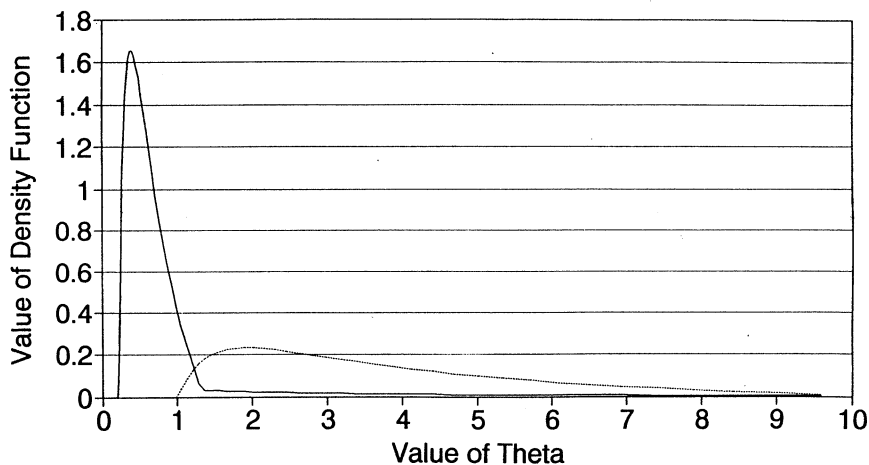
FIGURE 1

———— *Model A, ... Model S.*

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Figure 2 plots the density of $d(\theta)$ for the model S and model A parameter estimates with rw_{it} set equal to its sample mean. Because $(1-\alpha)/\gamma$ is very close to one $(d(\theta) = \theta^{(1-\alpha)/\gamma})$, these plots closely resemble the plots of θ given in Figure 1. Figure 3 presents a plot of the density function of a, the elasticity of θ with respect to rw_{it} for both models S and A. Figure 4 presents the density of the elasticity of $d(\theta)$ with respect to rw_{it} for the two models. Table 11 gives the expected values associated with the densities given in Figures 3 and 4. The major conclusion to emerge from the comparison of densities and expected elasticities is that the model A parameter estimates imply that labor efficiency is substantially more responsive to changes in the real wage (rw_{it}). In fact, for model A the expected elasticity of $d(\theta)$ with respect to rw_{it} is essentially -1.0, which implies that a one percent increase in rw_{it} leads to a one percent increase in the labor efficiency deflator $(d(\theta))$. The model S results imply that labor efficiency is substantially less sensitive to changes in rw_{it}.

Estimated Density of d(Theta)
Models A and S
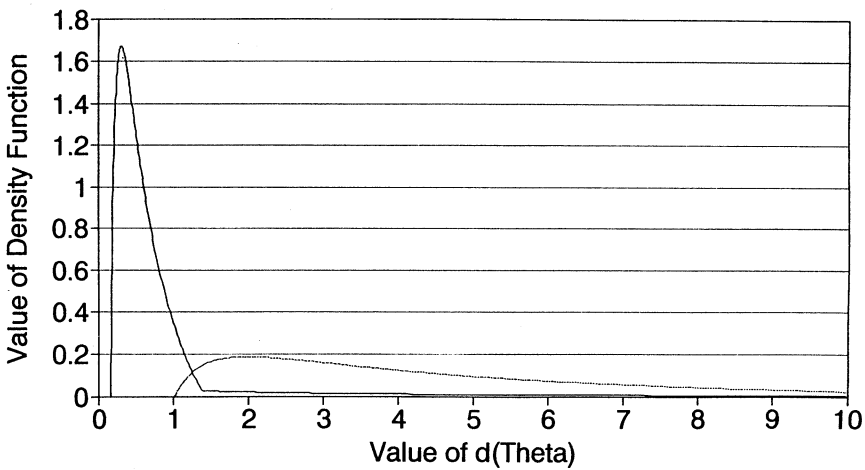
FIGURE 2

——— Model A, ... Model S.

To give the reader some idea of the degree of heterogeneity inherent in any utility's labor efficiency parameter, we computed equal-tailed confidence intervals for both θ and $d(\theta)$ for both sets of parameter estimates and for its various size confidence intervals setting rw_{it} equal to its sample mean. These confidence intervals are equal-tailed in the sense that if $1 - \tau$ is the size of the confidence interval, then $1/2\tau$ of the probability lies below Z_L, the lower bound, and $1/2\tau$ of the probability lies above Z_H, the upper bound. Two conclusions emerge from Table 12. First, for any size confidence interval, the ratio Z_H/Z_L is always much larger for model S

Density of Elasticity of Theta
With Respect to the Real Wage (RW)
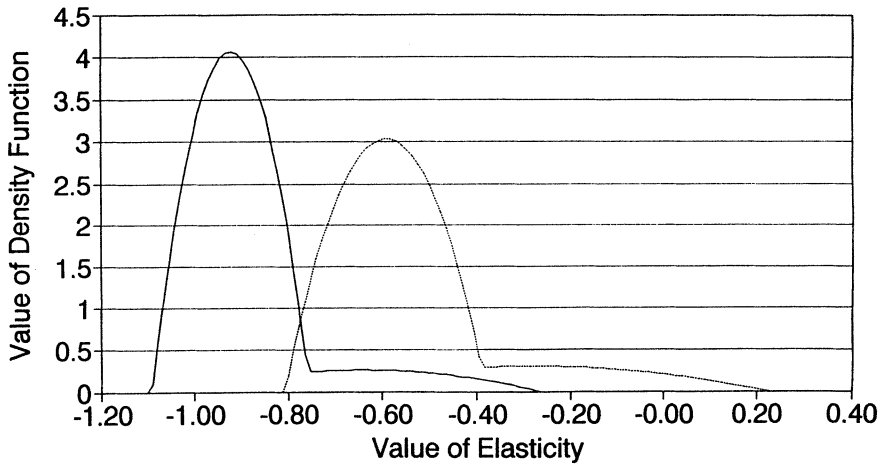
FIGURE 3

