Abstract

Title of Dissertation: The Economics of Nuclear Power

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We extend economic analysis of the nuclear power industry by developing and employing three tools. They are 1) compilation and unification of operating and accounting data sets for plants and sites, 2) an abstract industry model with major economic agents and features, and 3) a model of nuclear power plant operators.

We build a matched data set to combine dissimilar but mutually dependant bodies of information. We match detailed information on the activities and conditions of individual plants to slightly more aggregated financial data. Others have exploited the data separately, but we extend the sets and pool available data sets. The data reveal dramatic changes in the industry over the past thirty years. The 1980s proved unprofitable for the industry. This is evident both in the cost data and in the operator activity data. Productivity then improved dramatically while cost growth stabilized to the point of industry profitability. Relative electricity prices may be rising after nearly two decades of decline. Such

demand side trends, together with supply side improvements, suggest a healthy industry.

Our microeconomic model of nuclear power plant operators employs a forward-looking component to capture the information set available to decision makers and to model the decision-making process. Our model includes features often overlooked elsewhere, including electricity price equations and liability. Failure to account for changes in electricity price trends perhaps misled earlier scholars, and they attributed to other causes the effects on profits of changing price structures. The model includes potential losses resulting from catastrophic nuclear accidents. Applications include historical simulations and forecasts.

Nuclear power involves risk, and accident costs are borne both by plant owners and the public. Authorities regulate the industry and balance conflicting desires for economic gain and safety. We construct an extensible model with regulators, plant operators, insurance companies, and consumers. The model possesses key attributes of the industry seldom found in combination elsewhere. We then add additional details to make the model truer to reality. The work extends and corrects existing literature on the definition, effects, and magnitudes of implicit subsidies resulting from liability limits.

The Economics of Nuclear Power

by

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Dedication

To my grandfather

Edwin Noah Martin

1918-2000

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Table of Contents

List of Tables

List of Figures

The Economics of Nuclear Power

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Nearly finished!

This comment page is not part of the dissertation.

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Chapter 1

Introduction

Nuclear power both offers great promise and poses tremendous threat to the American economy. On the one hand, it provides the greatest source of energy without carbon dioxide emissions, and it provides a domestic energy supply that does not add significantly to trade deficits. On the other hand, at every moment a disaster on the scale of the Chernobyl accident is unlikely but remains possible at over 100 U.S. reactors. No other private industry imposes such extreme risks on so many, and few industries offer such benefits relative to existing alternatives. Few industries have been the focus of more research than the nuclear power industry. Among the narrow field of nuclear industry economics, a vast array of publications span topics from the speed of technology adoption to costs of regulation to the nature and magnitude of lingering effects of the Three Mile Island accident. Given the size of the literature, what is left to study?

Despite the wide array of fine papers published by leading economists, important questions remain unanswered, and on many topics consensus remains elusive. For several decades, no new construction was begun, and it seemed that rising costs would force closure of existing plants. Profitability seems now to be improving, and the ever increasing American demand for energy forces us again to consider whether increasing our capacity of nuclear power generation might be the optimal course. Even some environmentalists recently have called for increasing reliance on nuclear power in order to reduce carbon dioxide emissions. For these reasons, we must take another look at the questions and problems unique to this industry.

Of particular importance are the means by which we handle the risks of nuclear accidents. For nearly fifty years, the federal government has offered liability protections to the industry, so that they bear only partial liability for offsite damages in the event of a serious accident. Many are concerned about the effects of such protections, fearing that operators have too little incentive to operate safely and that the public has no guarantee of compensation. Unfortunately, few academic papers have been published on the topic to define or measure the benefits to operators of these protections or to determine their effects on operator behavior.

Problems for nuclear power began while the industry was young. First, plants proved more costly to construct than was expected. Next, they proved more expensive to operate than was expected. Finally, the regulatory burden and public opposition proved greater than anticipated. These matters have been studied at great length, and many factors are known to contribute to each. Far less work has been done to determine the effects on the industry of weakening demand, and it seems that while many agree that high costs and burdensome regulations largely caused the industry's troubles, there is little consensus on the relative importance of each factor and how they might be related.

We find it essential to begin by constructing a model of the nuclear power industry in order to determine the relationships among costs, demand, and regulation, and to determine the nature and magnitude of effects of liability protections.

We begin by building a unifying model of the nuclear power industry. Given the breadth and depth of the literature, the work summarized within reveals but a glimpse at the potential of such efforts. Still, constructing an adequate conceptual framework requires thinking about nuclear industry economics in unconventional fashions, so that establishment of stylized facts leading to unifying economic model in itself illuminates truths before unseen. Even small models, we will see, help to answer challenging questions. And so as we begin, we keep our goal in mind. We will not exhaust the possibilities in this present study. Rather, our present goal is to begin by offering a small but powerful model of the industry that reveals crucial economic and regulatory relationships and sheds light on the little understood topic of liability limits. If we succeed, then much work will remain to be done, supported and prompted by these beginnings.

Three frameworks are established and employed. Each has much potential in present form and much is revealed as we begin to exploit that potential. The greater promise, however, may be realized by extending further the work begun. Present work may be summarized as 1) compilation and unification of operating and accounting data sets for individual plants and sites, 2) construction of an industry model with nuclear power plant operators, industry regulators, and consumers, and 3) construction of a detailed model of nuclear power plant operators.

The first framework is the assemblage of data. Our key contribution is the construction of a matched data set that combines dissimilar but mutually dependant bodies of information. On the one hand, we have detailed information on the activities and conditions of individual reactor units. On the other hand, we have slightly more aggregated financial data on each site, which may include several reactor units, and we have regional data on electricity prices. Others have exploited the data separately, but we extend the sets and we go further. By pooling available data and matching reactor, site, and regional information, we produce a very rich data set with great potential.

The second framework is an extensible model that provides foundations to support broad coverage of nuclear power economics. The present model exhibits primary agents important to the industry, including regulators, power plant operators, insurance companies, and consumers. The model possesses key attributes of the industry seldom found in combination elsewhere. Also, the scope of the model encompasses more than is typical in models of nuclear power economics. Model solutions and applications yield two important contributions. First, the model reveals relationships between costs, demand, and regulation that existing literature fails to make clear, and it shows the impacts of these factors on the well-being of firms and consumers. Second, the model yields definitions of the implicit subsidies provided to firms through liability protections. These definitions are derived from models of regulated firms, and they extend understanding of the scope of the matter. Our work demonstrates the importance of considering the entire scope of regulatory impacts on firms when attempting to determine effects of liability limits on safety and when attempting to quantify the benefits to the industry of liability limits. These contributions are important, though even greater promise of the model may be seen by considering a few of the possible extensions fully supported by this work. For example, political activists clamoring both for expanding and banishing nuclear power surely affect regulators, so that levels of regulation and the severity of its enforcement depend on the public's opinions and level of concern. As a second example, the model easily could be extended to feature explicitly a broad set of electricity generating technologies, each with its own advantages and shortcomings, in order to gain perspective on nuclear power's inherent risks relative to fossil fuel technology's degradation of the environment. In this way, we can consider the benefits of continued operations of nuclear plants versus reduction of nuclear output. Our construction of a basic economic model with the key economic players together with key industry features make such extensions and applications feasible and relatively simple.

The third framework develops models at the microeconomic level. We offer a model of the firm, where in this case the firms are nuclear power plants. To support the modeling efforts, we also construct a software package to aid in the construction of similar models. Our model includes several features often overlooked in other empirical and theoretical work. These include incorporation into the model electricity prices and their effects on revenue and profits. The effects on profits affect the behavior of operators that our model is designed to represent. Our model also incorporates measures of risk and the liability associated with the possibility of catastrophic accidents. We attempt to determine whether liability protections induce detectable changes on operator behavior.

Even cursory analysis of the data we compile reveals dramatic changes in the industry over the past thirty years. We see that the 1980s proved very costly and unprofitable for the nuclear industry. Using our matched set, this is revealed both in the cost data and in the activities of individual plants. In following decades, however, our extensions show that productivity improved dramatically. At the same time, cost growth stabilized and profits per unit of output improved to the point that operations currently seem to generate healthy profits. Our panel data allow us to learn about the variation of costs and productivity across plants that the aggregate figures typically reported by the industry fail to reveal. The improved economic picture may be seen too by glancing at recent media reports on the energy industry. For the first time in decades, new nuclear power plant construction is being proposed and permits are being acquired. It is striking both that plant operators believe themselves capable of building and operating plants profitably and that regulators believe it politically feasible to grant building permits and even to negotiate potential tax incentives.

The regional price data indicate that after nearly two decades of falling relative prices, electricity prices may be rising again. National energy efficiency continues to improve, and so electricity demand growth remains far lower than rates seen forty years ago. Still, the growing American population and economy demands ever more power to facilitate expansion. These demand side trends, together with supply side improvements observed in the cost and operating data, indicate that the industry is healthy and may continue to thrive for years to come.

On the other hand, disaster is possible. Costs of disastrous nuclear accidents clearly are borne not solely by plant owners but also by the public. For this reason, government authorities ostensibly representing public interests regulate the industry and balance the conflicting desires for economic gain and safety. Yet regulation of an industry so technically complex, while dealing both with powerful industry lobbies and consumer and environmental political activism, yields a terribly thorny problem. We begin to deal with the problem by building a big-picture model. That is, we assemble a structure with the major players and a vague representation of critical industry details. On this foundation, we add, piece by piece, additional details to make the model ever truer to reality. Even in these early stages and with the relatively simple forms presented here, we extend existing literature on the nature, magnitude, and effects of the liability limits often assumed essential to corporate survival yet still poorly understood.

While it is essential to make sense of the overall economic world of nuclear power, we have particular interest in the operation of nuclear power plants. We thus take a close look at their operation. Nuclear power plants were designed and are permitted to operate for a limited number of years. Operators have a clear interest in considering potential profits in all remaining years rather than to focus solely on the current period. We thus employ a forward-looking model in an attempt to capture the information set available to decision makers and then to model the decision-makers as they employ this information. Given the nature of forward-looking models and the limitations of current analytical and econometric tools and technology, it is difficult to employ all available data in the operators' information sets; of course, available data is but a small part of the complete information set possessed by operators. It thus is a struggle to select a sufficient set of data for the model that will produce satisfactory results. We believe that earlier efforts to model power plant operators left out key data and that their results suffered accordingly. An important contribution of this work is the inclusion of electricity price information. Electricity price trends have varied over the past several decades. Failure to account for these changes may have led earlier scholars to attribute to other causes the effects on profits of changing price structures. In particular, economic effects of weakening demand may have been mistaken for impacts of heightened regulation. Our model also includes potential losses resulting from catastrophic nuclear accidents. The models can be employed in several important applications, including 1) optimal lifespan predictions given various assumptions about electricity price growth, 2) structural stability tests to analyze the effects of changing regulations while accounting for structural price shifts occurring at the same time, and 3) analysis of the effects of modifications to policies that limit liability.

And so, we have assembled data and models and employed them to learn much about the nuclear power industry, yet they offer far more potential than developed here. Some possible extensions are suggested throughout the following chapters. Hopefully, the reader will find the work sufficiently promising that additional possibilities continually will become obvious.

We thus begin. We start with the history of the American nuclear power industry, and based on this picture we build a static model of the industry and its regulation. The static model proves sufficient to reproduce a number of major historical events. We then extend the static model to a multiperiod framework in order to determine the optimal evolution of operators' decisions and regulatory policies. Finally, we extend the dynamic model to a numerical framework in order to incorporate additional important features of the industry. A key application of our model is a close look at liability protections offered to the industry and their effects on firm and regulatory policies. These protections are considered throughout the first section.

The second section begins with the development of regional price data, monthly operations data for each commercial nuclear reactor, and annual cost data for each nuclear site. We employ the price and available output data to construct estimates of revenue earned through the generation of electricity. Perhaps because estimation and even definition of such revenue is difficult, such estimates are not available in other scholarly work, and because they are not forced to do so, plant owners do not release revenue information. While it is difficult to establish the accuracy of our estimates, the patterns revealed over the past three decades correspond nicely to well-known historical facts and thus inspire confidence in our results. Other data work summarizes changes in operating policies, which yielded much improved productivity and reliability, and development and descriptions of cost data that also show dramatic improvements in performance. Very likely, regulatory reforms contributed to these improvements. By developing dynamic programming models of nuclear power plant operators, we gain improved understanding of truths hidden in the data. We summarize estimation results of the model, and conclude with applications of the model.

The text concludes with a summary our work and a description of intended extensions. An appendix describes software developed to support this work and similar modeling efforts.

Part I

Economics and Regulation of U.S. Nuclear Power

Should operators of nuclear power plants continue to run their plants given the current economic circumstances and regulatory policies? Should regulators adopt a conciliatory stance to feed the economic desires of producers and consumers, or should they enforce hard-line standards to lessen the risks of nuclear accidents? What are the effects of liability limits on the decisions of plant operators, and what is the economic benefit to plant owners?

The four chapters comprising this section summarize the history of nuclear power economics in the United States, and they describe and apply a series of economic models in search of answers to these questions.

Chapter 2 begins with a review of the history of nuclear power industry operations, regulation of the industry, and the evolving economics of nuclear power. We go on to develop models of the economics and regulation of the nuclear power industry, similar to the models developed by Steven Shavell of the Harvard Law School. While the models are intended to capture matters of political economy and ultimately should prove capable of portraying such details, we begin by studying models that focus on regulation and economics, and we then extend the model to illustrate effects of changing political climates. Nevertheless, we continue to label them as political economy models to remind us of intended directions of development. Politics certainly play important roles in the industry, and so it remains desirable to portray such features along with other key aspects. An important contribution is offered when we apply the model in the analysis of liability protections to the industry. We employ our model to derive a broad view of potential benefits that nest earlier efforts. Deriving benefits to the industry from a model of firms and regulators reveals that earlier concepts of implicit subsidies was too narrow. We show the importance of considering additional factors that heavily may affect the level of safety and economic benefits to operators.

We find the relative simplicity of a static model adequately powerful to develop a model core that is sufficient to support many extensions, including dynamics. First, though, we take a closer look in Chapter 3 at protections offered to the nuclear power industry in the form of liability limits. These protections originally were passed as the Price-Anderson Act of 1957. Many assume that survival of the nuclear industry depends on these provisions. It remains unclear, however, whether this is true or even what is the magnitude of economic benefits afforded to the companies. We examine earlier attempts to quantify the amounts. However, in addition to taking too narrow a view of potential benefits, we show that published calculations are flawed and their models improbable. We offer corrected calculations and improved models. These imply that the magnitude of implicit subsidies may be far lower than reported earlier.

We next return to our model in Chapter 4 and extend it to a multiperiod framework. The dynamics are simple, but they are sufficient to capture the importance of forward-looking behavior both by plant operators and by regulators. The pattern of private investment in maintenance and safety is of particular interest, and we are able to derive investment rules that vary over the life of the plant. We also derive optimal regulatory policies that take these tendencies into account. We apply the model to extend our understanding of the effects of the Price-Anderson liability limits in a multiperiod framework. The result yields a means of calculating the value to the industry of maintaining liability protection policies.

In Chapter 5, we construct a numerical version of our dynamic model. The numerical framework allows us freedom to add features that under the previous analytical model proved infeasible or at least cumbersome. Many of the features that will be present in our model of the firm, including stochastic price evolution, are introduced here to provide a bridge between our theoretical model of the industry and our empirical model of the firm. Unique contributions of our work include the specification of insurance premiums paid by operators, taking into account the behavioral policies of the firms, and the modeling of the shared liability features specified by American regulatory policies. We employ the model in two exercises. First, we check the reaction of our model, measured as changes to profits and optimal behavior, to changes in the evolution in electricity prices as occurred in the American economy in the 1980s. Second, we check the model's response to extensions of allowed maximum lifespans, as recently was made possible by nuclear regulatory authorities. In a chapter appendix, we derive a means by which we can speed calculation for a class of numerical problems, and we show how to apply the method to numerical dynamic programming problems like ours.

Chapter 6 concludes the first section and summarizes our findings. We now set out on our quest to summarize the American nuclear power industry.

Chapter 2

A Static Approach

2.1 Introduction

This study develops models of the political economy of the nuclear power industry, which extend greatly theoretic work developed by Shavell [57] and applies it to the nuclear power industry. The primary motivations of nuclear power operators and of nuclear industry regulators are considered. Optimal rules are computed to govern behavior of each agent. These rules take into account the effects of the agents' own actions on the behavior of others. It is assumed that operators' primary motivations are to maximize profits. Operators' choices include whether to operate and how much to invest in maintenance and safety enhancements. Regulators seek to ensure adequate electricity supplies while minimizing costs and expected damage from nuclear accidents. We consider four cases. First, we consider the case in which regulators are benevolent social planners who can guide the economy to the first-best solution. Next, we consider the cases in which regulators employ either regulatory standards for safety enhancements or liability levels for damages, but not both. Finally, we consider the case in which regulators govern with both instruments. It is this last case that best describes oversight of the nuclear power industry, while other cases provide important reference points and limiting cases for consideration of liability protections.

We review the history of nuclear power industry operations, regulation of the industry, and the evolving economics of nuclear power. The results of the model developed here then are compared to the economic history of the industry to see whether the model qualitatively reproduces observed phenomena. Finally, the model is employed to construct measures of subsidies created by adoption of potentially sub-optimal liability levels. These measures are compared to others in the literature.

The models are based closely on Shavell [57]. In that paper, he derives optimal regulatory policies when firms face liability. However, there are several significant discrepancies between his model and the nuclear power industry. This work seeks to eliminate some, but not all, such discrepancies. In the process, we extend his theoretical work significantly and make it far more useful and realistic.

