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Decision Support

Robust optimization policy benchmarks and modeling errors in natural gas[☆]

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ABSTRACT

The problem of regulating natural gas procurement has become a huge burden to regulators, especially due to the plethora of complicated financial contracts that are now being used by local distribution companies (LDCs) for risk management purposes. Muthuraman, Aouam, and Rardin (2008) proposed a new benchmarking scheme, called *policy benchmarks* and showed that these benchmarks do not suffer from the usual criticisms that are made against existing regulatory methods. Such policy benchmarks based regulation has however faced hurdles in being adopted. One of the primary reasons has been concerns over its robustness.

We demonstrate in this paper that when modeling errors are present, the policy benchmarks proposed earlier can backfire and are hence, as suspected, not well suited for regulation. We begin our analysis with a more general model than the one that has been used earlier by accommodating the LDC's ability to reduce cost by exerting effort, as in classical economics. We derive solutions to the LDCÕs problem, find closed form solutions for the regulator's optimal fee fraction along with risk sharing implications, and provide insights into the policy benchmark selection. We then construct a robust-optimization based policy benchmarking mechanism that inherits all the original benefits. We further demonstrate that these, unlike the earlier benchmarks, are robust against modeling errors.

1. Introduction

Utility firms that usually have natural monopolies are always subject to government regulations (Laffont & Tirole, 1993). Firms that procure natural gas from various well-heads and suppliers, and distribute it to consumers, are called local distribution companies (LDCs). These consumers usually do not have a choice of their natural gas provider. Naturally, government oversight of this procurement process and the passing of a fee to consumers is necessary. This oversight has in the recent past become very complicated and unmanageable due to the multitude of derivatives and financial products that LDC's have begun to use in their procurement for risk management. Deregulation of several related sectors and other market changes are further adding to this complication. Under the usual *cost of service* based regulation, the regulator carries the burden of digging through and understanding the rationality behind every line item of the LDC's books. One can also argue that such a regulatory framework gives the LDCs little incentive to manage their procurement activities efficiently (Shleifer, 1985), and more incentive to just justify their activities. Formal models that demonstrate this lack of incentive can be found in Baron and Bondt (1981) and Isaac (1982). Instead, benchmarking-based regulatory schemes are being increasingly perceived as the right direction to pursue. Benchmarking schemes simply contrast the LDC incurred cost to a specific benchmark and provide incentives to beat the benchmark. Various regulatory bodies have been experimenting with simple benchmark mechanisms for several years now and still find inherent deficiencies in the ones they have tried. Existing benchmarking schemes are often criticized as unfair either to the consumer or to the LDC since they just use historical data or future spot prices to compute the benchmark, both of which can result in significant biases.

Other contracts that have been considered include *fixed price* contracts and *linear incentive* contracts. Fixed-price contracts offer the highest incentive for cost reduction (Brennan, 1989). However, due to the uncertainty inherent in natural gas prices, the regulator must set a relatively high fixed price in order to ensure the financial viability

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of the LDC. This results in a high fee to consumers (Laffont & Tirole, 1993 and Joskow, 2006). Cost of service and fixed price contracts are two extremes, one offering a maximum, and the other a minimum incentive. A linear incentive contract (or profit sharing contract), lies between the two (Schmalensee, 1989). Here, the fee to consumers, is a fixed component plus a fraction of the LDC's realized cost. The challenge obviously being in the regulator picking the right magnitudes for the fixed and the proportional components to steer the LDC to behave in a manner that the regulator needs. Regulators have also used various other mechanisms, like yardstick regulation (Lan, Zhao, & Tang, 2013; Shleifer, 1985). Yardstick regulation uses average spot prices or the weighted average purchase cost (WAPC) of a set of LDCs, to contrast against and calculate incentives (Crew, 1997). These are criticized for the obvious fact that one cannot compare LDCs that differ in size, geographical location, pipeline connectivity, demand distribution, and various other factors.

In a previous work, Muthuraman et al. (2008), we proposed a new benchmarking scheme, called *policy benchmarks* along with detailed and rigorous characterizations. We showed that these policy benchmarks do not suffer from the usual criticisms. Rather than use historical data or future spot prices to compute benchmarks, these simply prescribe a specific procurement policy and an incentive fraction. At the end of the valuation period, the incentive is calculated as being proportional to the cost difference between the LDC's procurement cost and the cost incurred by the prescribed benchmark policy. Procurement policy choices are restricted to depend only on publicly available contracts. The regulator is tasked then only with the problem of picking the right policy for the benchmark and the fraction to be used. To do this the regulator has to rely upon a natural gas price model. The paper showed how to pick a benchmark procurement policy amongst a class of policies that only use a fixed fraction of various contracts and also demonstrated that the fee to consumers was minimized, provided the natural gas price model was correct. The restriction on the class of fixed-fraction portfolio based policies helped the analysis significantly while making it very restrictive in comparison to the commonly used dynamic policies and hence poses significant challenges in being implemented in the real world.