——— *Model A,* .... *Model S.*

Density of Elasticity of d(Theta)
With Respect to the Real Wage (RW)
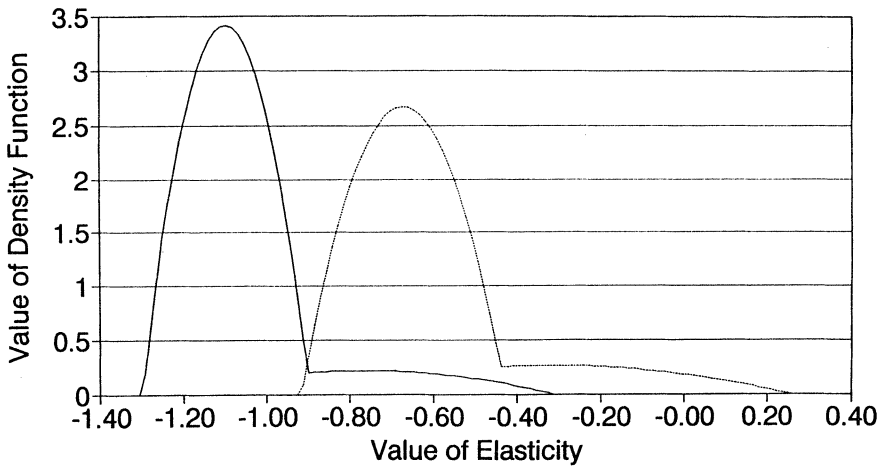
FIGURE 4

——— *Model A,* .... *Model S.*

versus model A. The second conclusion, is that for values of $\tau < 0.15$, the degree of heterogeneity in labor efficiency (θ) for the model A parameter

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TABLE 11

	Expected Values of Elasticities of θ and $d(\theta)$ with respect to rw	
Regulatory Process	$E(d\ln(\theta)/d\ln(rw))$	$E(d\ln(d(\theta))/d\ln(rw))$
Model S	-0.54	-0.61
Model A	-0.89	-1.06

TABLE 12

	Confidence Intervals for θ and $d(\theta)$			
Regulatory Process	Parameter	Z_L	Z_U	prob $[Z_L,Z_U]$
Model S	θ	1.3	80.3	0.95
Model S	θ	1.5	45.5	0.90
Model S	θ	1.7	17.7	0.80
Model A	θ	0.27	6.2	0.95
Model A	θ	0.29	3.5	0.90
Model A	θ	0.33	1.3	0.80
Model S	$d(\theta)$	1.1	143.1	0.95
Model S	$d(\theta)$	1.5	75.6	0.90
Model S	$d(\theta)$	1.8	26.1	0.80
Model A	$d(\theta)$	0.21	8.6	0.95
Model A	$d(\theta)$	0.22	4.4	0.90
Model A	$d(\theta)$	0.26	1.3	0.80

estimates appears to be within the realm of plausibility. For example, for the 80 percent confidence interval, Z_H is approximately 4 times larger than Z_L. These results suggest that model A, may yield a more plausible description of the actual utility-regulator equilibrium.

We now more directly address this issue. Because the same parameters enter into both models A and S, neither model is nested within the other, so that a conventional nested hypothesis test cannot be used to assess which model provides a superior description of the data. Both models do specify the form of the joint distribution of q and $\ln(VC)$ using different functions of the same set of exogenous variables, so that we can take advantage of recent theoretical work by VUONG [1989] and perform a non-nested hypothesis test of model A versus model S. The null hypothesis for Vuong's test is that both model A and model S are equally far from the true data generating process (DGP) in terms of Kullback-Liebler distances. The alternative hypothesis is that one model, in our case model A is closer to the true DGP. Table 13 presents the test statistic, which is asymptotically $N(0,1)$ for this null hypothesis. We find very substantial evidence in favor of the alternative hypothesis that model A is closer to the true DGP. A comparison of the likelihood function values given at the bottom of Table 8 and 10 shows that the value for model A is substantially larger, and the non-nested hypothesis test confirms that this difference is statistically significant.

We now examine the validity of one final implication of our structural model. As discussed in section 3 and shown in Appendix A, if $H(\theta)$ is monotone increasing in θ then the solution to the model A regulator's problem (12) will yield price, capital, and fee schedules which lie within

TABLE 13

Non-nested Test of Model A versus Model S H: Model A and Model S equidistant from True Model K: Model A closer to True Model than is Model S	
Test Statistic	4.30
$\alpha = 0.01$ Critical Value	2.58

the set of feasible (globally incentive compatible) mechanisms. Figure 5 presents a plot of $H(\theta)$ for the model A parameter estimates. The estimated value of $H(\theta)$ in monotone is θ so that our model A estimates will yield an optimal second-best regulator-utility equilibrium. This upward sloping plot of $H(\theta)$ is an additional specification check for model A. Although it is not required for the validity of the model S solution, those parameter estimates also yield an upward sloping $H(\theta)$.

H(Theta) Function
Model A Estimates
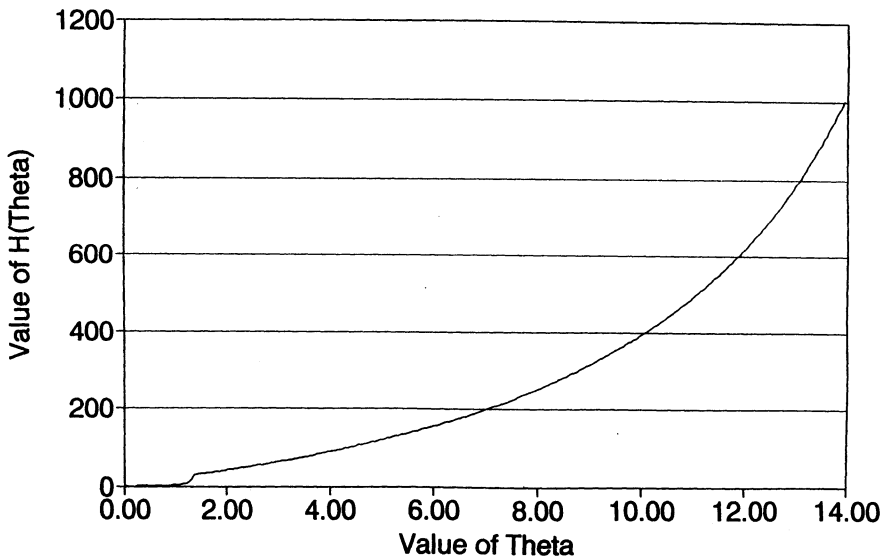
FIGURE 5