First, Shavell assumes that in the event of an accident causing damages to third parties, the firm escapes liability with a positive probability. Instead, we assume that operators cannot avoid liability for damages. This assumption, which admittedly is too strong, is based on terms of the Price-Anderson Act. This policy specifies minimal levels of insurance that each nuclear power plant operator must carry. It also sets terms for industry self-insurance in addition to the commercial insurance coverage. Operators are exempt from liability for damages in excess of the amount specified in the policy. We assume that operators cannot escape liability for the reason given in the MIT study [6, p. 81]: "The compensation provision of both the first and second layers of insurance are 'no fault' and not subject to civil liability litigation."

The second and primary difference between this model and Shavell's is that output matters here. In Shavell's model, profits implicitly were assumed always positive, so that firms never exited the market. Similarly, it implicitly was assumed that social welfare always was greater with production than without, so that regulators never forced individual plants or the industry to close. In this model, firms' output decisions are binary: they produce at full capacity if expected profits are non-negative, and otherwise the firms close. Hence, output does not decline continuously with regulation. In the aggregate, however, output is a decreasing function of regulation. If expected damages are too great, so that social welfare is believed greater without production, then regulators can force plants with the greatest risk to close, so long as their policy instruments allow them sufficiently precise control. Similarly, if liability or regulation becomes too great, then firms will decide to exit the market.

Among a variety of applications that we provide, perhaps the most important is employment of the model to determine the benefits to firms, effects on firm behavior, and the impact on safety of offering the industry limits on liability. In the past, the benefits to firms, or "implicit subsidies," typically were defined as the difference in insurance premiums between insuring against all possible damages and insuring against the maximum amount of liability set by regulators. In addition, it has been assumed that liability limits leave operators with too little incentive to enhance and maintain safety standards, so that risk to the public is unnecessarily high. In contrast to earlier approaches, our model shows the importance of considering simultaneously the overall effects of regulation, including both liability protections and other policies. If regulators optimally determine these policies, then regulations on safety should account for limited liability. Our results show that the net effect of regulation and liability protections on safety and profits cannot be determined without additional empirical work, and our results provide guidance for conducting such research while taking into account the existing work of others.

2.1.1 Economics of the American Nuclear Power Industry

The economics of operating nuclear power plants proved far less favorable for operators than was expected. Construction costs proved higher, operating costs proved greater, and electricity demand growth and price growth fell sharply.

Many papers have been published that analyze the economics of constructing nuclear power plants (See, for example, Ellis and Zimmerman [18] for the history of construction, and see the University of Chicago study [8] for a comparison of many results on the topic.) While there is little consensus in ranking possible causes, it is clear that it proved more expensive to build plants than was predicted. Two primary reasons are that 1) expected increasing returns to scale failed to materialize, so unit costs for constructing large commercial reactors were not much lower than for small research reactors, and 2) plants took longer to build than was expected. One reason for long construction times is greater regulation of the construction process, but there is not a clear consensus on the importance of this factor. The NRC [30, footnote 57] reports that lengthened construction times were due, in part, to reluctance of operators to open plants for fear that demand was too weak to absorb the additional production.[1]

Once plants were completed and began operations, they proved more costly to operate than was expected (EIA [2]). Operating costs grew rapidly through the 1980s and early 1990s, although expenditure growth has slowed and efficiency has increased (Rust and Rothwell [56]).

Finally, demand side conditions deteriorated as the nuclear power industry gained momentum (Nelson and Peck [39] and NRC [30]). Average annual electricity demand growth exceeded seven percent in the decade or more prior to 1973. Growth rates then fell abruptly to less than three percent. (See, for example, Price [43, p. 107]. See Haltiwanger, et al [14] for a historical review of electricity prices.) The NRC reports that the ratio of electricity demand growth to overall economic growth fell from 1.5 in the 1970s to 1.0 in the 1980s, while energy spending per dollar of GDP fell at 2% per year. Price [43] reports worldwide increases in energy efficiency following the oil price shocks of the 1970s. Relative electricity prices continued to grow steadily until the early to mid1980s. At that point, however, relative prices began a long, slow decline. Rothwell and Eastman [51] report that from 1979 to 1981, the realized or allowed rate of return was less than the cost of capital for U.S. electric utilities. The need for ever more base load capacity became much less pressing in the 1970s, and the shift in electricity price growth forced increases in efficiency for plants to remain viable. Nelson and Peck show that the reality of weakening demand set in slowly, and that the industry consistently over-estimated future demand growth from the mid1970s to the mid1980s. Price also notes that the industry was slow to react to signs of deteriorating economic conditions.

[1] See Price [43, p. 9] for a similar argument.

Many partially constructed plants, and even some completed plants, were abandoned as it became clear that demand growth was weakening. Similar phenomena were observed among coal-fired plants (Ellis and Zimmerman [18] and Price [43]). A number of operating plants were decommissioned, and no new starts were made in the following two decades. In recent years, though, growing interest in new construction has developed, although significant excess baseload capacity remains (Nivola [41]).

When the U.S. government was considering the creation of a private nuclear power industry, they realized that the enormous risks associated with operating a nuclear facility meant that liability would need to be limited in order to ensure viability of the industry. In 1957, the government enacted the Price-Anderson Act (PAA) which provides liability caps for off site damages. The stated objectives of this policy were 1) to protect the public by ensuring prompt compensation after an accident and 2) to foster the development of the nuclear power industry (Dubin and Rothwell [16]). Such liability caps eliminated the need for plant operators to protect themselves from possible losses for damages in excess of the liability limit, thus limiting the need to purchase liability insurance. Many argue that by enabling operators to avoid these additional insurance premiums regulators provide an implicit subsidy to the industry. While estimates for the value of these subsidies are fairly small (Dubin and Rothwell [16], Heyes and Heyes [28, 29], and Denenberg [15] (note that problems exist in the estimates of Dubin and Rothwell and Heyes and Heyes)), many still argue that the industry would not survive without them. Unfortunately, these estimates are difficult to compute, and little faith should be put in most published estimates (Heyes [26]).

Many consider the 1979 accident at the Three Mile Island (TMI) plant to be the primary cause of the deterioration of the nuclear power industry. However, there are numerous causes, including those listed above. In fact, the backlog of new orders fell and plants under construction were abandoned even before the TMI accident (Ellis and Zimmerman [18]). Hence, all of these factors should be incorporated in any model claiming to portray the economics of the nuclear power industry. Unfortunately, most models focus only on one, or perhaps a few, such factors. Given the growing interest in resuming construction of nuclear power plants (University of Chicago [8] and MIT [6]), it is important that we improve our understanding of the political economy of nuclear power.

2.1.2 Layout of this paper

Our work develops a model of nuclear power plant operations and industry regulation. First, the model is described, with timings, objective functions for operators and regulators, and derivation of optimal decision rules. Next, a series of propositions are stated and proved, following closely the lead of Shavell [57] while extending greatly his work. Next, predictions of the model are compared to observed phenomena in the 1970s and 1980s. The model is used to derive measures of implicit subsidies created by enforcement of limited liability levels, and the measures are compared to others in the literature. Finally, limitations are noted and possible extensions are suggested.

Before beginning, we note that our initial efforts, summarized here, are concerned more with regulation of the nuclear power industry than with political economics. However, politics are of great importance in the nuclear power industry and such features readily may be added to extend our work. We will return to the topic in our conclusions.

2.2 The Model

2.2.1 Timing

This model has two primary groups of players, nuclear industry regulators and power plant operators, who move sequentially in a static game-theoretic framework. Regulators seek to maximize social welfare, and the firms' problem is to maximize profits while satisfying the demands of regulators. It is assumed that a continuum of markets exists, with one nuclear facility per market. No attempt is made to explain the existence of power plants, and for simplicity prices and demand for electricity are exogenous. Firms are identical, except for the amount of damage that they cause if an accident occurs. We consider only one period. At the end of the period, assuming that the firm survives, the firm incurs shutdown costs and closes permanently.

The level of demand first is announced. Next, regulators determine the optimal level of liability to impose on the nuclear power industry, and the level is announced. Given this announcement, power plant operators decide an optimal level of investment in safety-enhancing maintenance and similar expenditures. If production yields more expected profits than the cost of decommissioning, then firms invest, produce electricity, collect the revenue, and pay operating and investment expenses. Accidents then occur with an endogenously determined probability dependent on the level of investment. These accidents cause damage to third parties, for which regulators may hold plant operators liable. If expected profits are less than the cost of decommissioning, then operators make no investments and close their plants immediately.

Exposure to liability with corresponding spending on safety, or spending to meet regulatory requirements, reduces profits. We assume that aggregate output may fall with profits, as unprofitable firms exit the market, so that greater safety comes at the expense of output. The model has firms that either produce or shut down, depending on whether profits are non-negative; non-negativity is the condition for production, given our assumption for sake of simplicity that shut-down costs are zero. We assume that regulators care about both output and safety, and are cognizant of the effects on output of their own actions. Essentially, we assume a continuum of identical markets, where prices and preferences are exogenous. Hence, regulators consider separately consumers' utility in each market. In each, either firms produce at full capacity and consumers receive utility from the product, or firms close and consumers receive a level of utility from zero consumption.

The definition of regulation is narrow, such that policies specify minimal standards for investment in safety-enhancing goods and services. We consider regimes with various combinations of regulation and liability, and we compare social welfare for each.

We note an important paper by Baron and Myerson [10] in which they consider the optimal regulation of a monopolist with costs that are unknown to the regulator. Regulators have three instruments: to close the firm or to allow operations, to set the quantity produced or the market price, and to offer a subsidy or to impose a tax on the firm. While we do not include some of the details of the Baron-Myerson model, their paper does contain material of some relevance for the nuclear power industry. Given our focus on nuclear power plant operators, however, and given the existence of mixed generating technologies in nearly every market, it is not clear that their model would be ideal in this case. Regulated electricity prices must accommodate not only the most efficient generating technology but a sufficient number of plants in each market to satisfy demand, including plants with higher marginal costs. That is, regulators cannot tailor market prices to individual plants or technologies. Hence, we consider prices exogenous and instead focus on other matters. Still, the idea of Baron and Myerson of tailoring regulatory policies so that firms will reveal private information is of great importance. In their study, the private information was the structure of firms' operating costs. In our case, firms have private information about potential damages. Unfortunately, the present model does not yet incorporate the policy instruments required to entice firms to reveal private information.

2.2.2 Definitions

The continuum of (nearly) identical firms are indexed by the level of potential damages, h, that they pose to their communities. In fact, h is the only distinguishing characteristic of the firms. We assume that h is an exact amount. This magnitude of potential damage, known only to the firm, is such that $h \in [a, b]$ where $0 < a < b < \infty$. Regulators do not know potential damages for individual firms, but they do know the distribution of damages across firms $f(h)$, which is nonzero on and only on $[a, b]$. We use a proper probability distribution $f(h)$ only for convenience, in that it integrates to one and we can use familiar techniques from statistics. More general specifications of $f(h)$ could integrate to any positive value, as it simply specifies the number (or measure) of firms. Industry capacity and potential output is Q. We assume that all plants have the same capacity. We assume that electricity prices, less unit production costs, are identically equal to one, so that net potential revenue at full capacity also equal

Q. Firms may invest in goods and services, indexed by x such that $0 \leq x$, to lessen the probability of an accident. The probability of an accident $p(x)$, given the level of investment x, is identical for each firm and depends only on investment. The first derivative of the probability function is negative and the second derivative is positive. (See Dubin and Rothwell [17] for a similar specification.)

Regulators seek to maximize social welfare. A component of the social welfare function is U. For industry output q, where $q \in \{0, Q\}$, $U(q) \equiv q + u(q)$. Hence utility U is a quasilinear utility function, and is determined by the sum of industry net revenue and the benefit to consumers $u(q)$ of consuming q. The numeraire in this utility function is industry net revenue. The balance of the social welfare function is in the same units (dollars) and is composed of investment and potential damages, as described below. Hence, regulators care about the utility consumers obtain from consumption, industry profits, and potential damages.

2.2.3 Industry Regulators

Industry regulators seek to balance the need for adequate electricity supplies and the need for safety from nuclear accidents. If there is excess demand without operation of nuclear plants, then neither desire can be satisfied fully without sacrificing the other. We model these conflicting desires with a welfare function for which regulators seek 1) to maximize output to satisfy consumers' demand and operators' profit motives and 2) to minimize expected losses from accidents.

We consider various regulatory regimes with various combinations of regulation and liability. We assume that the level of liability is outside the control of regulators. Regulators thus have at most one instrument for governing the industry: they choose a minimum level of investment for operators.

We consider only cases in which operators bear either zero liability or liability not exceeding the value of the firm. Whether firms face liability is not under the control of regulators. We do not consider the possibility that regulators will compensate firms for losses, nor do we consider punitive damages.

Similarly, we do not consider the possibility that regulators or consumers will compensate firms for higher levels of investment, in the sort of exchange proposed by Coase. The model could be extended to include such possibilities, but such exchanges have not been observed and thus such possibilities are ignored.

2.2.4 The Social Planning Problem

The social planners' optimization problem, in which they seek to maximize social welfare for each market i, is specified as

$$\zeta(h_i) = \max\left\{U(0), \max_{x_i \geq 0} U(Q_i) - x_i - p\left(x_i\right) h_i\right\} \tag{2.1}$$

for control of plant i with potential losses h_i. We assume that social planners know h_i. Social planners thus know more than the simple regulators considered later, for the regulators know only the distribution $f(h)$. The planner must decide whether to keep the plant idle or to allow operation. If the plant is closed, then social welfare in the corresponding market is $U(0)$. If the plant operates after investing x_i, then expected damages are $p(x_i)h_i$, and social welfare in the corresponding market is $U(Q) - x_i - p(x_i)h_i$.

The optimal level of investment is found by differentiating the second term on right-hand side of Equation 2.1.

$$\frac{\delta\zeta_i(h)}{\delta x} = -1 - p'(x)h_i = 0 \tag{2.2}$$

After simplifying, we have a rule for investment as a function of potential damages[2]:

$$x^{SP}(h_i) = (p')^{-1}\left(\frac{-1}{h_i}\right)$$

where $(p')^{-1}$ is the inverse of the derivative of the probability function p. We see that optimal investment increases with potential damages.

Clearly, social welfare declines with potential damages. Hence, social planners may find it optimal to allow plants with little risk to operate (that is, plants with h close to a), but plants with high risk shut down (that is, plants with h close to b). We can define the level of damages $\tilde{h}^{SP}$ such that social planners are indifferent between operating and closing the plant:

$$\left\{\tilde{h}^{SP} : \ U(0) = U(Q) - x^{SP}(h) - p\left(x^{SP}(h)\right)h\right\}$$

We limit the range for $\tilde{h}^{SP}$ such that $\tilde{h}^{SP} \in [a, b]$. Hence, plants with $h < \tilde{h}^{SP}$ close, and remaining plants operate:

$$\text{Output}=\begin{cases} 0 & : \ \tilde{h}^{SP} < h_i \\ Q & : \ h_i \leq \tilde{h}^{SP} \end{cases}$$

We confirm that social welfare strictly decreases with potential damages, assuming that it is optimal to produce:

$$\frac{\delta\zeta_i^{sp}}{\delta h} = \begin{cases} 0 & : \ q_i^{SP} = 0 \\ -p(x^{SP}) < 0 & : \ q_i^{SP} > 0 \end{cases}$$

[2]Note also that the SOC holds: $\frac{\delta\zeta_i(h)^2}{\delta^2 x} = -p''(x)h < 0$

Hence, social welfare strictly decreases in potential damages, regardless of the probability function p.

Total social welfare, or the sum of welfare across all markets, is found by integrating welfare for individual markets:

$$\begin{aligned}
\zeta^{SP} &= \int_a^b \max\left\{U(0), U(Q) - x^{SP}(h) - p\left(x^{SP}(h)\right)h\right\} f(h)dh \\
&= \int_a^{\tilde{h}^{SP}} \left\{U(Q) - x^{SP}(h) - p\left(x^{SP}(h)\right)h\right\} f(h)dh + [1 - F\left(\tilde{h}^{SP}\right)] \times U(0)
\end{aligned}$$

where $F(g) = \int_a^g f(h)dh$ for $g \in [a, b]$ is the measure of plants that operate. Aggregate output is

$$\begin{aligned}
&\int_a^{\tilde{h}^{SP}} Qf(h)dh \\
=&Q \times F(\tilde{h}^{SP})
\end{aligned}$$

2.2.5 The Case of Liability Only

We next consider a market in which private firms are permitted to operate freely of regulation, but they do face liability. We assume that the level of liability y is given, and may be assumed to be the level of assets or the value of the firm. Alternatively, it may be set to any arbitrary level. In this analysis, we assume that $y \in (0, b]$. That is, we assume that maximum liability is a positive number that is no greater than potential damages in the worst case. For reasons given in the introduction, we assume that firms are held liable for damages with probability 1. We do not allow the possibility that firms will escape responsibility for damages.

Operators

Power plant operators seek to maximize expected profits. They do so first by determining an optimal level of investment in safety improvements and maintenance, given their level of liability and revenue. If expected profits are greater than decommissioning costs given the optimal investment level, then operators choose to produce. The level of potential plant-level output, Q, is given by the level of installed capital. Electricity prices less unit production costs are assumed positive and are normalized to one, and so for positive production levels, Q both is the level of output and revenue less operating costs. If the value of the firm (revenue less operating and investment costs less expected liability claims) are less than decommissioning costs, the plants close immediately and incur shutdown costs. In this version of the model, shutdown costs are assumed zero for simplicity.