1.1. Modeling errors and our contribution

If the natural gas price model used by the regulator has a modeling error, it is not clear how it will impact the fee to consumers. This problem is the central focus of this paper. Modeling errors are a fact of life in energy markets and hence this is a fundamental question to resolve, especially if we are hoping for a widespread adoption of such incentive mechanisms. Let's say that the regulator chooses a policy benchmark and an incentive fraction using a model with error, and the LDCs react to that benchmark with their response procurement strategy. We show that policy benchmarks using fixed-fraction portfolios may backfire and provide a much higher fee to consumers. Realizing that fixed-fraction portfolio families will not suffice, we construct more sophisticated policies and show how to pick policy benchmarks under this setting. While pursuing this central objective, we also extend the previous set up in several ways. As in classical economics, we now allow the LDC to invest "effort" to reduce procurement costs. As in the classical principal-agent setting, effort includes all cost reductions actions. These include bargaining, marketing, search for suppliers, expert consulting, creating demand-side management (DSM) programs (Crew, 1997), etc. We further, unlike in Muthuraman et al. (2008), obtain closed-form solutions for incentive fractions.

An ad-hoc way of mitigating the sensitivity to modeling errors would be to benchmark against a portfolio of policy benchmarks. Aouam, Rardin, and Abrache (2010) discusses this kind of diversification. They call these ad-hoc portfolios, *Robust Strategies*, and demonstrate through simulation that for the examples considered in the paper, these yield better performance. It is understandable that this better performance comes from diversification, that helps against modeling errors. However, guarantees of better performance, precise optimization, analysis or the characterization of these ad-hoc portfolios is not possible. In contrast, the approach adopted in this paper is to construct one robust benchmark based on Robust Optimization (RO). One robust benchmark, while better allowing to deal with modeling errors, also provides a much better and precise handle on crafting these benchmarks such that they align with the regulator's incentives. Practically too, calibrating and implementing a portfolio of benchmarks is much harder, if not impossible, in comparison to using one policy benchmark. We will also demonstrate in the paper that this one robust benchmark can easily yield a much better fee to consumers in comparison to the hard to manage and ad-hoc portfolio of diversified benchmarks.

The rest of the paper is organized as follows. Section 2 lays out the model formulation. Section 3 derives the solution to the LDC's problem, characterizes the optimal incentive fraction along with risk sharing implications, and provides insights into the policy benchmark selection. Section 4 argues why benchmarks should be used in incentive contracts for LDC regulation. Section 5 deals with the issue of modeling errors. It first shows how one can construct robust optimization strategies for policy benchmarks. It also describes two other kinds of policy benchmarks against which the proposed robust polices are contrasted. Finally, illustrations of robustness are presented here. This section also demonstrates of how previously formulated policy benchmarks can backfire in the presence of modeling errors. We make concluding remarks in Section 6.

2. Model formulation

Consider the procurement of natural gas by a given LDC for a specified service period, typically a year. The state regulator oversees the pricing of natural gas to consumers. This is entirely equivalent to the regulator (the principal) delegating the procurement of natural gas to the LDC (the agent). The LDC's cost of procurement for the service period is denoted by the random variable C_0 with mean μ_0 and standard deviation σ_0. This cost can be considered as the cost of procurement under a cost-of-service type of regulation scheme. The LDC can invest in cost reduction actions through bargaining, marketing, search for suppliers, expert consulting, or propose demand side management (DSM) programs. By expending a cost $\psi(e)$, the LDC can expect a reduction in the cost of gas procurement of $e > 0$ that is called effort. In such case, the cost $C(e)$, after effort is,

$$C(e) = C_0 - e + \epsilon,$$

where $E(\epsilon) = 0$ and $\text{Var}(\epsilon) = \sigma^2$. For tractability, as is common, the cost of effort function is assumed of the form $\psi(e) = \frac{1}{2}de^2$ with $d > 0$ insuring that $\psi' > 0$ and $\psi'' \geq 0$ (Laffont & Tirole, 1993 and Predergast, 1999). Let β denote a benchmark against which costs will be contrasted. Let μ_β and σ_β represent the mean and standard deviation of the benchmark, respectively. σ_{β,C_0} denotes the covariance, while $\rho = \rho_{\beta C_0} \geq 0$ is the correlation. These quantities are assumed to be known symmetrically to the LDC and the regulator, furthermore ϵ is assumed to be independent from C_0 and β. We assume that both the regulator and the LDC have mean-variance preferences with risk aversion coefficients $\lambda^p \geq 0$ and $\lambda \geq 0$, respectively.

Although the regulator cannot observe the effort of the LDC for cost reduction, a performance measure that depends on the actions of the LDC can be used. In our case, we consider $\beta - C$ as an *objective* measure of performance. It is called an objective measure because it can be verified at the end of the evaluation period, refer to Predergast (1999). As in Muthuraman et al. (2008), we use the compensation function (bonus)

$$g(\beta, C) = a(\beta - C),$$