As discussed above, model A and model S each provide a different rationalization of the same observed regulator-utility equilibrium. This observation leads is to ask the following question. Suppose that model A is a true description of the observed data, so that the regulator-utility interaction is characterized by asymmetric information, and somehow the regulator manages to implement the the optimal second-best equilibrium–the model A equilibrium or something very close to it. How much less would it cost to produce the same level of output under the symmetric information

regulator-utility equilibrium assuming the same input prices and distribution of θ? Using the parameter estimates from our structural models we can compute estimates of both the change in variable and total costs in moving from the asymmetric to the symmetric information equilibrium. For example, taking the ratio of VC (A) given in (25) to VC (S) given in (23) yields:

$$(44) \qquad\qquad \text{VC (A)}/\text{VC (S)} = [\text{H}^*(\theta)]^{-\alpha}$$

for $\text{H}^*(\theta)$ as defined in equation (40). In Appendix A, we solve for the total cost function for models A and S as a function of the input prices and output level. Taking the ratio of total costs yields:

$$(45) \qquad \text{TC (A)}/\text{TC (S)} = \frac{[\text{H}^*(\theta)][((1-\alpha)/\alpha) + \text{H}^*(\theta)]}{[((1-\alpha)/\alpha) + 1]}$$

under the assumption that $\eta_K = 1$ and

$$\{\varepsilon_d/\varepsilon_q\}^{-(\delta/(1-\alpha))} = \text{E}\left[\{\varepsilon_d/\varepsilon_q\}^{-(\delta/(1-\alpha))}\right].$$

By examination of equation (40) we can see that $[\text{H}(\theta)/\theta]$ will always be greater than zero and less than one. Hence, equation (44) implies that to produce the same level of output at the same input prices under the asymmetric information regulator-utility equilibrium requires less variable costs than it does under the symmetric information equilibrium. However, we can show that under these same restrictions on α, the ratio of total costs under the two equilibria will always be greater than one. The cost of the informational asymmetry is the substantially larger capital costs (relative to the symmetric information equilibrium) that must be paid by all but the most inefficient utilities. All other utilities must overinvest in capital in the asymmetric information equilibrium because of the signaling role that a utility's capital stock plays in this equilibrium.

Figure 6 contains a plot of these two ratios for all of the observations in our sample for the model A parameter estimates. Each ratio is evaluated at the expectation of θ_{it} for that observation so that rw_{it}, the real wage for $(i, t)\,th$ observation, enters into the computation of $\text{E}(\theta_{it})$ rather than the sample mean of the real wage. These plots show that in terms of total production costs, the informational asymmetry between the regulator and utility implies 5 to 12 percent higher total production costs, with an average increase of approximately 8 percent. On the other hand, variable costs are 8 to 13 percent lower under the asymmetric information equilibrium. Implicit in these cost differences is the fact that under the model A equilibrium the firm's optimal capital stock is substantially higher it would be under the model S solution, hence the higher total production costs under model A.

For comparison, in Figure 7 we compute this same plot for the model S parameter estimates. In this case the increase in total costs ranges from 50 percent to 150 percent, with an average of about 100 percent. The variable cost is approximately 50 percent less under model A versus model S. These estimates of the cost of asymmetric information are clearly excessive. This is not surprising given that the parameter estimates on which they are based assume the data is generated by model S. We

Relative Cost of Asymmetric Information
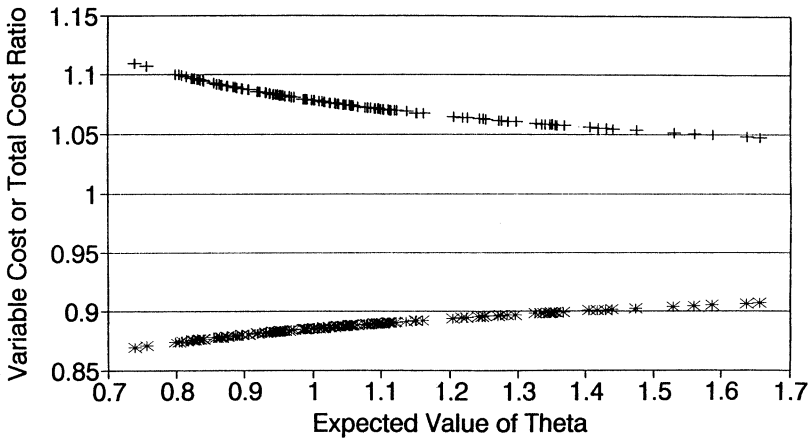## Model A Estimates (301 Observations)

FIGURE 6

$\star$ VC(A)/VC(S), $+$ TC(A)/TC(S).

include these estimates to show that for seemingly reasonable parameter estimates, unbelievable estimates of the cost of asymmetric information can be obtained.

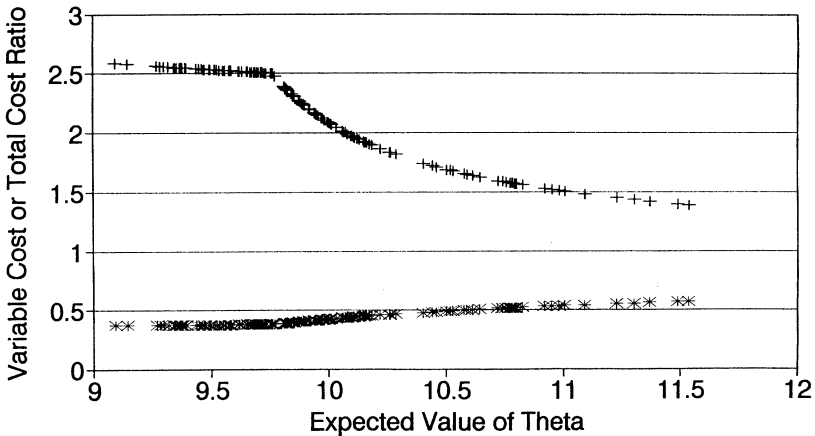# Relative Cost of Asymmetric Information
Model S Estimates (301 Observations)

FIGURE 7

$\star$ VC(A)/VC(S), $+$ TC(A)/TC(S).

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The costs of asymmetric information obtained from the model A parameter estimates do not seem large when viewed in terms of a percentage of the model S total costs. Nevertheless, given the large dollar magnitude of total production costs for each utility, summing these production costs over all of the utilities in our sample and multiplying by 8 percent yields a very large dollar magnitude.