The profit maximization problem for firm i with potential damages h_i is specified as

$$\Pi^L(h_i) = \max\left\{0, \max_{x_i \geq 0} Q_i - x_i - p\left(x_i\right)\min\left\{h_i, y\right\}\right\} \tag{2.3}$$

If the firm does not produce, then the firm exits the market with zero profits. If the plant does produce, then the firm earns net revenue Q, less investment x and expected liability $p(x)\min\{h, y\}$. Note that the firm's liability either is the total amount of damage h or the value of the firm y, which ever is less.

There is no capital investment in this model. Because we assume that demand equals or exceeds Q, there is no load following. Hence, the firms' output decision is whether to invest and to produce Q units of electricity or whether to close permanently. We assume that no output is lost when operators invest. Of course, output likely is lost as the result of investment, adding costs in addition to the direct expenditures. The assumption is made solely to simplify the model.

Optimal investment is determined by differentiating Equation 4.3:[3]

$$\frac{\delta \Pi^L(h_i)}{\delta x} = -1 - \frac{\delta p(x)}{\delta x} \min\{h_i, y\} = 0 \tag{2.4}$$

For simplicity, we ignore the constraints that are required to ensure that $x \geq 0$, so that maintenance expenditures are irreversible for all probability functions p; this assumption is not restrictive so long as p is sufficiently steep for low investment. After simplifying, we have the investment rule as a function of potential damages:

$$x^L(h_i) \quad = \quad (p')^{-1}\left(\frac{-1}{\min\{h_i, y\}}\right) \tag{2.5}$$

We see that the investment rule is identical to that of the social planner, so long as liability covers all damages. Profits are non-increasing in potential damages:

$$\frac{\delta \Pi^L}{\delta h} \quad = \quad \begin{cases} 0 & : \; y \leq h \\ -p(x^L) & : \; h < y \end{cases}$$

Hence, we may determine a point $\tilde{h}^L$ such that firms are indifferent between closing and operating:

$$\left\{\tilde{h}^L : \; Q = x^L(h) + p\left(x^L(h)\right) h\right\}$$

where $\tilde{h}^L \in [a, b]$. Firms with $h \leq \tilde{h}^L$ find operations profitable, and remaining firms close:

$$q_i = \begin{cases} Q & : \; h_i \leq \tilde{h}^L \\ 0 & : \; \tilde{h}^L < h_i \end{cases}$$

[3]Note also that the SOC holds: $\frac{\delta {\Pi^L}^2}{\delta^2 x} = -p''(x)h < 0$ for $h < y$.

We see that investment increases with potential damages, so long as liability covers those damages:

$$\frac{\delta x^L}{\delta h} = \frac{\delta\left((p')^{-1}(h)\right)}{\delta h} \frac{\delta\left(\frac{-1}{\min\{h_i, y\}}\right)}{\delta h} \geq 0$$

Regulators

Social welfare may be found as under social planning, but now taking the firms' investment function as given:

$$\zeta^L = \int_a^{\tilde{h}^L} \left\{U(Q) - x^L(h) - p\left(x^L(h)\right)h\right\} f(h)dh + [1 - F(\tilde{h}^L)] \times U(0)$$

Aggregate output is

$$\int_a^{\tilde{h}^L} Qf(h)dh = Q \times F(\tilde{h}^L)$$

2.2.6 The Case of Regulation Only

We next consider the case in which firms operate without liability, but regulators impose a minimal standard for investment. Ignoring the possibility of subsidies, this scenario presents a lower bound for liability limits, measured as the benefits presented to firms by limiting their liability levels. We later will compare these results to those for the case of both regulation and liability, which provides the other relevant extreme when considering the effects of liability limits.

Operators

The profit function is specified as:

$$\Pi_i^R(h) = \max\left\{0, \max_{s \leq x}\{Q - x\}\right\}$$

Given zero liability and zero damages to to value of the firm, and because this model has only one period, firms clearly find it optimal to invest as little as possible. Hence, each sets investment to the regulated level s:

$$x^R(h_i) = s$$

For $s \leq Q$, firms find it profitable to operate, but not otherwise. Hence, the output rule is:

$$q_i = \begin{cases} 0 & : \quad Q < s \\ Q & : \quad s \leq Q \end{cases}$$

Either all firms operate, or all firms close.

Regulators

Regulators take into account the effects of their policies on the decisions made by plant operators. Hence, in effect they choose whether output will be zero or positive. The regulators' optimization problem is

$$\begin{aligned} \zeta^R &= \max\left\{U(0), \max_{0\leq s\leq Q} \int_a^b \left[U(Q) - s - p\left(s\right)h\right] f(h)dh\right\} \qquad (2.6) \\ &= \max\left\{U(0), \max_{0\leq s\leq Q} \left\{U(Q) - s - p\left(s\right)E(h)\right\}\right\} \end{aligned}$$

We see that the regulator must set a single minimal standard for investment expenditures for all firms. The regulator cannot impose regulations tailored to individual firms because we assume that h is known only by the firms themselves. In the second line of the optimization problem, we see that the regulators' problem is identical to the social planners' problem for the average firm, with one exception. The exception is that the regulation s must be no greater than Q so that operations for the average firm are profitable. If both regulators and social planners find it optimal for the average firm to operate, but regulators find the constraint binding, then it may be optimal for them to set higher standards but also to subsidize production, so that firms remain profitable. However, we do not consider this form of subsidies in this chapter.

The optimal level of regulation may be found by differentiating the social welfare function given by Equation 4.6:[4]

$$\begin{aligned} \frac{\delta \zeta^R}{\delta s} &= -1 - \frac{\delta p}{\delta s} E(h) \leq 0 \\ \Rightarrow s^R &= \min \left\{ Q, (p')^{-1} \left(\frac{-1}{E(h)} \right) \right\} \end{aligned} \tag{2.7}$$

We see that either regulation is set to the optimal level of investment for the average firm under social planning, or investment exhausts profits. Again, investment is equal to the socially optimal level for the average firm or is equal to Q, whichever is less.

We can calculate the level of social welfare under optimal regulation:

$$\zeta^R = \max \left\{ U(0), U(Q) - s^R - p\left(s^R\right) E(h) \right\}$$

Note again that either the industry is closed or all firms operate under regulation. Hence, output either is 0 or Q.

2.2.7 Liability and Regulation

The final regulatory regime that we consider includes both regulation and liability.

[4]Note also that the SOC holds: $\frac{\delta \zeta^{R^2}}{\delta^2 s} = -p''(s)E(h) < 0$.

Operators

Operators again seek to maximize profits, given their levels of liability. Their choice concerning investment now is constrained by the lower bound set by regulators. Firms either find regulation binding, and thus invest at level s, or they do not find the policy binding and so invest as if there were no regulation. In the latter case, the firm invests according to the rule derived in Section 4.2.5. Hence, the firm first determines their optimal investment according to the rule in Section 4.2.5. If this level is greater than the mandated level, then the firm sets its investment level accordingly. Otherwise, the firm sets its investment level to the regulatory standard. Next, the firm determines whether, given its investment level, operations are expected profitable. If so, the firm invests, produces, collects revenue, and pays any damage claims up to their level of liability. If firms determine that operations are not expected to be profitable, then the firm exits with zero profits.

We specify the profit function:

$$\Pi^{LR}(h_i, s) = \max\left\{0, Q - \max\left\{s, x^L(h_i)\right\} - p\left(\max\left\{s, x^L(h_i)\right\}\right)\min\left\{h_i, y\right\}\right\} \tag{2.8}$$

and corresponding investment rule.

$$x^{LR}(h_i, s) = \max\left\{s, x^L(h_i)\right\}$$

As we found earlier, we may find a point $\tilde{h}^{LR}(s)$ for which firms with this level of potential damages are indifferent between operating and closing. Now, the indifference point depends on the level of regulation s. The point may be found as:

$$\left\{\tilde{h}^{LR}(s) : Q = \max\left\{s, x^L(h)\right\} + p\left(\max\left\{s, x^L(h)\right\}\right)\min\left\{h, y\right\}\right\}$$

although we constrain values of $\tilde{h}^{LR}(s)$ to the interval $[a, b]$. To solve the regulators' optimization problem, we must determine how $\tilde{h}^{LR}(s)$ changes with the level of regulation s. To determine this, we use the implicit function theorem. First, define

$$C(h, s) \equiv \max\left\{s, x^L(h)\right\} + p\left(\max\left\{s, x^L(h)\right\}\right)\min\left\{h, y\right\} = Q$$

as the function which determines the combination of regulatory policies s and potential damages h that yield zero profits. By differentiating C with respect to h, we find

$$\frac{\delta C}{\delta h} = \begin{cases} \frac{\delta x^L}{\delta h}\left[1 + p'(x^L)h\right] + p(x^L) & : \; h < y, s < x^L \\ p(s) & : \; h < y, x^L \leq s \\ \frac{\delta x^L}{\delta h}\left[1 + p'(x^L)h\right] & : \; y \leq h, s < x^L \\ 0 & : \; y \leq h, x^L \leq s \end{cases}$$

After simplifying, using the first order condition from Section 4.2.5, we have

$$\frac{\delta C}{\delta h} = \begin{cases} p(\max\left\{s, x^L\right\}) & : \; h < y \\ 0 & : \; y \leq h \end{cases}$$

Because regulation either binds or has no effect on the firm, the derivative is zero for $s < x^L$. The derivative of C with respect to s is:

$$\frac{\delta C}{\delta s} = \begin{cases} 1 + p'(s)\min\left\{h, y\right\} & : \; x^L \leq s \\ 0 & : \; s < x^L \end{cases}$$

With these equations, we can compute the derivative of $\tilde{h}^{LR}(s)$ with respect to s:

$$\begin{aligned}
\frac{\delta \tilde{h}^{LR}(s)}{\delta s} &= -\frac{\frac{\delta C}{\delta s}}{\frac{\delta C}{\delta h}} \\
&= \begin{cases} -\frac{1+p'(s)\tilde{h}^{LR}(s)}{p(s)} & : \quad h < y, x^L \leq s \\ 0 & : \quad \text{o.w.} \end{cases} \\
&\Rightarrow \begin{cases} \frac{\delta \tilde{h}^{LR}(s)}{\delta s} < 0 & : \quad h < y, x^L < s \\ \frac{\delta \tilde{h}^{LR}(s)}{\delta s} = 0 & : \quad \text{o.w.} \end{cases}
\end{aligned}$$

Hence, we see that $\tilde{h}^{LR}(s)$ is non-increasing in regulation. We claim that this is so by noting that $\partial C/\partial s$ is zero for $s = x^L(\tilde{h}^{LR}(s))$, according to the first order condition from Section 4.2.5. For regulation to bind, it must be true that $x(\tilde{h}^{LR}(s)) < s$, and so $\partial C/\partial s$ must be less than zero.

Output is determined according to profitability of operations. Production for firm i may be determined by comparing h_i to $\tilde{h}^{LR}(s)$:

$$q_i = \begin{cases} 0 & : \quad \tilde{h}^{LR}(s) < h_i \\ Q & : \quad h_i \leq \tilde{h}^{LR}(s) \end{cases}$$

Aggregate output is

$$\int_a^{\tilde{h}^{LR}(s)} Qf(h)dh = Q \times F(\tilde{h}^{LR}(s))$$

We employ the graph in Figure 2.1 to outline the implications of various parameter values for the profits. In the figure, the x-axis covers the relevant range of potential damages (a to b), and the y-axis depicts profits. We assume that maximum liability is $y \in (a, b)$. The upper graph ($\{S_1, S_2, S_3, G\}$) is the level of profits, assuming that regulation is not binding, so that firm h_i invests

$x^L(h_i)$. Points on the graph marked $\{S_i\}$ are points of indifference between the level of regulation s_i, for $s_1 < s_2 < s_3$, and private investment.

Consider first the possibility that point A on the vertical axis is less than or equal to zero. Then clearly profits are less than or equal to zero for firms with $h = a$, and so profits are negative for all $h > a$. Aggregate output will be zero, regardless of the level s_1.

Consider next the possibility that point B on the vertical axis is zero, and suppose regulation is s_2. Then firms with $h_2 < h$ close, as profits are negative. Remaining firms operate, but they find regulation binding and so they invest s_2. Their profits are given by $\{E, S_2\}$. The slope of the profit function is $-p(s_2)$.

Consider next the possibility that point C on the vertical axis is zero, and suppose first that regulation is s_2. Then the profit function is $\{E, S_2, S_3, G\}$. Firms with $h \in [a, h_2]$ find regulation binding. Firms with $h \in (h_2, y]$ invest $x^L(h)$, and firms with $h \in (y, b]$ invest $x^L(y)$. Suppose instead that regulation is s_3. Then all firms find regulation binding, and the profit function is $\{F, S_3, G\}$. Note that firms with $h \in (y, b]$ earn zero profits and are indifferent between regulation and private investment levels.

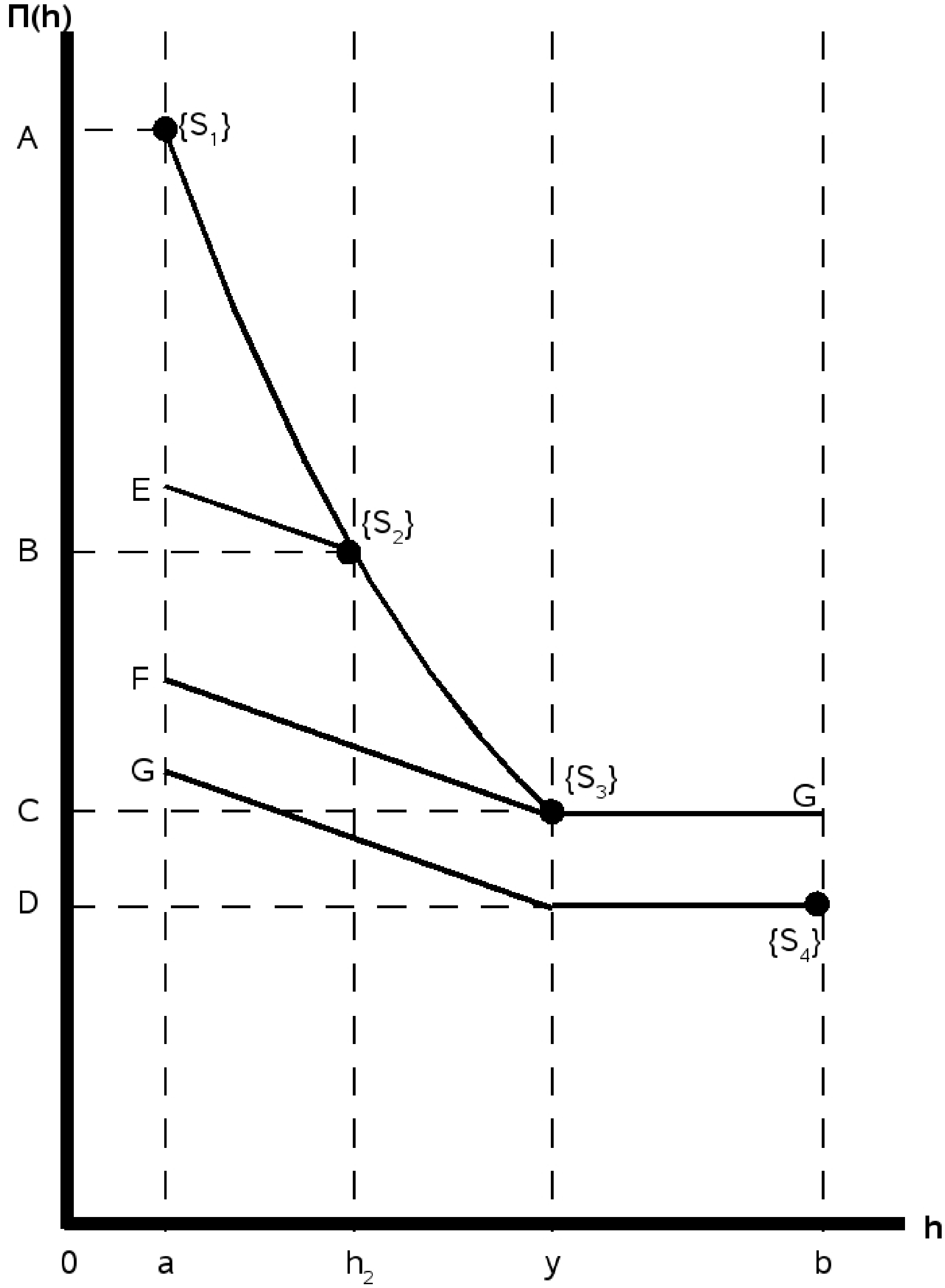
Finally, suppose that point D on the vertical axis is greater than or equal to zero, and suppose regulation is s_4. Then again, all firms find regulation binding, and all firms earn less than if they invested at privately-optimal levels.

Regulators

Regulators choose a minimal standard for investment in order to maximize social welfare as before. This time, we consider three sets of parameters.

1. $\tilde{h}^L \leq a$

Figure 2.1: Profits



$\{\{S_i\} : s_i = x^L(\min\{y, h\})\}$

First, we assume that technology and the market is such that it is privately optimal for all firms to close, even if regulators set the minimal standard to its lowest level ($s = 0$). In this case, the only possibility for regulators to foster output is through subsidies; however, we do not consider such subsidies. In this case, we obtain the same solution as in the liability-only case, and social welfare with zero output is

$$\zeta_1^{LR} = \zeta^L = \ U(0) \tag{2.9}$$

2. $a < \tilde{h}^{LR}(s) \leq h(s)$

In this scenario, at least some firms find it profitable to operate despite liability, but regulation is sufficiently high so that all firms that operate find regulation binding. The regulators' objective function is:

$$\zeta_2^{LR} = \max \left\{ \begin{array}{c} U(0), \\ \max\limits_{x^L(a)<x^L\left(\tilde{h}(s)\right)\leq s} \int_a^{\tilde{h}(s)} \left\{U(Q) - s - p\left(s\right)h\right\} f\left(h\right)dh \\ +[1 - F(\tilde{h}(s))] \times U(0) \end{array} \right\} \tag{2.10}$$

Regulators choose between forcing the market to close and allowing profitable operations. Regulations are constrained. First, let us define $h(s) \equiv \left(x^L\right)^{-1}(s)$ as the point of indifference between s and x^L. Then any solution to the problem above must satisfy the following constraints:

$$\tilde{h}^{LR}(s) \leq h(s) \Rightarrow x^L(\tilde{h}^{LR}(s)) \leq x^L(h(s)) = x^L((x^L)^{-1}(s)) = s$$

Regulation must be sufficiently high that all firms that find operations profitable also find regulation binding. At the same time, we assume that regulation is sufficiently low that some firms find operations profitable:

$$a < \tilde{h}^{LR}(s) \Rightarrow x^L(a) < x^L(\tilde{h}^{LR}(s))$$

3. $a \leq h(s) < \tilde{h}^L(s)$

   Finally, we consider the case in which at least some firms operate, and at least some do not find regulation binding.

$$\zeta_3^{LR} = \max \left\{ \begin{array}{c} U(0), \\ \max\limits_{0 \leq s < x^L(\tilde{h}^{LR}(s))} \int_a^{h(s)} \{U(Q) - s - p\,(s)\,h\}\, f\,(h)\, dh \\ + \int_{h(s)}^{\tilde{h}^L} \left\{U(Q) - x^L(h) - p\left(x^L(h)\right) h\right\} f\,(h)\, dh \\ +[1 - F(\tilde{h}^L)] \times U(0) \end{array} \right\} \tag{2.11}$$

   As before, regulators choose between forcing the market to close and allowing operations. If any firms find regulation binding, it will be those with lowest h. To find social welfare, regulators add together the benefits of production for firms investing at the regulated level, plus the benefits of firms investing higher levels, plus the benefits of zero production for firms that close. Policy choices are constrained on the lower end by zero; we do not consider subsidies. We set an upper bound on regulation for this scenario:

$$h(s) < \tilde{h}^{LR}(s) \Rightarrow x^L(h(s)) = x^L((x^L)^{-1}(s)) = s < x^L(\tilde{h}^{LR}(s))$$

   At least some firms find it profitable to operate while investing above mandated levels. We define the point of indifference between s and x^L as

$$h_t(s) \equiv \left(x_t^{LR}\right)^{-1}(s)$$

We can find solutions to the objective functions above. First, we solve for the case in which regulation binds for all operating firms. By differentiating the welfare function with respect to s, we see that

$$\begin{aligned}
\frac{\delta \zeta_2^{LR}}{\delta s} &= -\int_a^{\tilde{h}^{LR}(s)} f(h)dh - p'(s)\int_a^{\tilde{h}^{LR}(s)} hf(h)dh \\
&\quad + \frac{\delta \tilde{h}^{LR}}{\delta s}\left\{U(Q) - s - p(s)\,\tilde{h}^{LR}(s)\right\} f\left(\tilde{h}^{LR}(s)\right) - f(\tilde{h}^{LR}(s))\frac{\delta \tilde{h}^{LR}(s)}{\delta s}U(0) \\
&\quad = -\int_a^{\tilde{h}^{LR}(s)} f(h)dh - p'(s)\int_a^{\tilde{h}^{LR}(s)} hf(h)dh \\
&\quad + \frac{\delta \tilde{h}^{LR}(s)}{\delta s} f(\tilde{h}^{LR}(s))\left[U(Q) - U(0) - s - p(s)\tilde{h}^{LR}(s)\right] \\
&= 0
\end{aligned}$$

Consider the last term in the simplified form of the equation. Note that the derivative is non-zero only if $h < y$ and $s > x^L$. In specifying the problem, we assumed that $s > x^L$. To determine the sign of the term in brackets, we assume that $h < y$, for otherwise the preceding derivative is zero and so the bracketed term is not relevant. By definition, profits for firms with $h = \tilde{h}^{LR}(s)$ are zero. Recall that we defined social welfare as profits plus utility from consumption less consumers' liability. Consumers have no liability when $h < y$, and profits are zero for $\tilde{h}^{LR}(s)$. By employing these facts, we can simplify the last term in the equation above.

$$\begin{aligned}
\frac{\delta \zeta_2^{LR}}{\delta s} &= -\int_a^{\tilde{h}^{LR}(s)} f(h)dh - p'(s)\int_a^{\tilde{h}^{LR}(s)} hf(h)dh \\
&\quad + \frac{\delta \tilde{h}^{LR}(s)}{\delta s} f(\tilde{h}^{LR}(s))\left[u(Q) - u(0)\right] \\
&= 0
\end{aligned}$$

Hence, we see that at the optimum (assuming an interior solution), the cost of additional investment, plus the benefits of lower expected damages, less the net benefits to consumers of production from firms that exit the market sum to zero.

If we suppose that $\int_a^{\tilde{h}(s)} f(h)dh > 0$, as it will be if this case is relevant, then we can simplify the first order conditions for the second case, and we have

$$
\begin{aligned}
1 &= -p'(s^{LR}) \left[\frac{\int_a^{\tilde{h}(s)} hf(h)dh}{\int_a^{\tilde{h}(s)} f(h)dh} \right] + \frac{\delta \tilde{h}(s)}{\delta s} \frac{f(\tilde{h}(s))}{\int_a^{\tilde{h}(s)} f(h)dh} \left[u(Q) - u(0) \right] \quad (2.12) \\
&= -p'(s^{LR}) E(h|h < \tilde{h}(s^{LR}) + \frac{\delta \tilde{h}(s)}{\delta s} f(\tilde{h}(s)|h \leq \tilde{h}(s)) \left[u(Q) - u(0) \right]
\end{aligned}
$$

Because $\partial \tilde{h}^{LR}(s)/\partial s \leq 0$, we know that $1 \leq -p'(s^{LR})E(h|h < \tilde{h}(s^{LR})$. Thus, we have

$$s_2^{LR} \leq x^{SP} \left(E(h|h < \tilde{h}(s_2^{LR})) \right)$$

If all firms find operations profitable, then this rule is identical to that in the case of regulation only. For $\tilde{h}^{LR}(s_2^{LR}) < y$, regulation will be lower than in the regulation-only case due to the loss of consumption benefits. Given the profitability constraint on regulation, and denoting the solution to Equation 2.12 as s_2^*, we have

$$s_2^{LR} = \min \left\{ Q - p(s_2^{LR}) \tilde{h}^{LR}(s_2^{LR}), s_2^* \right\}$$

The solution for the third case is found in similar fashion:

$$
\begin{aligned}
\frac{\delta \zeta_3^{LR}}{\delta s} &= -\int_a^{h(s)} f(h)dh - p'(s) \int_a^{h(s)} hf(h)dh \\
&= 0
\end{aligned}
$$

In this third case, assuming that $\int_a^{h(s^{LR})} f(h)dh > 0$, we can find a similar rule to that in the second case:

$$
\begin{aligned}
\Rightarrow 1 &= -p'(s)\left[\frac{\int_a^{h(s)} hf(h)dh}{\int_a^{h(s)} f(h)dh}\right] \qquad (2.13)\\
&= -p'(s)E\left(h|h<h(s)\right)
\end{aligned}
$$

By solving for regulation, assuming an interior solution, we have

$$s = x^{SP}\left(E\left(h|h<h(s)\right)\right)$$

Again, we find that the rule for regulation is similar to the solution for the regulation-only case. The optimal policy is to set regulation to the social optimum for affected firms. Given the profitability constraint, and denoting the solution to Equation 2.13 as s_3^*, we have

$$s_3^{LR} = \min\left\{Q - p(s_3^{LR})\tilde{h}^{LR}(s_3^{LR}), s_3^*\right\}$$

In summary, we reviewed three cases. The first requires that firms close, regardless of the level of regulation, because of unfavorable technological and economic conditions. If the first case does not hold, then regulators choose between the second and third cases. Given the optimal levels of regulation s_2^{LR} and s_3^{LR} for the respective cases, the regulators' decision may be summarized as follows:

$$
\zeta^{LR} = \max\left\{\begin{array}{c}
U(0),\\
\int_a^{\tilde{h}^{LR}(s^{LR})}\left\{U(Q) - s_2^{LR} - p\left(s_2^{LR}\right)h\right\}f(h)dh\\
+[1-F(\tilde{h}^{LR}(s_2^{LR}))]\times U(0),\\
\int_a^{h(s_3^{LR})}\left\{U(Q) - s_3^{LR} - p\left(s_3^{LR}\right)h\right\}f(h)dh\\
+\int_{h(s_3^{LR})}^{\tilde{h}^L}\left\{U(Q) - x^L(h) - p\left(x^L(h)\right)h\right\}f(h)dh\\
+[1-F(\tilde{h}^L)]\times U(0)
\end{array}\right\} \qquad (2.14)
$$

Regulators choose between closing the industry, forcing all firms that operate to invest the mandated amount, and allowing some to invest at the private optimum while forcing others to invest the standard amount. In the following section, we will determine more precisely the regulatory levels s_2^{LR} and s_3^{LR}.

2.3 Propositions

In this section, we establish a series of claims about optimal regulation and operations in the markets described above. These correspond to the propositions given in Shavell [57], while incorporating our extensions to the model and applying the results to the case of nuclear power.

2.3.1 Proposition 1:

The level of care taken by risk-bearing firms as a function of their liability is

$$\begin{aligned} x^L(h) &= x^{SP}\left(\min\{h, y\}\right) \\ &\leq x^{SP}(h) \end{aligned} \tag{2.15}$$

Hence, the level of care of taken by operating firms is less than or equal to the first-best; in fact, it is equal to the first-best level so long as the magnitude of the potential harm is less than the level of assets.

If $\zeta^{SP}(a) \leq U(0)$ and $\Pi^L(a) \leq 0$, then $Q^{SP} = Q^L = 0$. Likewise, if $\zeta^{SP}(b) \geq U(0)$ and $\Pi^L(b) \geq 0$, then $Q^{SP} = Q^L = Q$. In both cases, output under liability matches output under social planning. In all other cases, either too many firms or not enough firms operate relative to the social optimum.

- Proof

1. The equality for Equation 2.15 is clear, since Equation 2.5 is of the same form as Equation 2.2. Note that x^{SP} is increasing in h, while $\min\{y, h\}$ is increasing for $h < y$ and is constant for $h \geq y$. These imply the inequality.

   The conditions listed for $Q^{SP} = Q^L$, such that $\tilde{h}^{SP} = \tilde{h}^L$, are obvious. We list remaining feasible cases, and categorize them either as $Q^{SP} < Q^L$ or $Q^{SP} > Q^L$.

   Too many firms operate under liability, so that $\tilde{h}^{SP} < \tilde{h}^L$, if 1) $y < a$, $U(0) < \zeta^{SP}(a)$, $\zeta^{SP}(b) < U(0)$, and $0 \leq \Pi^L(a)$; 2) $\zeta^{SP}(a) \leq U(0)$ and $0 \leq \Pi^L(a)$; or 3) $U(0) \leq \zeta^{SP}(y)$, $\zeta^{SP}(b) < U(0)$, and $0 \leq \Pi^L(y) = \Pi^L(b)$. Regarding the third, suppose $\Pi^L(y) \geq 0$. Then $\Pi^L(b) \geq 0$ since liability does not increase past y, and optimal investment is constant for all $h \geq y$. In this case, all firms will operate. If $\zeta^{SP}(b) < 0$, then not all firms will operate under social planning, and $Q^{SP} < Q^L$. If $U(0) \leq \zeta^{SP}(b)$ and $0 \leq \Pi^L(b)$, then $Q = Q^L = Q^{SP}$.

   Too few firms operate under liability, so that $\tilde{h}^{SP} > \tilde{h}^L$, if 1) $y < a$, $U(0) < \zeta^{SP}(a)$, and $\Pi^L(a) < 0$; or if 2) $U(0) < \zeta^{SP}(a)$ and $\Pi^L(y) < 0$. Regarding the second, suppose $\zeta^{SP}(y) \leq U(0)$. Then $\zeta^{SP}(y) - \Pi(y) = U(Q) - Q > 0$, for $U(Q) = Q + u(Q)$, since $x^{SP}(h) = x^L(h)$ for all $a \leq h \leq y$. Hence, for all $h \leq y$, profits and output are zero when social welfare is less than $u(Q) > 0$, and thus $Q^L < Q^{SP}$.

2.3.2 Proposition 2

The optimal regulatory standard equals the level of investment in the social planning case for the firm posing the average level of potential damage, so long as regulated firms remain profitable:

$$\begin{aligned} s^R &= \min\{Q, x^{SP}(E(h))\} \\ &\leq x^{SP}(E(h)) \end{aligned} \tag{2.16}$$

The optimal regulatory level equals the first-best level of care for the average firm so long as it does not exceed its revenue (i.e. so long as $Q \leq x^{SP}(E(h))$). The regulator chooses between shutting down the industry and allowing all firms to operate with this level of care. If the industry remains in operation, then parties posing less risk of damage than $E(h)$ invest more than the social planning level, and those posing greater risk than $E(h)$ invest less than the first-best level.

If all firms close in the first-best solution, then all firms close under regulation. If all firms operate in the first-best solution, and if the firms are profitable under regulation, then the optimal level of output is achieved, but social welfare is less than first-best. If only some firms operate under the first-best solution, then output under regulation either will be to little (if the industry closes) or too great (if all firms operate). Clearly, social welfare is less than first-best.

- Proof

1. Since the simplified RHS of Equation 2.6 is of the same form as Equation 2.1, then Equation 2.16 follows, so long as $x^{SP}(E(h)) \leq Q$. Since $x^{SP}(h)$ increases with h, parties posing less risk than $E(h)$ invest too much and parties posing more risk invest too little, assuming that production remains profitable under regulation.

If the social planner finds it best for all firms to close, then because it is feasible and no superior solution is possible, so too does the regulator.

If $s^R = x^{SP}(E(h)) \leq Q$, and if $U(0) \leq \zeta^{SP}(b)$, then all firms operate both under social planning and regulation; hence output is the same for both. Because only the average firm invests optimally under regulation, social welfare is lower.

Under regulation, either no firms operate or all firms operate. If only some firms close under social planning, then either too few or too many will operate under regulation, depending on the level of social welfare for zero output versus full output.

If $U(Q) - s^R - p(s^R)E(h) < U(0)$, then regulators force the industry to close. If instead social welfare is greater with production but $Q < x^{SP}(E(h))$, then it may be socially optimal to set regulation so that all firms operate with zero profits, while investing less than the first-best level for the average firm.

2.3.3 Proposition 3

Social welfare is greater under regulation than under liability if the liability is sufficiently low (y sufficiently low) or if the range of potential damages is sufficiently small (h tightly distributed about $E(h)$); otherwise social welfare under liability is greater than under regulation. The exception is when, despite bankruptcy protection, high levels of liability cause firms to exit and output to fall. If consumers value the lost products more than the risk reduction, then it may be better to regulate a profitable level of investment with zero liability rather than simply to offer zero regulation and bankruptcy protection.

- Proof

1. We first want to show that there is a $\tilde{y}$ where $0 < \tilde{y} < b$ such that regulation is superior to liability for $y \leq \tilde{y}$, but not otherwise.

   We can compute the benefit of regulation versus liability as

$$\zeta^R - \zeta^L = \max \left\{ \begin{array}{c} \int_a^{\tilde{h}^L} \left\{ U(0) - \left[U(Q) - x^L(h) - p(x^L(h))h \right] \right\} f(h)dh, \\ \left[1 - F(\tilde{h}^L) \right] \left[U(Q) - U(0) \right] - \left[s^R - \int_a^{\tilde{h}^L} x^L(h) f(h) dh \right] \\ - \left[p(s^R)E(h) - \int_a^{\tilde{h}^L} p(x^L(h)) h f(h) dh \right] \end{array} \right\}$$

   where the first term holds for $Q^R = 0$ and the second holds for $Q^R = Q$. If y equals 0, then Equation 2.15 implies that investment is equal to 0 for all $h \in [a, b]$, and thus the situation for firms under liability is identical to the situation for firms under regulation facing the policy $s = 0$. The equation above becomes

$$\zeta^R - \zeta^L = \max \left\{ \begin{array}{c} U(0) - \left[U(Q) - p(0)E(h) \right], \\ -s^R - \left[p(s^R) - p(0) \right] E(h) \end{array} \right\}$$

   since $x^L(h) = 0$ and $\tilde{h}^L = b$. Note that this equation is equivalent to

$$\begin{aligned} &\zeta^R(s = s^R, q = Q^R) - \zeta^R(s = 0, q = Q) \\ &= \max \left\{ \begin{array}{c} U(0) - \left[U(Q) - p(0)E(h) \right], \\ -s^R - \left[p(s^R) - p(0) \right] E(h) \end{array} \right\} \end{aligned}$$

From this equation, it is clear that the left-hand side is non-negative, for social welfare under regulation can be no greater than at $q = Q^R$ and $s = s^R$. If the first term in brackets is greater, then regulators find it better to close the industry than to choose any feasible level of regulation such that production is positive, including the feasible level $s = 0$. However, this means that the first term must be positive, since optimal closure of the industry means that utility of zero consumption is greater than full production and zero investment. If the second term in brackets is greater, then regulators find it better to choose a feasible level of regulation that allows non-negative profits and thus a positive level of production. For the optimal level of regulation $s^R > 0$, the second term must be positive, as it is equivalent to the difference between social welfare with optimal regulation $s^R > 0$ and suboptimal regulation $s = 0$. Hence, since s^R is the (unique) optimal s and is positive, social welfare must be higher under regulation than under liability when y equals 0. This and the continuity of social welfare in y prove that regulation yields better outcomes than liability for sufficiently low liability levels.