The calculations shown in Figures 6 and 7 measure the increased production costs for the same level of output under the two information structures. However, given the same set of primitives–input prices, demand and production functions and the value of θ–for a given utility, the level of output produced will differ under the two information structures. Taking the ratio the two reduced form output equations given in Appendix A, equations (A.11) and (A.15) respectively, yields

$$(46) \qquad\qquad Q_d(A)/Q_d(S) = H^*(\theta)^{\kappa(1-\alpha)\iota}$$

where $\kappa(1-\alpha)\iota$ is the coefficient on $\ln(H(\theta))$ in the reduced form output equation. Equation (46) gives the ratio of output produced under the two information structures for the same set of economic primitives. From this calculation we can assess the welfare impacts to consumers of asymmetric information. Figure 8 plots this ratio for all observations in the sample evaluated at $\theta_{it} = E(\theta_{it})$. This output reduction due to informational asymmetries as computed using our model A parameter estimates ranges from 32 to 23 percent. These estimates imply sizeable welfare losses to consumers due to asymmetric information at this value of θ_{it}. However, at the sample median of θ_{it} this range drops to an 8 to 12 percent reduction in output. Thus, the major cost of asymmetric information in the regulatory

Output Reduction from Asymmetric Info
(301 Observations, Model A Estimates)
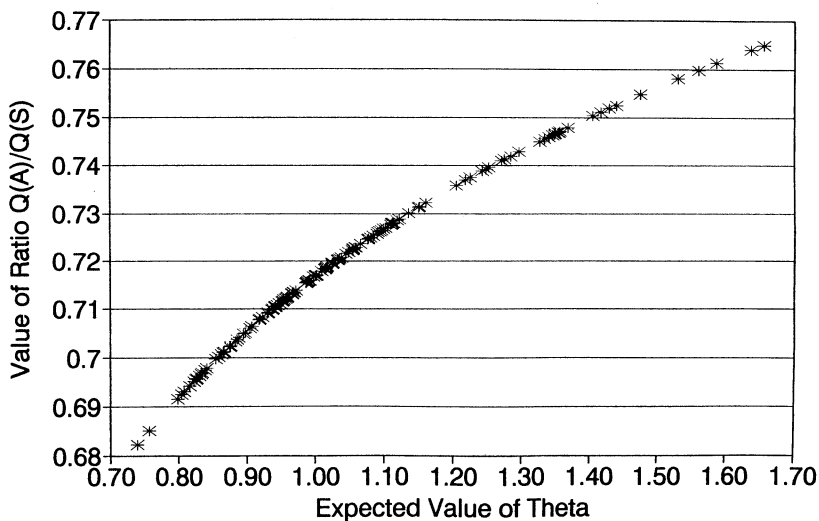
FIGURE 8

process appears to be the welfare loss to consumers from higher prices (and therefore reduced output) under the model A versus model S solution.

Our final set of graphs plots several observable magnitudes associated with each observation as function of that observation's expected value of θ for the model A parameter estimates. Figure 9 contains the plot of the expected value of θ against that observation's output. From this plot it appears that there is a positive relationship between efficiency (lower values of θ) and total output. Figure 10 plots total variable costs and finds the expected relationship given the results of Figure 9–higher costs are associated with greater efficiency, because the more efficient utilities tend to produce more output. Finally, Figure 11 shows that the more efficient utilities also tend to have larger absolute returns to capital, as measured by the difference between total revenues and variable costs.

Output in Millions of CCF
Model A Estimates (301 Observations)
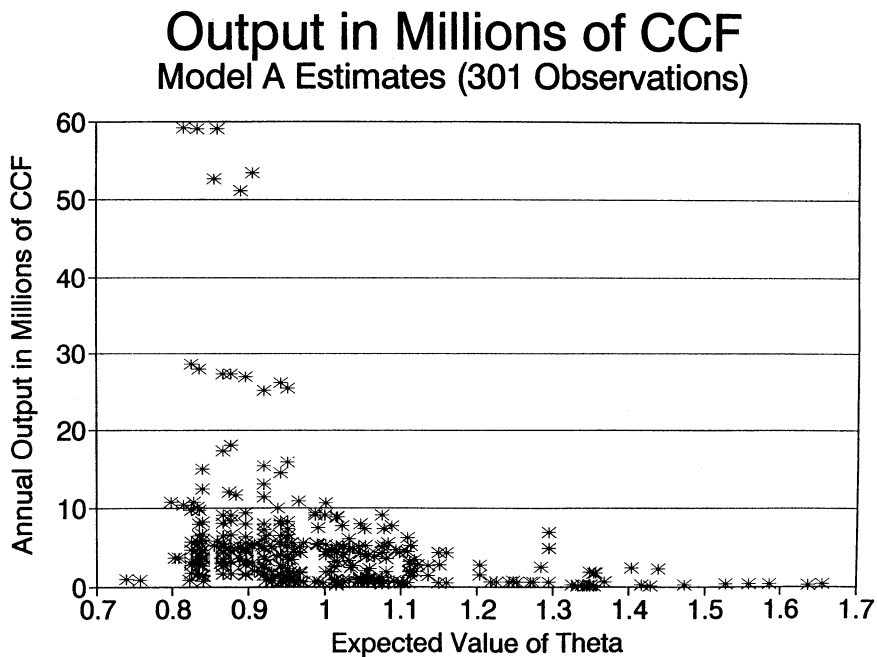
FIGURE 9

Summarizing our results, there are three implications of our private information model estimates for the California Class A Water Utility Industry. First, once all factors of production are allowed to vary, returns to scale in the industry are slightly decreasing. Second, the increased cost of production due to the existence of informational asymmetries are significant, although by no means excessive. The major impact of asymmetric information is the higher prices and lower output, rather than the increased production costs for given level of output. Finally, among the two private information models, model A appears to provide a statistically significantly superior description of the actual regulator–utility equilibrium for the functional forms for production and demand we have chosen, despite estimating the same number of parameters as model S.

Annual Production Variable Costs (VC)
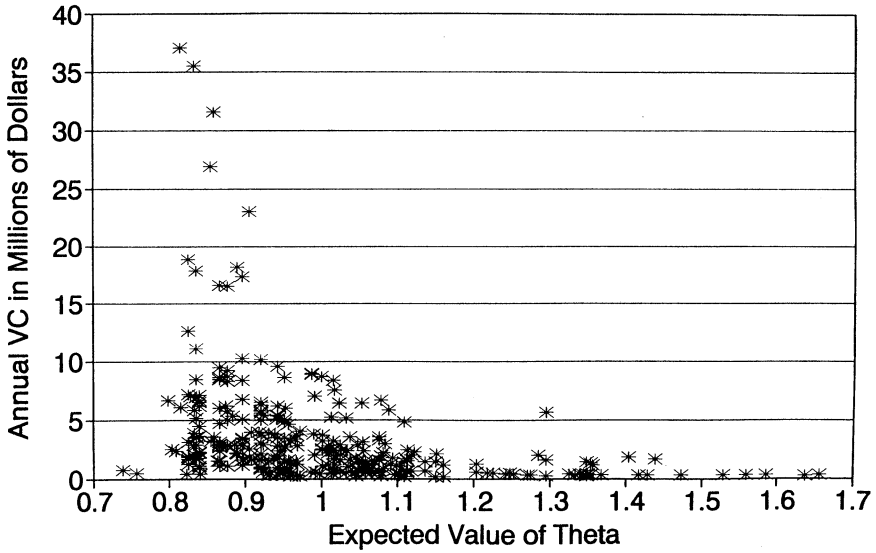## Model A Estimates (301 Observations)