Taking the derivative of social welfare under liability with respect to y, we see that

$$\frac{\delta \zeta^L}{\delta y} = \begin{cases} 0 & : \quad \tilde{h}^L < y \\ \int_y^b \{-\frac{\delta x^L}{\delta y} - \frac{\delta p}{\delta x}\frac{\delta x^L}{\delta y} h\} f(h) dh & : \quad y < \tilde{h}^L = b \\ [1 - F(y)][u(0) - u(Q)] & : \quad \Pi^L(y) = 0 \\ +p(x^L(y)) \int_y^b \{h - y\} f(h) dh & \end{cases}$$

When potential damages for all operating firms fall short of the value of the firm, then small changes in the maximum level of liability do not affect the firms' behavior, and so social welfare is not affected. If all firms find it profitable to operate, and some mass of firms operate under the protection of limited liability, then social welfare strictly increases with small changes in liability, since these same firms invest greater amounts. Because the increases move their investment levels closer to the socially optimal amounts, welfare increases.

If firms that operate under the protection of limited liability just break even, so that $\Pi(y) = 0$, then a small increase in liability could have a large effect on output and social welfare. A small increase in y would cause profits for $[1 - F(y)]$ firms to become negative, so these firms would exit the market and output would fall by a proportional amount. Consumers would lose the benefit of consuming the foregone products, which would have an adverse affect on social welfare. On the other hand, the amount of liability that $[1 - F(y)]$ firms had been escaping, and thus had been falling on consumers or some other entity, would disappear. This would enhance social welfare. The net effect depends on the preferences of consumers and the magnitude of liability that firms escape.

Hence, if liability is superior to regulation for some y_1, then generally the same must be true for any $y_2 > y_1$, for in almost all cases we see that social welfare is non-decreasing in y under liability, but is unaffected by y under regulation. The possible exception occurs for y_1 and y_2 such that $\Pi^L(y_1) \geq 0$ and $\Pi^L(y_2) < 0$, so that the increase in liability causes firms to exit. In this case, if consumers prefer the reduction of risk over the benefits of consumption, then ζ^L would rise. Otherwise, if consumers value the products more than escaping their share of potential damages, then ζ^L falls. In this last case, social welfare is not non-decreasing in y, and welfare could be higher under regulation both for low y and for relatively large y.

For $y \to b$ and $\Pi^L(y) \geq 0$, $\zeta^L \to \zeta^{SP}$, since investment under liability is at the first best level for all $h \leq y$. Under these conditions, regulation cannot do better and surely will do worse if the variance of h is sufficiently large. For $\Pi^L(y) < 0$ as $y \to b$, regulation either could prove superior in all cases or could prove superior for small and large y, depending on consumers preferences for consumption versus the escape of liability.

Hence, we prove that there is a $\tilde{y}$, where $0 < \tilde{y} < b$, such that regulation is superior to liability for $y \leq \tilde{y}$, and that liability will yield greater welfare otherwise, with the notable exception of when consumption losses outweigh safety gains in terms of social welfare.

To see the result of h tightly distributed about its mean, consider first the average firm as it operates either under regulation or liability. Note from Equation 2.15 that for $0 \leq \Pi^L(E(h))$,

$$\begin{aligned} x^L\left(E(h)\right) &= x^{SP}\left(\min\{E(h), y\}\right) \\ &\leq x^{SP}\left(E(h)\right) \end{aligned}$$

and that

$$
\begin{aligned}
s^R &= \min\{Q, x^{SP}(E(h))\} \\
&\leq x^{SP}(E(h))
\end{aligned}
$$

For $E(h) \leq y$ and $x^{SP}(E(h)) \leq Q$, then $x^L(E(h)) = s^R$ and regulation is as good as liability in maximizing social welfare for the average firm. If $x^{SP}(y) < Q$ and $y < E(h)$, then $x^L(E(h)) < s^R$ and regulation is superior to liability for maximizing social welfare for the average firm. If $Q < x^{SP}(E(h))$ and $Q < x^{SP}(y)$, then investment and output are zero under liability but may be positive under regulation; they will be positive only if it is socially optimal. Hence, regulation generally is superior to liability for the average firm.

In cases where $x^L(E(h)) < s^R$ so that $\zeta^L(E(h)) < \zeta^R(E(h))$, then continuity implies that there is a non-degenerate interval including $E(h)$ in which $U(Q) - s^R - p\left(s^R\right)h > U(Q) - x^L(h) - p\left(x^L(h)\right)h$. If the probability mass within the interval is sufficient, the difference in expected social welfare between liability alone and regulation alone, given by

$$
\int_a^{\tilde{h}^L} \left\{\left[U(Q) - x^L(h) - p\left(x^L(h)\right)h\right]\right\} f(h)dh \\
- \left[U(Q) - s^R - p\left(s^R\right)E(h)\right]
$$

will be negative, and regulation will be superior to liability.

If $h = E(h)$ for all firms, so that all firms are identical, then clearly the first-best solution can be reached under regulation so long as $x^{SP}(E(h)) \leq Q$, for then either $s^R = x^{SP}(E(h))$ or all firms are closed, with the decision following the first-best. This solution would not be reached under liability when $y < E(h)$ and $\Pi^L(E(h)) \geq 0$, for then $x^L(E(h)) < x^{SP}(E(h))$. If instead $y \geq E(h)$ and $\Pi^L(E(h)) \geq 0$, then $s^R = x^L(E(h)) = x^{SP}(E(h))$, and so regulation is as good as liability. If $\Pi(E(h)) < 0$ under liability, but optimal regulation allows operation, then regulation is superior; however, $s^R = \min\{Q, x^{SP}(E(h))\}$ in this case, and so the social-planning level of welfare might not be reached. Hence, regulation is at least as good as liability when all firms are identical. As argued above, continuity allows us to extend the argument to the case where the distribution of potential damages is sufficiently small.

2.3.4 Proposition 4

For the optimal use of both regulation and liability, we classify three potential outcomes:

1. For $a < y$, the optimal minimum level of investment is less than the level required in the regulation-only case, and it equals the investment level in the liability-only case for those parties posing the least potential damage:

$$s^{LR} = x^{SP}(a) < s^R \tag{2.17}$$

   No firms' decisions are constrained by the regulations. All are induced by liability to take at least as much care as the required standard s^{LR}. A sufficient condition for Equation 2.17 is

$$x^L\left(\tilde{h}^L\right) > s^R \tag{2.18}$$

or, equivalently, that the motivation to lower risk is sufficiently great (y sufficiently high), while profits remain sufficiently high for firms with $h = a$.

- Proof

(a) $s^{LR} \in [x^{SP}(a), s^R]$: For every h, expected social welfare is greater at $s = x^{SP}(a)$ than at lower levels of investment, so that $s^{LR} \geq x^{SP}(a)$. Of course, this assumes that firms with potential damages a find it profitable to operate at $s^{LR} = x^{SP}(a)$. If this is not the case, then Equation 2.18 does not hold, and either the industry optimally is forced to close or Proposition 4b or Proposition 4c holds.

To prove that $s^{LR} \leq s^R$, let $W(s;r)$ be expected social welfare under regulation only, and let $W(s;rl)$ be expected social welfare under combined regulation and liability. Then for any $s_1 < s_2$

$$W(s_1;r) - W(s_2;r) \quad \leq \quad W(s_1;rl) - W(s_2;rl) \tag{2.19}$$

WE show this by establishing the corresponding weak inequality for each $h \leq \tilde{h}^L$ and $s_2 \leq Q$:

$$\left[\begin{array}{c} \max\left\{U(0), U(Q) - s_1 - p\left(s_1\right)h\right\} \\ -\max\left\{U(0), U(Q) - s_2 - p\left(s_2\right)h\right\} \end{array}\right] \leq$$
$$\left[\begin{array}{c} \max\left\{U(0), U(Q) - \max\{s_1, x^L(h)\} - p(\max\{s_1, x^L(h)\})h\right\} \\ -\max\left\{U(0), U(Q) - \max\{s_2, x^L(h)\} - p(\max\{s_2, x^L(h)\})h\right\} \end{array}\right] \tag{2.20}$$

To verify Equation 2.20, note that equality holds for h such that $x^L(h) \leq s_1$. For h such that $s_1 < x^L(h)$, both for $s_1 < x^L(h) \leq s_2$

and for $s_2 < x^L(h)$, the inequality is strict. The argument easily can be modified to show the same condition when $s_1 < s_2 \leq Q$ and $\tilde{h}^L < h$, when $s_1 < Q \leq s_2$, and when $Q < s_1 < s_2$.

As s^{LR} maximizes $W(s;rl)$ over s, $W(s^R;rl) - W(s^{LR};rl) \leq 0$. But then if $s^R < s^{LR}$, Equation 2.19 would imply $W(s^R;r) - W(s^{LR};r) \leq 0$, which would contradict our finding that s^R is the unique optimum under regulation. Thus $s^{LR} \leq s^R$.

(b) $s^{LR} < s^R$ while $\Pi^{LR}(\tilde{h}^L) > 0$ at investment level $s^{LR} < x^L\left(\tilde{h}^L\right)$ implies that some firms invest amounts exceeding s^{LR}, that is, $s^{LR} < x^{LR}(\tilde{h}^L)$, so long as $0 < \Pi^{LR}(a)$: If not, then it must be that $x^{LR}(\tilde{h}^L) \leq s^{LR}$, and so for $s \geq s^{LR}$, Equation 2.10 is relevant. Since Equation 2.10 has a unique maximum either at s^R or at the point $s^{LR} > x^L(\tilde{h}^L)$ such that $\Pi^{LR}(\tilde{h}^L) = 0$, and we assumed that $s^{LR} < s^R$ while profits at $\tilde{h}^L$ were positive given investment level s^{LR}, then Equation 2.10 must have a unique maximum over $s \geq s^{LR}$ at s^R. But then the social welfare function could not have had a maximum at $s^{LR} < s^R$. This contradiction is our proof.

(c) $s^{LR} < s^R$ while $\Pi^{LR}(\tilde{h}^L) > 0$ at investment level s^{LR} implies that s^{LR} is determined by $s^{LR} = x^{SP}(a)$, so long as $\Pi^{LR}(a) \geq 0$: From (b), we know that if $s^{LR} < s^R$ while $\Pi^{LR}(\tilde{h}^L) > 0$ at investment level s^{LR}, then Equation 2.11 is relevant for all s in an interval properly including $x^{SP}(a)$ and s^{LR}. We can split the equation into three of the following four integrals:

$$\begin{aligned}
&\int_a^{h(s)} \left[U(Q) - s - p(s)h\right] f(h)dh \\
&\qquad + \int_{h(s)}^{\min\{y,\tilde{h}^L\}} \left[U(Q) - x^{SP}(h) - p(x^{SP}(h))h\right] f(h)dh \\
&\qquad + I_{y<\tilde{h}^L} \left\{ \int_y^b \left[U(Q) - x^L(y) - p(x^L(y))h\right] f(h)dh \right\} \\
&\qquad\qquad\qquad\qquad + I_{\tilde{h}^L \leq y} \left\{ [1 - F(\tilde{h}^L)]U(0) \right\} \quad (2.21)
\end{aligned}$$

Note that for $s \in [x^{SP}(a), x^{SP}(y)]$, the terms in the third and fourth lines of Equation 2.21 are constant and thus are irrelevant for the optimization problem. Note also that the second integral, on the second line, is maximized for all $h \in [h(s), \min\{y, \tilde{h}^{LR}\}]$. The first integral, finally, falls short of the social welfare maximum for $h(s) > a$, or

$$\begin{aligned}
& \int_a^{h(s)} \left[U(Q) - s - p(s)h\right] f(h)dh \\
< \; & \int_a^{h(s)} \left[U(Q) - x^{SP}(h) - p(x^{SP}(h))h\right] f(h)dh
\end{aligned}$$

since $s > x^{SP}(h)$ for all $h \in [a, h(s))$. The two terms are equal only for $s = x^{SP}(a)$, so that all firms with $h \in [a, y]$ invest the first-best amounts. Firms with $h \in (\min\{y, \tilde{h}^{LR}\}, b]$ either close or invest in the amount determined by their liability, $x^{LR}(h) = x^L(h)$. Hence, if $a < y$, a possible solution is that regulation is not relevant. In this case, all firms invest the privately-optimal amount $x^L(h)$.

(d) If Equation 2.18 holds, then $s^{LR} < s^R$: Suppose not. Then by (i), $s^{LR} = s^R$. But suppose Equation 2.18 implies that Equation 2.11 is relevant at s^R; we need only follow the argument in (1c) to show that $s^{LR} = x^{SP}(a) < s^R$.

2. All firms operate and find regulation binding. Either the optimal level equals the optimal regulation-only level, or regulation drive profits to zero for for firms with the most potential damage; that is, either

$$s^{LR} = s^R$$

or

$$\Pi^{LR}(y) = 0$$

given $x^L(y) < s^{LR} < s^R$. Liability is insufficient to inspire greater investment than s^{LR}. This will result for $x^L(y)$ sufficiently low for $a \leq y$ and $0 < \Pi^L(y)$, so that $x^{SP}(y) < s^R$.

   (a) If $\Pi^{LR}(y) \geq 0$ at investment level s^R, and if $s^{LR} = s^R$, then no firm invests more than s^R: Otherwise, $x^L(y) > s^R$, which by (1d) implies $s^{LR} < s^R$, a contradiction.

   (b) If $\Pi^L(y) > 0$ but $\Pi^{LR}(y) < 0$ at investment level s^R, and if $x^L(y) < s^{LR}$, then $\Pi^{LR}(y) = 0$ and $s^{LR} < s^R$: Since profits fall with investment given a fixed liability level y, profits are lower for investment s^R than for $s^{LR} < s^R$. Since profits are zero at s^{LR}, no firm would choose to invest more. If profits were positive, then regulators could improve welfare by increasing regulation toward s^R.

   (c) If $x^L(y)$ is sufficiently low for $a \leq y$, and $0 \leq \Pi^L(y)$, then $x^L(y) < s^{LR} \leq s^R$, and either $s^{LR} = s^R$ or $\Pi^{LR}(y) = 0$: Assume the contrary. Then in particular it must be possible that $s^{LR} < s^R$ while $0 < \Pi^{LR}(y)$ for an $x^L(y) \leq x^{SP}(a)$. But by (1b) we know that if $s^{LR} < s^R$ and profits are positive, then $x^L(y) > s^{LR}$. Hence, $x^{SP}(a) > s^{LR}$. This, however, contradicts (1a), so that certainly for all $x^L(y)$ as low as $x^{SP}(a)$, $x^L(y) < s^{LR} \leq s^R$.

Note that as the liability limit decreases, so does investment, and it approaches $x^{SP}(a)$ as y approaches a. Hence, if y is sufficiently small, $x^L(y) < s^{LR} \leq s^R$.

3. The optimal regulatory standard allocates all profits when $y < a$, $0 \leq \Pi^L(a)$, and profits are negative for $s = x^{SP}(a)$; that is, the optimal liability level is

$$\{s^{LR} \;:\; Q = s + p(s)y\}$$

such that $x^L(a) \leq s^{LR} < Q$. If $U(0) < \zeta^R(s)$ for $s = s^{LR}$, then all firms operate. Otherwise, regulators force all firms to close. If firms operate, no party is induced by liability to take more care than $x^L(a)$, but all firms find regulation s^{LR} binding.

This will obtain if $y < a$ and production by all firms at $s^R < x^{SP}(a)$ both provides greater social welfare than zero consumption and allows those firms to earn non-negative profits. In this case, $x^L(y) \leq s^{LR} < x^{SP}(a)$. In other words, firms invest $x = \max\{s, x^{SP}(\min\{h, y\})\}$. Then, for $y < a$ and $0 < \Pi^L(a)$ and $U(0) < \zeta^R$ for $s = s^{LR}$, it may be optimal to set $x^L(a) \leq s^{LR} < x^{SP}(a)$ to gain the benefit of consumption despite sacrificing safety.

If production is positive under regulation, then $s^{LR} < s^R$.

(a) If $y < a$, $0 < \Pi^L(a)$, and profits are negative for $s = x^{SP}(a)$, then $x^L(a) \leq s^{LR}$: This follows from (1a).

(b) If $\Pi^{LR}(a) < 0$ for $s = x^{SP}(a)$ but $0 \leq \Pi^{LR}(a)$ for $s^{LR} < Q$, and if $U(0) < \zeta^R$ for $s = s^{LR} < Q$, then all firms operate: First, if $U(0) < \zeta^R$ for $s = s^{LR} < Q$, then it is welfare-maximizing for all firms to operate with $x \geq s^{LR}$. Because firms bear (limited) liability costs, liability levels strictly must be less than net revenue ($s^{LR} < Q$) for firms to remain profitable. Because $x^{SP}(h)$ and $x^L(h)$ are increasing in $h < y$, and because $0 < \Pi^L(a)$, investments of $x^L(a) < x^{LR} < x^{SP}(a)$ fall closer to the first-best solution while leaving profits non-negative. Hence, it is optimal to allow all firms to operate while forcing them to invest $s^{LR} > x^L(a)$, given the assumption that $U(0) < \zeta^R(s)$ for $s = s^{LR}$.

(c) If production is positive under regulation, then $s^{LR} < s^R$: If production is positive under regulation, then $s^R \leq Q$. Positive production under both liability and regulation requires that $s^{LR} \leq Q - p(s^{LR})y$, given the other assumptions listed above. If $s^R < x^{SP}(a)$, then it must be the case that $s^R = Q$, for otherwise it social welfare would be increased by moving s^R closer to the first-best solution for a. However, profits clearly are negative for $s^{LR} = s^R = Q$, and so given the assumptions above, it must be true that $s^{LR} < s^R$, with the difference being $p(s^{LR})y$. Essentially, this is the amount of the firms' insurance premiums, assuming that insurance is available at an actuarially fair rate. Hence, regulators find it optimal to set regulation lower than the optimum under zero liability, but the savings go to pay for insurance.

2.3.5 Summary

In this section, we examined optimal conditions under three regulatory regimes. First, we considered the case with limited liability but no regulation. Next, we considered the case in which there is regulation but no liability. We then compared the relative merits of the first two alternatives.

Finally, we considered the case in which there is both limited liability and regulation. In this case, assuming that technology and economics allow at least some firms to operate with the given level of liability as long as regulation is sufficiently low, regulators' choices depend on the level of liability limits. If all firms realize the benefits of liability limits, then regulators set regulation such that all firms find it binding. If profits were non-positive for all firms at investment level $x^{SP}(a)$, then regulators set their policies sufficiently high to drive profits to zero for all firms. If some firms face full liability, but the liability level is relatively low while profits remain positive for firms facing the greatest liability, then regulators set policies such that all firms operate and all invest at the regulated level. If the liability limit is relatively high, such that most firms invest at the first-best level, then regulators set policies sufficiently low that they fail to bind for any firm.

2.4 Applications

In this section, we consider a series of applications of the model. The first several consider whether this model responds to parameter changes in a way consistent with historical market changes. The final applications derive estimates of implicit subsidies to firms for liability limits, and we address the question of what is the optimal level of liability limits.

2.4.1 A Fall in Excess Demand

Demand growth was very high in the decade or more preceding 1973, with average annual growth rates exceeding seven percent. Following 1973, average annual growth rates fell to less than three percent. Suppliers had been preparing for continued high growth rates by investing heavily in new base load plants, especially nuclear and coal-fired power plants. This significant reduction in demand growth forced many planned and partially constructed plants to be abandoned, and less profitable plants were closed.

To allow for changes in demand, suppose that $U(Q)$ is scaled by parameter ϕ. When multiplied by utility $u(Q)$, ϕ becomes a preference parameter. Suppose it also affected profits directly, so that net revenue becomes ϕQ. Thus, changes in consumers' tastes affect firms directly as changes to market prices. In the model above, $\phi = 1$. The level of utility for zero consumption remains unchanged at $u(0)$. Hence, for a shift from $\phi = 1$ to $\phi < 1$, positive consumption becomes relatively less desirable compared to zero consumption.

A reduction of excess demand, in terms of our model parameters, would appear as an fall in ϕ. There is no construction in our model, and we assume that all produced electricity is sold. Hence, these changes have no direct effect on privately optimal investment x^L in our model. However, firms are more likely to exit as net revenue ϕQ falls. Hence, aggregate output may fall with ϕ.

If we ignore changes to production capacity, and if instead we assume that all changes to excess demand come through the preference parameter ϕ, then the level of maintenance spending remains unchanged for all firms that operate but are not bound by regulation. However, the condition for whether regulators should allow production is affected, as is the optimal level of regulation in relevant cases. We see in Equation 2.14 that for sufficiently large reductions in demand, regulators will shut down the industry.

Of course, the nuclear energy industry was not shut down completely in the 1970s or 1980s, when this shift in excess demand occurred. Hence, if we believe that $y < a$ as described in Proposition 2.3.4-3, then the predictions of our model require that regulators decrease s^{LR} in order to maintain profitability. This is so because under our assumptions, regulation either allows all firms to operate or all firms close. In reality, most agree that regulations were heightened. Continued production with a mere thinning of producers indicates that our model's predictions are too extreme. We will revisit the matter in the section below on exit costs. Still, our model does predict a qualitative response that at least vaguely is accurate under some parameter vectors.

2.4.2 Increased Aversion to Losses

The 1979 accident at the Three Mile Island (TMI) nuclear power plant made the possibility of a serious accident real to most Americans. While this accident turned out to be relatively minor, and little or no off site damage was caused by escaping radiation, the 1986 accident at Chernobyl truly was catastrophic. Such events led some to adjust upward their assessment of the probability of accidents that would cause harm to third parties, which is represented in this model as an increase in p. (See, for example, Zimmerman [63] and Price [43, p. 58].) Suppose that the perception of probability function p is scaled upward by parameter α

to become αp.[5] Under liability, privately optimal investment becomes

$$x^L(h) = (p')^{-1}\left(-\frac{1}{\alpha \min\{y, h\}}\right)$$

As operators perception of their own risk increases, so too does their investment. This reduces expected profits directly, so firms are more likely to exit and aggregate output may fall. In general, profits change by

$$\frac{\partial \Pi}{\partial \alpha} = -[1-\alpha]\frac{\partial x^L}{\partial \alpha} - p(x^L)\min\{y, h\}$$

For high levels of expected damage, the derivative is negative even for $\alpha > 1$.

Under regulation only, the optimal policy becomes

$$s^R = \min\left\{Q, (p')^{-1}\left(-\frac{1}{\alpha E(h)}\right)\right\}$$

In this case too, assuming an interior solution, regulation forces investment to increase and profits to fall, so aggregate output also may fall. The condition for whether regulators should allow production also is affected by aversion to losses, and it becomes more likely that regulators will force plants to close. Under both liability and regulation, investment will increase for all firms, since all invest either $x^L(h)$ or s^{LR}, and these terms both increase.

At lease some of the increase in aversion to loss, however, is represented better as a change in preferences. Specifically, the public developed greater concern for safety and relatively less concern for economic well-being. Consequent pressure on politicians may have caused regulators' preferences to shift similarly.

[5] Of course, α must be restricted such that $\alpha \in [0, 1/p(0)]$ so that $\alpha p \in [0, 1]$. These awkward restrictions make clear that the constant parameter should be generalized to a function $\alpha(h)$ such that $\alpha(h)\,p(x(h)) \in [0, 1]$ and satisfies our assumptions regarding derivatives. We then might consider shifts in the function α.

Such changes may be modeled simply as in the preceding section on decreasing demand.

Alternatively, we can redefine the parameter α in our analysis above to represent political preferences or public tolerance of nuclear power risks. In this case, there are no parameter restrictions. $\alpha < 0$ indicates a public comprised of thrill-seekers, and $\alpha = 0$ indicates an indifferent population. Increasing positive values of α indicate growing aversion to potential harm. For $\alpha \to \infty$, consumers reject nuclear power regardless of potential benefits. If we assume $\alpha > 0$, which seems reasonable, then we might ask what determines the magnitude of the preference parameter. In our static model in which each market and each group of consumers are identical, we might assume the parameter exogenous and perform comparative-statics analysis. A slightly more interesting approach would be to assume a range of randomly-distributed preferences. The distribution would be analogous to the real-world distribution of ideological and political persuasions concerning the corporate world, consumer safety, and the natural environment. Perhaps still more interesting and important cases could be analyzed with a dynamic version of this model. With such a model, tolerance for risk and perception of risk could be based on past performance of plants; of course, this particular application also would require other extensions to our model. If the public had imperfect information concerning the risk posed by the plant in their own market, and if past performance offered a signal of the true risk, then preferences might lean against nuclear operations (high α) following poor performance or misbehavior, and the public might be tolerant of operations (low α) following periods of good performance. Regulators would have political interests leading them to care about the public's perception of risk in addition to economic well-being and their own risk assessments. This methodology could incorporate problems of waste disposal that currently plague the industry. Waste disposal, especially temporary storage, perhaps poses greater political problems than technical problems. It thus would be better to consider waste storage as a political constraint that may force plants to close when allowed space is exhausted. These factors too best would be captured in a dynamic political economy model.

Increasing aversion makes it less likely that plants will be allowed to operate, which generally is consistent with the events of the late 1970s and 1980s. The perception of risk appears to have increased following the TMI accident, although there is evidence that it was trending upward throughout the 1970s. In the following years, many plants were closed, investment expenditures increased, and profits fell. However, Zimmerman [63] argues that existing power plants lost little value as a result of TMI once the uncertainty immediately following the accident was resolved. The primary impact of that accident was felt by those building new plants.

2.4.3 Increasing Maintenance Expenditures

It is difficult to find data on maintenance expenditures alone. Usually, this data is combined with operating costs. Such data are reported by the Energy Information Administration ([2, p. 9]) for 1974 to 1992 in constant dollars per kilowatt of plant capacity. Prices are assumed equal, or at least proportional to, the implicit price deflator for GDP. Most notable are rapid cost increases between 1975 and 1984, followed by falling costs through 1992. Costs reported by the EIA increased roughly six-fold in 1993 dollars, from about $10 per kilowatt in 1975 to about $60 per kilowatt in 1984. The aggregation over operating expenses and maintenance costs does not allow us to make claims about maintenance alone. We might reason maintenance costs generally grew at least as fast as operating costs, however, based on the stricter regulatory policies enacted in the late 1970s and early 1980s, and based on stricter enforcement of such policies.

Rothwell [48] reports that older plants, which generally are more expensive to operate, are most likely to close. Plants in regions with lower electricity prices also are more likely to close, although these pressures may be lessened by pollution controls and possible future taxes on carbon emissions. In this era of deregulation of electricity markets, we might expect acceleration of plant closings as profits are squeezed both by lower prices and the higher costs of maintaining aging plants. (Also see Rust and Rothwell [56] for a forecast of plant closings.)

Higher expected decommissioning costs and higher estimated accident probabilities also would lead to higher spending.

2.4.4 Exit Costs

In the work above, we assumed that decommissioning costs were zero. We can adjust the point of indifference $\tilde{h}^L$ between operating and closing for the liability-only case, given positive closure costs c:

$$\left\{\tilde{h}^L : Q + c = x^L(h) + p\left(x^L(h)\right) h\right\}$$

It is easy to see that $\tilde{h}^L$ increases with c so that firms are more likely to remain in the market when exit costs increase. Exit costs do not enter the investment function $x^L(h)$, nor do they enter the interior regulation rule $s^R = (p')^{-1}(-1/E(h))$. However, if the corner solution holds for regulation, then the optimal policy becomes $s^R = Q + c$ which is increasing in exit costs. Similar extension may be made for the case of both liability and regulation.

We see then that higher expected decommissioning costs would lead to higher spending. I do not have evidence that closure costs increased. We might suppose that they did, as regulatory standards generally increased through the 1970s.

Suppose that there is a distribution of exit costs, such that the cost for closing plant i is $0 < c_i$, and suppose that c is not correlated with h. Then the corner solution under regulation only becomes less clear. Before, aggregate output was Q for $s^R \leq Q$ and zero otherwise. With a distribution of exit costs, aggregate output will begin to fall as s^R increases past Q, and aggregate output reaches zero when $s^R = Q + \max(c)$. Hence, firms with low exit costs will close first when economic conditions deteriorate. In the section above on excess demand, we noted that the number of power plants fell at the same time that demand weakened, but aggregate output did not reach zero. A distribution of exit costs provides a simple, though simplistic, explanation.

Note that we have not accounted for on-site cleanup costs following an accident. We might expect that such considerations would lead firms to invest more. If cleanup costs are greater than normal decommissioning costs, then we also expect firms to be more inclined to exit. The expected cost of decommissioning Unit 1 at the Peach Bottom power plant was reported to be about \$130 million, and the cost of cleaning up the damaged Unit 2 at Three Mile Island was estimated to be \$433 million.[6] See Price [43] for an international comparison of decommissioning costs.

Surely the mandated changes and other regulatory policies, together with re-optimization and reassessment by plant operators, explain much of the be-

[6]Reported in the Lancaster New Era on December 3, 2003.

havior recorded in the data. Of course, this model assumes that maintenance is preventative rather than reactionary. We have no data on preventative maintenance. Also, there likely is some distinction between maintenance that makes production more reliable and that which reduces the likelihood of an accident. While there is some overlap, we model only the latter.

2.4.5 Liability Levels

While Shavell defined liability y as the value of the firm, making the model conform to standard bankruptcy rules, it equally well could be defined otherwise. In the U.S., liability is established under the Price-Anderson Act. This generally means that liability is less than the value of the firms operating nuclear power plants.

Prior to 1988, these levels were set in nominal terms and were adjusted infrequently. Since then, the levels are set in real terms and adjust automatically for general inflation. Still, the liability levels are not linked directly to potential accident costs. One obvious reason for this is the difficulty of establishing the distribution of accident costs, or even to establish an upper bound for these costs. Making cost estimation still more difficult are the great regional differences among plants. Some plants are located in rural settings with relatively low values for surrounding properties, while others are in urban settings with tremendous real estate values. However, commercial insurance companies do assess potential damages for each plant. Factors they consider are the size of the plant, population and property values in the surrounding area, and the probability of an accident at the plant (Dubin and Rothwell [17, 16]). Dubin and Rothwell [17] fail to find that power plants in highly-populated areas respond more quickly to opportunities to improve safety. This may indicate that Price-Anderson protections give too little incentive for operators to minimize risk and that regulators' ability to construct and implement optimal policies tailored to specific locations is limited.

The assumptions in our model regarding potential damages are not satisfactory. A troubling assumption is that operators have complete knowledge of h but that regulators know only the distribution. In reality, it seems that regulators should have an estimate of h that at least approaches the accuracy of the firm's assessment. A better assumption would be that firms have private knowledge of the probability of an accident p, which may be different for each firm. Another troubling assumption is that the potential damage for each firm is a single value. In reality, there is a distribution of potential damages for each plant (Dubin and Rothwell [16], Heyes and Heyes [29]). We might define h_i to be the expected value of potential damages for firm i, and $f(h)$ becomes the distribution of mean values across firms. In this case, all firms might benefit from liability limits, even if their mean damage assessment falls below the limit. We will continue to ignore such problems in the following analysis.

The definition of the value of the firm becomes troublesome when we consider the possibility of catastrophic accidents. Consider the possibility that all assets of a firm are devoted to a single plant. Suppose that the plant is destroyed in an accident. Whether the value of the firm had been defined as the present value of profits or as the value of the firm's capital (see Rothwell [50] for a comparison of the net present value of profits to resale plant prices), the value of the firm is destroyed. For liability laws to be credible and thus to affect investment, the firm must hold other assets or insurance. This problem is less apparent in a dynamic model, because the appeal of future profits make firms more inclined to avoid accidents today. However, it remains a problem in any finite-horizon model, for expected future profits diminish over time.

We could extend our model by allowing regulators to choose a level of liability $\hat{y} \in [0, y]$ to maximize social welfare, where y is the value of the firm. In such a model, it is possible that changes in other parameters, as described in the sections above, have been modest, and that the optimal liability level $\hat{y}$ would not have changed much. If so, then it is possible that such a model would be consistent with reality. However, it seems unlikely that regulators choose the liability level to maximize a simple welfare function as presented in this model. Recent difficulties with renewing the Price-Anderson Act, for example, show that political pressures affect significantly the establishment of policies.

In our model, we assume that maximum liability is specified exogenously, and is not under the control of the regulator. If we define y as the value of the firm, which is the maximum liability level under standard bankruptcy law, then we already have analyzed the relevant extremes: the regulation-only case sets liability to zero, and the regulation and liability case sets liability to the full value of the firm. If we define $\hat{y} \in [0, y]$ as the actual level of liability, then we might use the results above to analyze the current regulatory framework. A comparison of results for y and $\hat{y}$ would begin to address the arguments that Price Anderson should be abandoned. We begin such comparisons in the next section, where we construct measures of the benefits to firms for setting $\hat{y}$ below the full value of the firm.

2.4.6 Implicit Subsidies

The benefit to plant owners of liability caps $\hat{y} < y$ can be computed using the operators' objective function from Equation 2.8. We must remember that private benefits do not mean necessarily that social welfare suffers, given our specification of the welfare function. We consider later the effect of $\hat{y} < y$ on social welfare. Nevertheless, we adopt the common phrase "implicit subsidies" to describe the difference in profits for the two regimes.