FIGURE 10

Annual Total Return to Capital
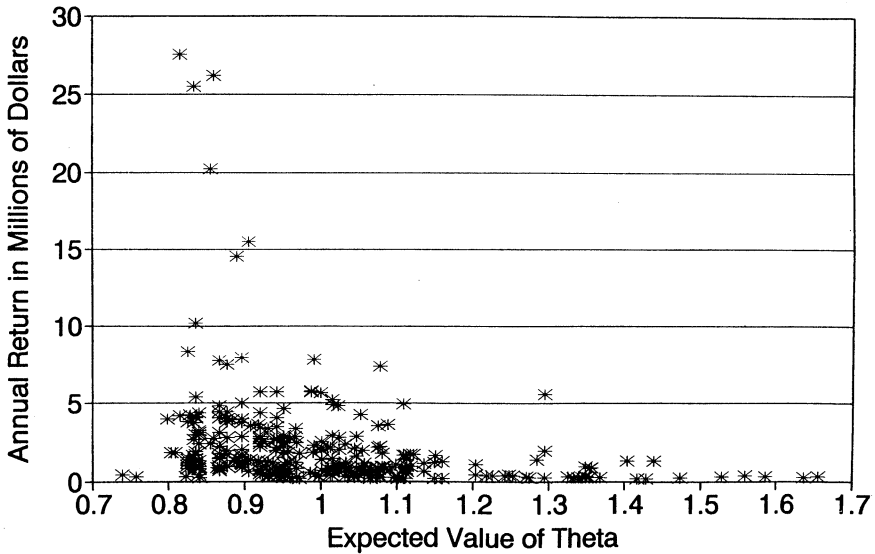## Model A Estimates (301 Observations)

FIGURE 11

7 Conclusions and Caveats

In this paper we presented two models of the utility-regulator interaction when the utility possesses private information about its production process which is either known or unknown to the regulator, but always unknown to the econometrician. We solved for the utility-regulator equilibrium for both of these models and derived the form of the utility's unconditional variable cost function for both of these models. We then assumed a parametric functional form for the utility's underlying production technology and derived the parametric form of the variable cost function in terms of the parameters of the utility's production function. Using assumptions on the distributions of the three kinds of underlying structural disturbances, we derived a procedure to consistently estimate the parameters of the utility's production function taking into account this unobservable private information possessed by the utility and the assumed utility-regulator interaction.

The parameters of the water delivery technology estimated using our proceedure were quite different from those obtained using conventional full-information cost function approaches. We found far less economies to scale in the production technology. In fact, our estimates indicate the water delivery production process exhibits very slight decreasing returns to scale, whereas conventional techniques implied substantial scale economies as well as nonsensical elasticities of total cost with respect to input prices for most of the conventional models estimated. On the other hand, for both the symmetric and asymmetric private information models, all of the cost elasticity estimates are within the realm of economic plausibility.

Comparing the symmetric information model to the asymmetric information model we concluded (based on the production function parameter estimates and the estimated distributions of the unobserved labor efficiency parameters) that the regulator-utility equilibrium implied by the asymmetric information model led to more reasonable estimates for both of these magnitudes. In addition, a non-nested hypothesis test led to rejection of the equality of models A and S in terms of proximity of the true data generating process in favor of the superiority of model A. Our modeling framework also allowed us to compute a model-based estimate of the increased production costs borne by producers due to the presence of asymmetric information versus full-information in the regulatory process. In addition, we also computed an estimate of the output reduction due to informational asymmetries in the regulatory process. Although we did find noticeable increases in production costs due to informational asymmetries at the expected value of θ_{it} for each utility, the greatest impact seems to be the welfare loss to consumers in the form of higher prices and lower output under the asymmetric information equilibrium.

As with any structural econometric model estimation exercise, there are numerous caveats associated with our results. First is the choice of the specific behavioral assumptions for each of the agents. Second is the selection of the specific functional forms used. Although we can by no

means test our model against all possible unrestricted alternatives or examine the validity or reasonableness of all possible implications of our structural model, we have tried to address both of these major caveats associated with our modeling effort by presenting various specification tests or checks throughout the empirical analysis.

In light of the results presented here, we do feel that our model has substantial promise as an economic-theory-based methodology for incorporating into an econometric model of the utility-regulator equilibrium the distortions from cost-minimizing behavior due to informational asymmetries. Although our stylized description of the regulatory–utility interaction cannot describe the actual regulatory review process, our econometric model based on the assumptions of model A appears to yield a satisfactory characterization of the observed economic magnitudes arising from this economic interaction. In addition, these structural models have the useful feature of recovering estimates of the increased production costs and reduced output which arise from the asymmetric private information possessed by the utility in the regulatory process.

The telecommunications industry appears to be a particularly promising future application of this private information econometric modeling framework [15]. All previous econometric studies of the structure of technology in this industry have used the standard duality theory approach which assumes cost-minimizing behavior on the part of the utility to recover estimates of the characteristics of its underlying production technology. Examples of this work are CHRISTENSEN, CUMMINGS and SCHOECH [1983] and EVANS and HECKMAN [1983 and 1986]. This research has focused on estimating of economies of scale and scope in the supply of telecommunications services to answer the question of whether the industry exhibits the characteristics of a natural monopoly. CHARNES, COOPER and SUEYOSHI [1988] have also addressed this question of subbaddivity using an alternative modeling approach. In addition, in a discussion of the divergence between the results in EVANS and HECKMAN [1983] and those in CHARNES, COOPER and SUEYOSHI [1988], EVANS and HECKMAN [1988] question the assumption of cost minimization embodied in the use of Shepard's Lemma to recover the characteristics of the Bell System's production technology. Given the large differences in the returns to scale estimates obtained using the private information modeling framework versus the conventional minimum-cost framework in this study and the necessity of consistent estimates of an industry's underlying technology to deciding the question of the presence of natural monopoly, the present modeling framework may provide useful input into deciding this important question.

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15. I am grateful to an anonymous referee for suggestioning this application.