We can compute the value of subsidies for a given firm i by comparing profits under two regulatory regimes; we omit the subscript i to simplify the notation. In the following equation, we first assume that production takes place under both regimes, and we first consider the case described in Proposition 4-1 ($a < y$ and $s^{LR} = x^{SP}(a)$). We consider two alternative liability rates $\hat{y}$ and y, where $\hat{y} < y < h$ so that $x^L(\hat{y}) < x^L(y)$ and $p\left(x^L(\hat{y})\right) > p\left(x^L(y)\right)$. The value of operations is $\hat{\Pi}$ and Π under policies $\hat{y}$ and y, respectively. The value of subsidies is

$$\begin{aligned} S &= \hat{\Pi} - \Pi \qquad (2.22) \\ &= \left\{Q - x^L(\hat{y}) - p\left(x^L(\hat{y})\right)\hat{y}\right\} - \left\{Q - x^L(y) - p\left(x^L(y)\right)y\right\} \\ &= \left[x^L(\hat{y}) - x^L(y)\right] + \left[p\left(x^L(\hat{y})\right)\hat{y} - p\left(x^L(y)\right)y\right] \\ &= \left[x^L(\hat{y}) - x^L(y)\right] + p\left(x^L(\hat{y})\right)\left[\hat{y} - y\right] + \left[p\left(x^L(\hat{y})\right) - p\left(x^L(y)\right)\right]y \end{aligned}$$

We see then that operators save by spending less on investment goods. Less investment means that the probability of an accident will be higher, but the lower liability level makes the net effect on profits ambiguous. From an earlier section, we saw that the left-hand derivatives of profits is $\left.\frac{\partial \Pi^{LR}}{\partial h}\right|_{h=y} = -p\left(\max\left\{s, x^L\right\}\right)$, so $0 < S$ at least for $\hat{y} \to y$. Expected liability can be decomposed into the expected difference in payments given the new accident probability, plus the difference in accident probabilities times the original liability level.

Most other attempts to estimate the benefits of liability caps consider only the second term in the last line of equation above. They assume that $y = h$, ignoring standard bankruptcy rules, and that $x^L(\hat{y}) = x^L(y)$. Hence, authors like Dubin and Rothwell ([16]) essentially estimate subsidies as $p\left(x^L(\hat{y})\right) \times (h - \hat{y})$.

Most debate compares current liability levels, where $\hat{y}$ clearly is less than h, at least in the worst case, to an alternative regime where operators bear full liability (i.e. $y = h$). Such arguments in reality concern whether it is optimal to allow operations, as it commonly is assumed that no plant would operate if forced to shoulder full liability. However, if there is a $\tilde{y}$ such that $\hat{y} < \tilde{y} < h$, and if $\tilde{y}$ is the liability level that leaves firms indifferent between decommissioning and operations, then private benefits are not greater under a $\tilde{y}$ regime than under a regime with full liability h. If we maintain the assumption that exit costs are zero, then $\tilde{\Pi} = 0$. To calculate subsidies, we replace Π in the equation above with $\tilde{\Pi}$

$$\begin{aligned} S &= \hat{\Pi} - \tilde{\Pi} \\ &= \hat{\Pi} - 0 \\ &= \hat{\Pi} \end{aligned} \tag{2.23}$$

Note that we obtain the same result for any $y > \tilde{y}$, so that subsidies do not increase without bound as potential damages $h > \tilde{y}$ increases, regardless of the limited liability level $\hat{y}$. Implicit subsidies are equal to reported profits less expected liability.

If we were to follow other authors in assuming that $y = h$, that firms operate despite expected losses, and that investment is $x^L(\hat{y})$ under both regimes, then for $\hat{y} < \tilde{y} < y$ the results above show that our estimated subsidies would be exaggerated as

$$
\begin{aligned}
\chi &= \left\{Q - x^L(\hat{y}) - p\left(x^L(\hat{y})\right)\hat{y}\right\} - \left\{Q - x^L(\hat{y}) - p\left(x^L(\hat{y})\right)y\right\} \\
&- \left[\left\{Q - x^L(\hat{y}) - p\left(x^L(\hat{y})\right)\hat{y}\right\} - \left\{Q - x^L(\hat{y}) - p\left(x^L(\hat{y})\right)\tilde{y}\right\}\right] \\
&= -\left\{Q - x^L(\hat{y}) - p\left(x^L(\hat{y})\right)\tilde{y}\right\} - \left\{Q - x^L(\hat{y}) - p\left(x^L(\hat{y})\right)y\right\} \\
&= -\left\{Q - x^L(\hat{y}) - p\left(x^L(\hat{y})\right)y\right\} \\
&= -\Pi
\end{aligned}
$$

Note that $-\Pi > 0$ since profits for a firm with liability y would be negative. Hence, given our unlikely simplifying assumption about investment, which themselves may lead to exaggerated measures of implicitly subsidies, alternative estimates in the literature further exaggerate implicit subsidies by the losses that firms would incur if forced to remain in the market while bearing liability $y > \tilde{y}$.

In Proposition 4-1, we saw that under given conditions regulation played no role, as it was set sufficiently low so that it failed to bind for any firm. Hence, so long as $a \leq \hat{y}$, the optimal regulation level is not affected.

Under the conditions for Proposition 4-2, all firms find regulation binding. Since optimal investment increases with h, then regulation will continue to bind for $\hat{y} < y$, provided that the regulatory policy continues to exceed the private investment level. Assuming that policies do not change, the subsidy will be

$$
\begin{aligned}
S &= \hat{\Pi} - \Pi \\
&= \left\{Q - s^{LR} - p\left(s^{LR}\right)\hat{y}\right\} - \left\{Q - s^{LR} - p\left(s^{LR}\right)y\right\} \\
&= p\left(s^{LR}\right)[y - \hat{y}]
\end{aligned}
$$

For unchanged regulatory policies, then, the benefits to firms is the expected value of escaping liability $y - \hat{y}$. We ignore here the expenses of $s^{LR} > x^{LR}$, however, so the picture for operators might be less rosy than the result suggested. If $y = h \leq \tilde{y}$, then the approach to measuring subsidies taken by other authors is correct. If $\tilde{y} > y$ or if $h > \tilde{y}$, then those estimates are exaggerated by

$$\begin{aligned}
\chi &= \left\{Q - s^{LR} - p\left(s^{LR}\right)\hat{y}\right\} - \left\{Q - s^{LR} - p\left(s^{LR}\right)y\right\} \\
&- \left[\left\{Q - s^{LR} - p\left(s^{LR}\right)\hat{y}\right\} - \left\{Q - s^{LR} - p\left(s^{LR}\right)\tilde{y}\right\}\right] \\
&= \left\{Q - s^{LR} - p\left(s^{LR}\right)\tilde{y}\right\} - \left\{Q - s^{LR} - p\left(s^{LR}\right)y\right\} \\
&= -\left\{Q - s^{LR} - p\left(s^{LR}\right)y\right\} \\
&= -\Pi
\end{aligned}$$

This is the same result that we saw above. Alternatively, we can specify $\chi = p\left(s^{LR}\right)[y - \tilde{y}]$, so that other estimates exaggerate subsidies by expected damages in excess of $\tilde{y}$.

In the preceding paragraph, we assumed that s^{LR} is unaffected by changes in $\hat{y}$. However, we can show that $\frac{\partial \tilde{h}^{LR}}{\partial y} \leq 0$ for $\tilde{h}^{LR} \geq y$ and is zero otherwise. By considering the case of Proposition 4-2, we assume that all firms operate, or $\tilde{h}^{LR} = b$. If this is true both for y and $\hat{y}$, then optimal regulation s^{LR} indeed remains unchanged. Recall, however, that $s^{LR} = x^{L}(a)$ for relatively high liability limits (see Proposition 4-1), and $s^{LR} \in \left(x^{L}(y), s^{R}\right]$ is optimal for relatively low liability limits (see Proposition 4-3). Thus, for $\hat{y} < y$, then $s^{LR} = x^{L}(a)$ could be optimal under y while $s^{LR} \in \left(x^{L}(\hat{y}), s^{R}\right]$ could be optimal for $\hat{y}$.

In this case, assuming that $y < \tilde{y}$ and that $s^{LR} = s^R$ for $\hat{y}$, subsidies are

$$\begin{aligned}
S &= \hat{\Pi} - \Pi \\
&= \left\{Q - s^R - p\left(s^R\right)\hat{y}\right\} - \left\{Q - x^L(y) - p\left(x^L(y)\right)y\right\} \\
&= - \left[s^R - x^L(y)\right] - \left[p\left(s^R\right)\hat{y} - p\left(x^L(y)\right)y\right] \\
&= -[s^R - x^L(y)] - p\left(s^R\right)[\hat{y} - y] - \left[p\left(s^R\right) - p\left(x^L(y)\right)\right]y
\end{aligned}$$

On the last line, the first term is negative and the second and third are positive. Firms' gains from liability limits partially are offset by spending requirements that exceed privately-optimal levels. This case is quite interesting, for investment is higher for $\hat{y}$ than for y. If expected profits are negative under y, then a possible justification for setting $\hat{y} < y$ is that lower accident probabilities and higher aggregate output can be gained. Essentially, firms are able to save on insurance premiums but are forced to spend the money on investment.

For $y < a$, as described in Proposition 4-3, profits are zero for all firms. Hence, so long as $\hat{y} < y < a$, there are no subsidies under optimal regulation and limited liability. If $\hat{y} < a < y$, then the results in Proposition 4-3 are not relevant, for we assumed that profits are negative for $y < a$ and $s^{LR} = x^{SP}(a)$. If this is true for $\hat{y} < a$, then profits surely will be negative for $a < y$. Hence, given the conditions specified for Proposition 4-3, there are no subsidies if regulation is set optimally. The level of regulated investment, however, does depend on the liability limit. The optimal policy rule is

$$s^{LR} = Q - p(s^{LR})\hat{y}$$

We saw earlier that the break-even point falls as regulation rises. Thus, regulation increases to maintain zero profits when decreasing the liability limit from

$y > a$ to $\hat{y} < a$. This greater spending on safety measures again means that limiting liability can both decrease the probability of an accident and increase aggregate output.

2.4.7 Social Welfare Under Liability Caps

Again consider the regulatory regime in Proposition 4a. Consider liability levels $\hat{y} < \tilde{y} < h$, and again suppose that $\tilde{\Pi} = 0$. We now consider differences in social welfare among the alternative liability levels.

First, note that $\zeta(h) = \zeta(0)$ since firms close under liability h. If liability is lowered to $\tilde{y}$, output becomes positive and social welfare becomes $\tilde{\zeta} = U(Q) - x^L(\tilde{y}) - p(x^L(\tilde{y}))h = u(Q) - p(x^L(\tilde{y}))\,(h - \tilde{y})$. This is the sum of the benefit of consumption less the liability borne by consumers. If $\tilde{\zeta} > \zeta(0)$, then welfare improves with the reduction in liability to the point where firms earn zero profits. If liability is lowered further to $\hat{y}$, then social welfare becomes $U(Q) - x^L(\hat{y}) - p(x^L(\hat{y}))h = Q + u(Q) - x^L(\hat{y}) - p(x^L(\hat{y}))h$. If $\hat{\zeta} > \zeta(0)$, then welfare improves with the reduction in liability and firms earning positive profits. Without additional information, we cannot determine whether society is better off with liability $\hat{y}$, $\tilde{y}$, or h.

In the section above, we showed that investment spending can be higher under lower liability limits. In such cases, liability is transferred from firms to consumers. In exchange, firms are forced to spend their gains on additional safety measures. Clearly, this lowers expected damages. We might argue it best to take this to the extreme by adopting the regulation-only policy. In that case, net revenue may be exhausted by forced spending on investment goods. Barring explicit subsidies for investment products, this achieves the lowest possible accident probabilities. Given our specification of quasi-linear preferences in the social welfare function, regulators care only about the level of expected harm; they do not care about who bears liability in the event of an accident. If we believe that the distribution of liability matters, then we face a limitation of the present model.

2.5 Conclusions

We specified a model of firms and regulators that incorporates key features of the nuclear power industry. In particular, firms seek to maximize profits while facing required maintenance and safety standards, and they operate under the possibility of major accidents with corresponding liability for losses. Regulators seek to balance conflicting desires to satisfy the economic wishes of consumers and firms while ensuring that the public is afforded a reasonable degree of safety.

Our model thus combines industry output and profits, electricity demand and social welfare, and safety and liability regulation. Few other models of the nuclear power industry assemble these details. The resulting model thus proves useful in sorting and assembling alternative factors that contributed to the evolution of the industry. Other work in the literature typically focus on particular cost or regulatory factors, but we consider both along with additional critical matters concerning demand and liability. In current form and with simple extensions, we show the model capable of reproducing many crucial historical facts and events.

The key application of our model is the analysis of implicit subsidies. We show that only under special cases will the current accepted definition of implicit subsidies remain valid. We derive measures of implicit subsidies from a model of firms and regulators, in contrast to other attempts that simply propose equations with little support. We show that it is important to consider the full regulatory picture when attempting to understand and to quantify implicit subsidies, for otherwise the results tend to be exaggerated in terms of benefits to operators and increased risk to the public. In addition, we show the importance of considering standard bankruptcy rules as the alternative to Price-Anderson, a simple fact usually overlooked by other scholars and critics. Our resulting definitions of implicit subsidies should guide future attempts to calculate their levels.

This model would benefit from many improvements and extensions. Some already were described. Others include finding a solution for the optimal liability level. As was noted, we may be forced to move away from the convenient quasi-linear specification of social welfare in order to get an interesting solution.

Other possibilities include the allowance of differences across plants for $p(x)$, and to make $f(h)$ a distribution of potential damages for each plant. (See Dubin and Rothwell [17] for a similar specification.) This could improve the plausibility of assumptions regarding private versus public information. Liability limits would affect all plants in all cases.

Rothwell [47] notes the relationship between safety and plant performance. That is, plants with high accident probabilities generally are more troublesome and expensive to operate. Hence, operators have incentives to maintain their plants in order to maximize output and minimize repair costs, even if they face no liability. Dubin and Rothwell [17] find that operators of less-reliable plants moved more quickly to invest in safety equipment. They also report that reliability generally falls with the age of the plant, suggesting that older plants have higher accident probabilities. This correlation between reliability and accident probabilities likely will prove important in any future quantitative analysis and in more detailed theoretical work. Still, we might expect our qualitative results to survive.

A particularly useful extension will be to make the model dynamic. In a dynamic model, we can examine how optimal firm behavior and optimal policies change over time. If we relax the assumption that regulators observe investment perfectly, and if firms have incentives to misbehave, then we can introduce monitoring and penalties for misbehavior, including civil and criminal penalties. Penalties are best explored in a dynamic model, for firms often seem to suffer most from the costs of being forced to close temporarily. These costs include the purchase of replacement power and higher levels of investment spending. While regulators do impose fines, they have been relatively small and thus seem relatively unimportant. The EIA [2] reports that industries highest annual level of fines between 1975 and 1991 was less than $8 million in 1993 dollars. Following a near-accident at the Davis-Besse power plant in 2000, the NRC imposed a fine of about $6 million, but the owner reportedly spent hundreds of millions on replacement power and repairs. Price [43, p. 111] reports that the operator of TMI was fined "over a million dollars" and that 33 plant operators also were fined following the 1979 accident. Again, these amounts pale in comparison to the reported $250 million in retraining and improvements for the surviving plant, in addition to the costs associated with a two-year closure. This detail best can be captured in a dynamic model.[7]

[7] Shavell and Polinsky [42] provide similar analysis in a static model. They derive optimal enforcement efforts, when observation and detection of misbehavior is costly, and the optimal

When we consider the possibility of plant closures, whether because of low social welfare or low profitability, the problem of optimal regulation becomes far more complex. While our results are similar to those of Shavell, they reflect the increased complexity of the model. For essential goods like electricity, and for great potential damages as with nuclear power production, it is important to consider whether it might be better to close individual plants or even the industry. At the same time, we must consider the effects of burdensome regulation both on the decisions of firm operators and on the corresponding effects on consumers. Hence, the increased burden of complexity is necessary as we seek optimal regulatory policies for the industry.

level of fines.

Chapter 3

Price Anderson Liability Limits

We turn briefly from our model to take a closer look at the Price-Anderson Act. We review other attempts to quantify the benefits to firms of these liability protections. We noted in the last chapter possible problems with the definition of implicit subsidies specified by others. Nevertheless, in this chapter we set aside those concerns and take seriously the work of others. We correct several mistakes made in earlier attempts and offer extended models, based on given facts regarding the industry and its history, in an attempt to lessen certain unlikely implications of existing models. This work provides quantitative estimates of implicit subsidies to firms that will be useful in later chapters.

The models of this chapter may be viewed as extensions of the applications of the previous chapter. We follow the lead of earlier authors, however, and so we do not consider all forms of potential benefits that firms may realize as the result of these protections. The estimates calculated here will be employed in the dynamic programming model developed in the second section of this dissertation. Immediately following this chapter, though, we will return to the modelling efforts begun in the previous chapter.

3.1 Introduction

The possibility of accidents leading to catastrophic destruction poses a significant concern for operators of nuclear power plants, industry regulators, and others. Because private insurers seem unwilling or unable to cover all potential losses, Congress passed the Price-Anderson Act (PAA) in 1957 to cap liability for power plant operators and to ensure prompt reimbursement to the public for losses. Dubin and Rothwell ([16], DR) proposed a simple technique to estimate the benefit of PAA to power plant operators using 1) private insurance premiums that operators purchase to cover a legislated amount of offsite damage and 2) expert assessment of the probability and magnitude of damage in the worst case. In 1998, Heyes and Heyes ([28], HH) corrected a mistake in DR's specification of private insurance terms. Benefits to the nuclear industry, as calculated by DR and HH, have been used to support PAA (e.g. Rothwell [49]) and to criticize liability caps (in Congressional testimony by PIRG Legislative Director Anna Aurilio ([9]) and in Canadian federal court testimony by Ralph Winter (Heyes [26])). PAA expired in 2002 but then was extended to December 2004. In 2005, the act was extended for another 20 years. Whether such policies continue to be offered may determine whether new plants are built in this country, and so it is imperative that we understand clearly the effects of such policies.