APPENDIX A

Introduction

This appendix derives the conditional (on the capital stock selection) variable cost function for the Cobb-Douglas production function used to estimate the parameters of the water delivery production process. Using this conditional variable cost function, we then derive the the the unconditional variable cost function and reduced form representation for the total output produced for both the symmetric information and asymmetric information utility-regulator equilibria. These are the two equations we estimate for both the symmetric and asymmetric equilibria to the recover the parameters of the water delivery production process. Next, we derive the form of the total cost functions for both model S and model A for our relative cost of asymmetric information calculations in section 6. We then derive the set of feasible (incentive compatible) mechanisms that satisfy the individual rationality constraint and can be implemented by the regulator for our econometric model. We then derive a necessary condition on the parameters of our econometric model which guarantees that the optimum of (12) lies in this set of feasible mechanisms.

Conditional Variable Cost Function

Simplifying equation (21) yields the following form for the water delivery production process:

$$(A.1) \qquad Q = \beta_0\, \theta^{-(\beta_L + \beta_E)}\, K^{\beta_K}\, L^{\beta_L}\, E^{\beta_E}\, \varepsilon_q$$

The first-order conditions from solving (3) subject to (A.1) yields the following conditional factor demand functions:

$$(A.2) \qquad E = \beta_0^{-1/(\beta_L+\beta_E)}\, \theta\, K^{-\beta_K/(\beta_L+\beta_E)}$$
$$\times \left[\frac{\beta_L\, pe}{\beta_E\, w}\right]^{-\beta_L/(\beta_L+\beta_E)} Q^{-1/(\beta_L+\beta_E)}\, \varepsilon_q^{-1/(\beta_L+\beta_E)}\, \eta_E$$

$$(A.3) \qquad L = \beta_0^{-1/(\beta_L+\beta_E)}\, \theta\, K^{-\beta_K/(\beta_L+\beta_E)}$$
$$\times \left[\frac{\beta_L\, pe}{\beta_E\, w}\right]^{\beta_E/(\beta_L+\beta_E)} Q^{-1/(\beta_L+\beta_E)}\, \varepsilon_q^{-1/(\beta_L+\beta_E)}\, \eta_L$$

The disturbances η_L and η_E are non-negative multiplicative mean-one random disturbances which have been added to the model to allow the first-order conditions from (3) to hold only in expectation from the perspective of the econometrician. These disturbances are assumed to be known by both the regulator and the utility, but are unknown to the econometrician. This

assumption implies that the two agents in the interaction are setting their first-order conditions exactly to zero, and the econometrician observes these same first-order conditions up to mean-one multiplicative errors. There are disturbances of the form η_k, where k indexes the choice variable in the optimization problem, included in all first-order conditions to both the model A and model S solutions to allow for fact that the value of a choice variable can deviate from that predicted by our model. For the case of (A.2) and (A.3), these errors allow for the fact that the factor demand functions for E and L do not predict the observed E and L without error for all observations for any values of the parameters. Accounting for presence of these errors is necessary to obtain an internally consistent statistical model which captures all sources of randomness in the actual underlying data generation process.

Substituting (A.2) and (A.3) back into the expression for variable cost given in (3) yields the conditional (on K) variable cost function given in (22) and the composite disturbance

$$(A.4) \qquad u = (\eta_L) \left[\left(\frac{\beta_L}{\beta_E} \right)^{\beta_E/(\beta_L+\beta_E)} + \left(\frac{\beta_L}{\beta_E} \right)^{-\beta_L/(\beta_L+\beta_E)} \left(\frac{\eta_E}{\eta_L} \right) \right].$$

We assume that ε_q, η_L and $a^* + b^* \left(\dfrac{\eta_E}{\eta_L} \right)$ are lognormally distributed, where

$$(A.5) \qquad a^* = \left(\frac{\beta_L}{\beta_K} \right)^{\beta_E/(\beta_L+\beta_E)} \qquad \text{and} \qquad b^* = \left(\frac{\beta_L}{\beta_K} \right)^{-\beta_L/(\beta_L+\beta_E)}.$$

These assumptions imply that the composite disturbance u is lognormally distributed, so that the product of u and $\varepsilon_q^{-1/(\beta_K+\beta_L)}$ is also lognormally distributed.

Unconditional Variable Cost Function

Using this conditional variable cost function, we now derive the unconditional variable cost function and the reduced form expression for the output level of the utility. The first-order conditions for the optimal capital stock selection yield the variable cost function. The first-order condition for the optimal price in combination with the output demand function yield the reduced form expression for the output produced.

As described in Section 3, both the utility and regulator are assumed to know the distribution of both ε_q, the post-capital-stock-selection shock to the utility's production function, and ε_d, the post-capital-stock-selection stochastic portion of the utility's demand for output. Consequently, the utility optimizes against these shocks, so that in formulating (5), the regulator takes this fact into account when solving for the optimal fee and price schedules. We assume that the disturbances η_L and η_E are known to both the regulator and the utility, but are treated as random variables by the econometrician so that the actual value of u must carried through in the computation of the unconditional variable cost function and output equation.

Solving (9) using the expression for the conditional variable cost function given in (22) yields the expression given in (23) with

(A.6) $\qquad D^* = \beta_0^{-\delta} \left[\left(\dfrac{\alpha}{1-\alpha} \right) [E_{q,\,d} \{(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}\}]^{-\alpha} \right.$

(A.7) $\qquad\qquad\qquad \nu = u^{1-\alpha}\, \eta_K^{-\alpha}\, \varepsilon_q^{-\frac{\delta}{1-\alpha}}\, \varepsilon_d^{\frac{\delta\alpha}{1-\alpha}}$

for δ and α as defined in (24).

To derive the reduced form expression for ouput demanded (and produced), we use the variable cost function (22) and the first-order condition for the optimal selection of p given in (8). This yields

(A.8) $\qquad\qquad\qquad p = C\, r^{\alpha}\, w^{\gamma}\, pe^{1-\alpha-\gamma}\, Q_d^{\delta-1}\, \theta^{1-\alpha}\, h$

where

(A.9) $\quad C = \beta_0^{-\delta}\, [E_{q,\,d}\,\{(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}\}]^{1-\alpha}\, (\delta/\alpha)\, \{E_d\,(\varepsilon_d)\}^{-1}\, (\alpha/(1-\alpha))^{1-\alpha}$

and

(A.10) $\qquad\qquad\qquad h = u^{1-\alpha}\, \eta_K^{-\alpha}\, \eta_p\, \varepsilon_d^{1-\delta}.$

Recall that the observed output of the utility is $Q_d = \exp(Z'b)\, p^{-\kappa}\, \varepsilon_d$. Using this equation and (A.8) yields the following expression for Q_d in terms of only exogenous variables and disturbances:

(A.11) $\quad Q_d = C^{\kappa\iota}\, \exp(\iota\,(Z'\,b))\, w^{\kappa\gamma\iota}\, r^{\kappa\alpha\iota}\, pe^{\kappa\,(1-\gamma-\alpha)\,\iota}\, \theta^{\kappa\,(1-\alpha)\,\iota}\, h^{\kappa\iota}\, \varepsilon_d^{\iota}$

where $\iota = 1/(1 + \kappa - \kappa\,\delta)$. Comparing (A.11) to (30), we can define ψ in terms of the all of the disturbances to the regulatory process as:

(A.12) $\qquad \psi = \kappa\iota \ln(h) + \iota \ln(\varepsilon_d) - E\,[\kappa\iota \ln(h) + \iota \ln(\varepsilon_d)].$

Taking the natural logarithm of both sides of (A.8) and substituting the logarithm of (32) for $\ln(\theta)$ gives:

(A.13) $\quad \ln(Q_d) = C^* + (Z'\,b)\,\iota + \kappa\gamma\iota \ln(w) + \kappa\alpha\iota \ln(r)$
$\qquad\qquad\qquad + \kappa\,(1 - \gamma - \alpha)\,\iota \ln(pe) + a\,\kappa\,(1-\alpha)\,\iota \ln(rw) + \psi,$

where $C^* = \kappa\iota \ln(C) + E\,[\kappa\iota \ln(h) + \iota \ln(\varepsilon_d)] + \kappa\,(1-\alpha)\,\iota \ln(B)$. Equation (A.13) defines the elements of Λ^* in terms of the parameters of the demand function and production function. Both ψ and $\zeta = \ln(\nu) - \mu_\nu$ are each linear functions of the same normally distributed random variables, $\ln(\varepsilon_d)$, $\ln(\eta_K)$, and $\ln(u)$, in addition to other structural disturbances which are not common to the two composite disturbances. Consequently, we would

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expect nonzero correlation between ψ and ζ $(\rho_{\psi\zeta} \neq 0)$, which we allow for in our estimation.

To derive the variable cost function and output demand equation for the asymmetric information solution we proceed in the same fashion as the symmetric information case. Solving (19) using the expression for the conditional (on K) variable cost function given in (22) yields the expression given in (25).

To derive the reduced form expression for output demanded (and produced), we use the variable cost function (22) and the first-order condition for the optimal selection of p given in (18). This yields

$$(A.14) \qquad p = C\, r^{\alpha}\, w^{\gamma}\, pe^{1-\alpha-\gamma}\, Q_d^{\delta-1}\, H(\theta)^{1-\alpha}\, h$$

where $H(\theta) = \left[\theta + \dfrac{F(\theta)}{f(\theta)}\right]$. The main difference between symmetric information and asymmetric information solutions is the presence of $H(\theta)$ in both the unconditional variable cost function and the price function (A.14).

To derive the reduced form expression for the utility's output, we utilize the demand function facing the utility and equation (A.14) to derive the following expression for Q_d in terms of only exogenous variables and disturbances:

$$(A.15) \qquad \begin{aligned} Q_d &= C^{\kappa\iota}\, \exp\left(\iota\left(Z'b\right)\right) w^{\kappa\gamma\iota}\, r^{\kappa\alpha\iota} \\ &\quad \times pe^{\kappa\,(1-\gamma-\alpha)\,\iota}\, H(\theta)^{\kappa\,(1-\alpha)\,\iota}\, h^{\kappa\iota}\, \varepsilon_d^{\iota}, \end{aligned}$$

Taking the natural logarithm of both sides of (A.15) and utilizing expressions (32) and (40) gives:

$$(A.16) \quad \begin{aligned} \ln(Q_d) &= C^* + (Z'b)\,\iota + \kappa\gamma\iota\ln(w) \\ &\quad + \kappa\alpha\iota\ln(r) + \kappa\,(1-\gamma-\alpha)\,\iota\ln(pe) \\ &\quad + \kappa\,(1-\alpha)\,\iota\ln(H^*(\theta)) + a\,\kappa\,(1-\alpha)\,\iota\ln(rw) + \psi. \end{aligned}$$

This equation defines the elements of Φ given in (39) in terms of the parameters the production function and demand function. As discussed in section 6, θ enters the logarithm of output function only through $\ln(H(\theta))$, or equivalently $\ln(H^*(\theta))$ and $\ln(\theta)$ have the same coefficient in the logarithm of output equation.

Model S and Model A Total Cost Functions

To derive the total cost function for model S we substitute the expression for the optimal capital stock selection arising from the solution of (5) into the expression for total costs given in equation (4). Performing this substitution

and re-arranging yields:

(A.17) $\text{TC}(S) = \beta_0^{-\delta}\, \theta^{1-\alpha}\, w^\gamma\, r^\alpha\, pe^{1-\gamma-\alpha}$

$$\times\, Q^\delta\, \eta_K^{1-\alpha}\, u^{1-\alpha}\, [\text{E}\,(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}]^{1-\alpha}$$

$$\times\, \left[\left(\frac{(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}}{\eta_K\, \text{E}\,[(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}]}\right)\left(\frac{1-\alpha}{\alpha}\right)+1\right]$$

The total cost function for model A is derived using the expression for the optimal capital stock selection from the solution of (12). Following this procedure we obtain:

(A.18) $\text{TC}(A) = \beta_0^{-\delta}\, \theta^{1-\alpha}\, [\text{H}\,(\theta)/\theta]^{-\alpha}\, w^\gamma\, r^\alpha\, pe^{1-\gamma-\alpha}$

$$\times\, Q^\delta\, \eta_K^{1-\alpha}\, u^{1-\alpha}\, [\text{E}\,(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}]^{1-\alpha}$$

$$\times\, \left[\left(\frac{(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}}{\eta_K\, \text{E}\,[(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}]}\right)\left(\frac{1-\alpha}{\alpha}\right)+[\text{H}\,(\theta)/\theta]\right]$$

Taking the ratio of (A.18) to (A.17) under the assumption that

$$\left(\frac{(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}}{\eta_K\, \text{E}\,[(\varepsilon_d/\varepsilon_q)^{\frac{\delta}{1-\alpha}}]}\right) = 1$$

gives the expression in equation (45).

Characterization of Set of Feasible Mechanisms

To derive the set of feasible (globally incentive compatible) mechanisms we follow the four step procedure given in BARON [1989]. Section 4 presents the first three steps of this procedure.

Step four involves deriving restrictions on the capital function $K\,(\theta)$ and the parameters of our model which yield globally incentive compatible price and fixed fee schedules, $p\,(K)$ and $T\,(K)$.

Consider the utility's capital stock choice problem given the regulator's announced price and fee functions (which depend on its capital stock choice), $p\,(K)$ and $T\,(K)$. We denote the utility's expected profits in this case as:

(A.19) $\text{E}_{q,d}\,[\pi\,(p\,(K),\, T\,(K),\, K,\, \theta)]$

$$= p\,(K)\, Q\,(p\,(K))\, \text{E}_d\,(\varepsilon_d) + T\,(K)$$

$$- \text{E}_{q,d}\,[\text{VC}\,(K,\, Q\,(p\,(K))\,\varepsilon_d,\, \theta,\, \varepsilon_q,\, u)] - r\,K$$

$$= \text{E}_{q,d}\,[\text{R}\,(p\,(K))]$$

$$- \text{E}_{q,d}\,[\text{VC}\,(K,\, Q\,(p\,(K))\,\varepsilon_d,\, \theta,\, \varepsilon_q,\, u)] - r\,K,$$

where $\text{R}\,(p\,(K))$ is the utility's total revenue function. We can now apply the results of Theorem 2.15 HOLMSTROM [1977], which in our case states that if

(A.20) $$\frac{\partial}{\partial\theta}\left[\frac{\partial\text{E}_{q,d}\,[\pi]/\partial K}{\partial\text{E}_{q,d}\,[\pi]/\partial p}\right] > 0,$$

then if $K(\theta)$ is nondecreasing, the resulting price function and fixed fee functions $p(K)$ and $T(K)$ are globally incentive compatibile. The theorem also states that if (A.20) holds and the price and fee functions are globally incentive compatible then $K(\theta)$ must be nondecreasing.

To apply the results of this theorem to our econometric model we must derive restrictions on the primatives of our economic environment (e.g., the utility's production function, demand function, and distribution of θ) which guarantee that the solution to (12) will yield a nondecreasing $K(\theta)$ and expected profit function which satisfies (A.20).

To derive the restrictions necessary for a nondecreasing $K(\theta)$ function we differentiate the first-order conditions for the regulator's optimal $p(\theta)$ and $K(\theta)$ functions given in (18) and (19) with respect to θ and solve for $K'(\theta)$, utilizing the deterministic portion of the utility's demand function $Q(p) = \exp(Z'b)p^{-\kappa}$. Although it is difficult to provide conditions on the regulatory environment which guarantee a nondecreasing $K(\theta)$ for a general production function, we are able to derive a sufficient condition for the Cobb-Douglas production function and constant elasticity demand function used in our empirical work.

In particular, if the density function $f(\theta)$ is such that

$$(A.21) \qquad H(\theta) = \left[\frac{F(\theta)}{f(\theta)} + \theta\right]$$

is nondecreasing in θ and the following condition holds

$$(A.22) \qquad \kappa \geq -1,$$

then the optimal $K(\theta)$ from solving (12) will be nondecreasing in θ and equation (A.20) will hold for all θ. As we show in Figure 5, the model A estimated $H(\theta)$ is montone increasing in θ. The restriction (A.22) implies that the demand for water cannot be too elastic. Given the nature of most goods produced by public utilities (in our case water), assuming $\kappa \geq -1$ is not unreasonable.

APPENDIX B

This appendix describes the construction of the three capital stock and capital service costs measures used in our conventional cost function estimation. The district annual reports give several measures of the capital stock, accumulated depreciation and the amount of investment expenditures. The first two measures are simply sums and differences of several of these magnitudes. The first measure of the capital stock takes the ending balance of the district's balance sheet capital stock and substracts the ending balance of the sum of all its accumulated depreciation to date. To construct the capital service costs associated with this measure, we simply multiply that period's rate of return on capital by this capital stock measure. This capital cost measure is then added to the utility's total operating expenses (available in the annual report) to yield the utility's total costs for that period. Because this measure of the capital stock closely tracks the utility's rate base, and multiplying its rate base by the required rate of return on capital yields the utility's capital stock servicing revenue requirements, we refer to this capital cost measure as the regulator's definition and abbreviate it REGC. Our other measure uses the same definition of the capital stock, but uses a different measure of capital service costs. This measure, what we call the utility's measure, uses the difference of ending accumulated depreciation and beginning accumulated depreciation plus current investment expenditures. We abbreviate this measure UTILC.

The final measure we use builds on the work on PAKES and GRILICHES [1984]. Following their lead, for each time period we look for the linear combination of the beginning and ending capital stocks (ENDBAL and BEGBAL), and beginning and ending accumulated depreciation stocks (DENDBAL and DBEGBAL), which best explains total revenues (REVTOT) less total operating expenses (TOTOPEX). Presumably, the difference of total revenues and total operating costs is the return to capital; we would expect that the linear combination of these four variables which best explains this return to capital is the best measure of capital service costs for that year. This best linear combination is found by regressing RETCAP = REVTOT-TOTOPEX on ENDBAL, BEGBAL, DENDBAL, and DBEGBAL interacted with a full set of time dummies (from 1980 to 1988), without a constant term. This model implies that the exact linear combination of the four capital variables which aggregate to give total capital service costs varies over time, but remains the same across districts for a given time period. This model takes the form:

$$(B.1) \quad \text{RETCAP}_{it} = \sum_{t=1980}^{1988} (b_{1t}\, \text{ENDBAL}_{it} + b_{2t}\, \text{BEGBAL}_{it}$$
$$+ b_{3t}\, \text{DENDBAL}_{it} + b_{4t}\, \text{DBEGBAL}_{it})\, \text{YEAR}_{it} + e_{it}$$
$$= r_{it}\, \text{K}_{it} + e_{it}$$

where K_{it} is the ith utility's true but unobserved capital stock in year t as assumed by this measure, and the b_{kt} $(k = 1, \ldots, 4)$ $(t = 1980, \ldots, 1990)$

are the time-varying coefficients which aggregate the capital stock measures into a measure of capital service costs. Finally, YEAR_{it} ($t = 1980, \ldots, 1988$) is a set of dummy variables which take on the value 1 for observations from that year and zero otherwise. To recover an estimate of K_{it} for each observation, we divide the fitted value from this regression, RETCAP (FIT), by that observation's rate of return on capital. The logic for this process is that RETCAP (FIT) is an estimate of $r_{it}\,\text{K}_{it}$, so that dividing these costs by the required rate of return yields the capital stock which gave rise to those capital costs. We call this measure the modified Pakes and Griliches capital stock measure (MPGC).

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