3.2 The Dubin-Rothwell-Heyes-Heyes Model

DR and HH (DRHH) calculated implicit subsidies to the nuclear industry by first solving a two-equation system for the parameters of an embedded density function $f(L)$, where L represents offsite losses. The first equation describes private insurance coverage purchased by each operator. In 1984, operators paid an average of \$0.4m per year[1] (Brownstein [11]) for coverage of offsite damages between \$1m and \$160m.[2] DR assume a 30% markup[3], leaving \$0.28m in expected losses. The insurance companies cover all offsite damages for totals between \$1m and \$160m, and they cover the first \$160m of damage for worse accidents. The second equation summarizes a 1985 NRC assessment: a worst-case accident will result in \$10,000m in offsite property damage and will occur with 0.00008% probability per reactor year. The equations are specified as follows:

$$0.28 = \int_{1}^{160} L \times f(L)\, dL + 160 \int_{160}^{\infty} f(L)\, dL \tag{3.1}$$

$$0.0000008 = \int_{10{,}000}^{\infty} f(L)\, dL = 1 - F(10,000).$$

Given an appropriate two-parameter density function, the system can be solved numerically. Calculation of expected losses above the liability cap, less the amount of industry liability and conditional on the parameter estimates, yields the implicit subsidy per reactor year to power plant operators. Implicit subsidies are the insurance premiums operators are spared for coverage above the liability cap; they are calculated as

$$Subsidy = \int_{\text{PAA}}^{\text{Disaster}} (L - PAA) \times f(L)\, dL + (Disaster - PAA) \int_{\text{Disaster}}^{\infty} f(L)\, dL \tag{3.2}$$

[1] Unless stated otherwise, all monetary figures are in millions m of 1985 dollars.

[2] Required coverage rose to \$300m by 2003, in current dollars (NEST-DOE [7]).

[3] If there are no accidents within 10 years, 70% of the premium is returned to the operators (Denenberg [15]). Hence, DR assume that expected losses amount to 70% of the premium.

where PAA is the industry's liability limit[4] and $Disaster$ is a worst-case damage estimate.[5] DR recommend the log-logistic cumulative distribution function

$$F(L) = \frac{1}{1 + e^{-(a + b \times \ln(L))}}, \tag{3.3}$$

and the corresponding density function

$$f(L) = \frac{e^{-(a + b \times \ln(L))}}{(1 + e^{-(a + b \times \ln(L))})^2} \times \frac{b}{L} \tag{3.4}$$

where a and b are parameters. Unfortunately, DR and HH omitted the term b/L in the density function and thus their results are not consistent with the intended model.[6] This problem caused estimates in both papers to be exaggerated.

Results for the corrected DRHH model are presented in the first column of Table 3.1, and the density function is plotted in Figure 3.1. Before the PAA was amended in 1988, the model suggests operators implicitly received an average subsidy of \$0.033m per reactor year, and they received about \$0.003m following the amendment. Before the Act expired in 2002, the implicit subsidy was valued

[4]Operators are equally and jointly liable for a portion of offsite damages. Liability for the industry is capped at \$560m, \$7,153m, \$6,018m (\$9,300 in 2002 dollars), and \$6,418m (\$10,100 in 2003 dollars) for pre1988, post1988, 2002, and 2003, respectively, in millions of 1985 dollars. Prices are deflated with the PCE deflator.

[5]Note that DR and HH omit the term $(Disaster - PAA) \times \int_{\text{Disaster}}^{\infty} f(L)\, dL$, which accounts for the probability mass at $L = Disaster$.

[6]See Meeker and Escobar [37] for details of the log-logistic density function. The functions shown here are equivalent to theirs with $1/b \equiv \sigma$ and $= a/b \equiv \mu$. Note that if $b \leq 1.0$, so that the upper tail approaches zero too slowly, the mean does not exist. Hence, the interpretation of the 1985 NRC assessment and the corresponding specification of Equation 3.1 are crucial: if losses truly are distributed according to the log-logistic distribution but if damages are not limited to a maximum Disaster, then the value $Subsidy$ in Equation 3.2 will be infinite for any calibration leading to $b \leq 1.0$.

at about \$0.005m per reactor year; the amount fell slightly in 1985 dollars with extensions of the PAA in FY2003 legislation. These values are far smaller than those reported by HH; their estimates were \$13.3m before 1988, and \$2.3m after the amendments.[7]

Integration of the density function from \$1m to infinity yields the implied likelihood of an accident causing significant offsite damage. The model predicts that such accidents will occur with a 6.84% probability per reactor year. This seems high given the industry's relatively safe operating history. Denenberg [15] calculated the insurance industry's estimate as 1/1700, or 0.059% per reactor year.[8] An alternative proxy for the probability of accidents may be the likelihood of core melt. In 1985, the NRC estimated this likelihood to be 0.03% per reactor year (New York Times [62]), which also is far less than the accident probability implied here. However, the insurance market characterization given by DRHH rules out both of these estimates. Beginning with the first equation in (1), we see again that expected losses for private insurers are the total of expected losses for "minor" accidents plus the probability of major accidents times the maximum payout of \$160m. Clearly, these expected losses are less than those under a hypothetical alternative insurance structure in which insurers pay \$160m for

[7] Denenberg [15] derived an accident probability of 1/1700, or 0.00059 per reactor year. He assumed damages of \$40,000m per accident. The product of probability and magnitude implies subsidies of about \$23.5m per reactor year. DR argue that this methodology is unreasonable since the true probability density is not uniform, and so these simple calculations are not reliable.

[8] Denenberg assumed a pure insurance component of 58%; hence, if a \$1000 premium buys \$1m of coverage, then the pure insurance component is \$580. This implies perceived risk of \$580 / \$1m, or 1/1700 .

accidents of any magnitude. However, we can divide the corresponding equation by \$160m and then simplify to obtain a lower bound for insurers' beliefs about the likelihood of an accident:

$$
\begin{aligned}
0.28 &= \int_{1}^{160} L \times f(L)\,dL + 160 \times \int_{160}^{\infty} f(L)\,dL \\
&< \int_{1}^{160} 160 \times f(L)\,dL + 160 \times \int_{160}^{\infty} f(L)\,dL \qquad (3.5) \\
\Rightarrow \frac{0.28}{160} &= 0.00175 < \int_{1}^{\infty} f(L)\,dL = P(1 < L)\,.
\end{aligned}
$$

According to the specified equation, insurers believe that accidents causing significant offsite damage will occur with probability greater than 0.175% per reactor year. Note that this result does not depend on the chosen density function, nor does it depend on assumed worst-case magnitudes or probabilities. While this lower bound is far below the estimate reported above, it still seems implausible given the industry's operating history and related risk assessments, and so we must consider alternative descriptions of the insurance market.

3.3 Alternative Models

If plants operate without offsite losses for 10 years, then they are eligible for a 70% refund of paid premiums (Denenberg [15]). DR thus assumed that expected losses totaled 70% of the premium, or \$0.28m, and that the remaining 30% was overhead and profit. Instead, we extend the DRHH equation to capture these details. Insurance premiums (\$0.4m per reactor year) are the sum of expected losses, overhead and profit, and the expected discounted value of refunds:

$$0.4 = \left\{ \int_{1}^{160} L \times f(L)\,dL + 160 \int_{160}^{\infty} f(L)\,dL \right\} + \{0.4 \times \pi\} + \left\{ 0.4 \times 0.7 \times \left[\frac{F(1)}{1+r} \right]^{10} \right\} \tag{3.6}$$

where π is the percentage of overhead and profits and r is the average yield of investments. The first bracketed terms are expected losses as described in DRHH. The second term in brackets is overhead, profit, and other expenses. Denenberg reported costs in 1972 that totaled 58% of premiums; this implies that π is 42%. The last term is the expected discounted value of refunds. Recall that 70% of the premium is eligible for return. This is discounted at the market rate[9] and is multiplied by the probability of safe operations for 10 years ($F(1)^{10}$), where $F(1)$ is the yearly probability of no significant accident.

Results for this model are displayed in the second column of Table 3.1. Calibration values are unchanged from the DRHH model. The rate of return r is set to 0.07, and the markup rate π is set to 0.42. The probability density is not plotted, but its shape is similar to the DRHH distribution. This model projects subsidies of \$0.028m per reactor year under the original terms of PAA and \$0.003m per reactor year after the 1988 amendments. For regulations in effect in 2002, the subsidy was somewhat higher (\$0.005m), but again the value fell slightly under the 2003 PAA extension. Note that these projections are slightly lower than those of the corrected DRHH model and that all values are in 1985 dollars.

The implied likelihood of an accident is 2.5% per reactor year. While implied risk is two-thirds lower than implied by the DRHH model, it still is well above

[9] Denenberg assumes a market rate of return of 7%; we do the same.

other risk assessments. We can derive a lower bound for this risk, from the perspective of insurers, corresponding to Equation 3.5:

$$
\begin{aligned}
0.4 &= \int_{1}^{160} L \times f(L)\, dL + 160 \int_{160}^{\infty} f(L)\, dL + 0.4 \times \pi + 0.4 \times 0.7 \times \left[\frac{1-\theta}{1+r}\right]^{10} \\
&< \int_{1}^{160} 160 \times f(L)\, dL + 160 \times \int_{160}^{\infty} f(L)\, dL + 0.4 \times \pi + 0.4 \times 0.7 \times \left[\frac{1-\theta}{1+r}\right]^{10} \\
&= 160 \times \theta + 0.4 \times \pi + 0.4 \times 0.7 \times \left[\frac{1-\theta}{1+r}\right]^{10} \Rightarrow 0.00057 < \theta. \qquad (3.7)
\end{aligned}
$$

Equation 3.7 is solved for $\theta \equiv \mathrm{P}(1 \leq \mathrm{L})$; one real, positive root exists. This characterization of insurance markets, when evaluated at the given rates of return and markup, implies that insurers perceive at least a 0.0565% chance per reactor year of incurring losses.[10] This lower bound is very close to Denenberg's perceived risk estimate of 0.059%, even though our methodology is more elaborate. However, our model must be modified if we are to obtain a probability distribution that approaches this lower bound. Of course, this lower bound for perceived risk levels still may be far from true levels of perceived and actual risk, but arguably it is more reasonable than levels implied by the models above.

Suppose we alter the model to allow explicit calibration of the probability of

[10]When evaluated with $r = 0.07$ and $\pi = 0.42$, the lower bound is 0.0565%. When $\pi = 0.60$, it is 0.0111%, and when $\pi = 0.20$, it is 0.1120%. Hence, the lower bound is sensitive to the choice of these values.

an accident. This value $\theta \equiv$P(1 $\leq$ L) can be employed in the following way:

$$0.4 = \left\{ \int_{1}^{160} L \times f(L)\, dL + 160 \int_{160}^{\infty} f(L)\, dL \right\} + \{0.4 \times \pi\}$$
$$+ \left\{ 0.4 \times 0.7 \times \frac{[1-\theta]^{10}}{[1+r]^{10}} \right\}$$
$$0.0000008 = \int_{10000}^{\infty} f(L)\, dL \tag{3.8}$$

where the density function $f(L)$ is constructed from a Bernoulli density function with parameter $\theta \equiv$P(1 $\leq$ L) and a three-parameter log-logistic density function with a threshold parameter equal to one:

$$f(L) = \begin{cases} \theta \times \dfrac{e^{-(a+b\times\ln(L-1))}}{(1+e^{-(a+b\times\ln(L-1))})^2} \times \dfrac{b}{(L-1)} & : \quad 1 \leq L \\ 1-\theta & : \quad 0 \leq L \leq 1 \end{cases} . \tag{3.9}$$

In this model, accidents occur with probability θ; given such an accident, losses are distributed according to the log-logistic function. Note that we are constrained in calibrating θ by the lower bound established in Equation 3.7. This lower bound is not theoretical only; numerical routines also begin to fail as θ approaches the limit. Hence, we could employ the Denenberg estimate of 0.059%, but we are unable to employ the NRC estimate for core melt (0.03%). Unfortunately, the results are rather sensitive to the choice of θ, but implied subsidies seem to remain relatively small even as θ approaches the bound.

Results for this model are displayed in the fourth column of Table 3.1. Again, calibration values are unchanged from the DRHH model, the rate of return is 7%, and markup is 42%. The probability of an accident is 0.057%, which is slightly above the lower bound derived above. The probability density between \$1m and \$10,000m is plotted in Figure 3.1. Note that earlier models distribute much probability mass in the neighborhood above \$1m, indicating that the probability of "minor" accidents is relatively high, and that probability density then falls monotonically as damages increase. Denenberg suggests that the actual distribution instead is bimodal, with a mass concentration at low damage levels and another at much higher levels. Our model calibrates a high probability mass for losses under \$1m. A second mode is evident in Figure 3.1 (the first is not shown) at approximately \$250m. Estimated subsidies are significantly higher than those of previous calculations in this paper: \$0.239m before the 1988 amendments, \$0.003m following the changes, and about \$0.012m in 2003. Estimates for policies after 1988 changed relatively little with the specification changes, but estimated subsidies under the original policies now are over 9 times greater. Note, however, that the mode and subsidy estimates depend heavily on the calibrated point mass at zero. Perhaps the value employed is appropriate, but we are unable to calculate results for lower perceived accident probabilities because of the limitations of the theory as shown in Equation 3.7. Hence, while some qualitative properties of this model seem superior, certain doubts remain even if we accept its many other assumptions.

A significant criticism of the DR model was its calibration of worst-case damages (\$10,000m). The employed statistic included only offsite property damage and, in particular, omitted damage to health and loss of life. Denenberg cites an Atomic Energy Commission study, conducted in the early 1960's, that estimates damage (in current dollars) at \$40,500m.[11] Suppose that we arbitrarily

[11] This figure includes \$17.0 billion for property damage, \$13.5 billion for deaths, and \$10.0 billion for injuries. The estimate accounts for 45,000 deaths, with lifetime earnings per person of \$300,000. It also accounts for 100,000 severe injuries, with a cost of \$100,000 per worker.

set the magnitude of damage in the worst case to \$500,000m in 1985 dollars but keep the NRC probability estimate of 8.0E-7. While this calibration is *ad hoc*, the corresponding results should indicate the sensitivity of the estimates to calibrated damages. Of course, the results also depend heavily on the many other assumptions.

Estimates are shown in the third column of Table 3.1 for our first alternative model with an accident probability of 0.08% per reactor year. Estimated subsidies were about \$1.158m per reactor year before 1988 and averaged about \$0.960m after the amendments. Note that these values are lower than those reported by HH even though their (erroneous) calculations covered losses only to \$10,000m. Hence, this model (given its calibrated values) suggests that implicit subsidies are significant but not enormous, and they are smaller than those predicted earlier for less severe scenarios.

Estimates are shown in the fifth column of Table 3.1 for the second alternative model with an accident probability of 0.057% per reactor year and assumed worst-case damages of \$500,000m. This model implies subsidies of about \$5.110m per reactor year before 1988 and about \$3.357m in 2003. The density function for this model is depicted in Figure 3.2. We see that the second mode for this distribution is approximately \$400m, where the first mode of course is between 0 and 1.

Tests for the DRHH model and the first alternative model were repeated using the Pareto distribution.[12] For all calibrations listed in this paper, the

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It does not account for diseases that develop years later, and it does not include dislocation costs for evacuation of the contaminated area. The study was performed by the Brookhaven National Laboratory for the Atomic Energy Commission.

[12]The Pareto PDF and CDF are $f(L) = a \times b^a/(L+b)^{a+1}$ and $F(L) = 1 - b^a/(L+b)^a$,

results were similar to those using the log-logistic distribution. Tests also were conducted with lower and higher markup rates (π in Equations 3.6 and 3.8). Expected losses and implicit subsidies fall as the assumed markup rate increases. However, even for markup rates of 20% (results shown here employ Denenberg's report of 42%) and the high damage assumption (where worst-case damages are \$500,000m) implicit subsidies are similar to those reported by HH.

3.4 Conclusion

What, then, can we conclude about the magnitude of implicit subsidies provided by PAA? First, we acknowledge the significant limitations of the model noted by previous authors. Rothwell [49] notes that results depend heavily on 1) the assumed distribution function and 2) on the assumed worst-case magnitude and probability. Heyes [26] doubts the ability of private insurers to assess accurately their expected losses. Further, he doubts the ability of any such method to reveal the truth accurately: "For use in informing policy, results from studies such as these should be heavily salted." Estimation of current subsidy levels based on the implied 1985 distribution requires the additional dubious assumption that the cost distribution has not shifted. That is, we assume that safety has not improved with operator experience nor has safety diminished with reactor age. Hence, we must exercise caution in the use of these results lest they mislead us.

While keeping such limitations in mind, we can conclude that the methodology proposed by DRHH and the alternatives suggested here imply implicit subsidies far lower than reported earlier. The results, together with the assump-

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respectively.

tion of perfect insurance markets, imply that PAA should make little difference since projected expected losses above PAA are small. Of course, insurance markets may not be perfect and may not offer complete coverage regardless of the probability distribution. Hence, construction of new plants in coming years may depend heavily on recent extensions to PAA.

Useful extensions of this work should incorporate the data reported in the 1998 NRC report [30]. This document summarizes the types of insurance offered the nuclear industry and offers details of PAA. Published in the document are aggregate annual premiums refunded to operators. Also published is a history of claims under PAA and corresponding payments. Some of the reported payments result from policies not considered here. Information on remaining policies should be reconciled with our stylized picture of the industry as related to risk and insurance coverage, and in particular the probability of claims against insurance companies.

3.5 Appendix

Table 3.1: Results

	DRHH Model	**Alt. Model 1**	**Alt. Model 1: Hi Damages**	**Alt. Model 2**	**Alt. Model 2: Hi Damages**
Calibration: Insurance Coverage	$160m	$160m	$160m	$160m	$160m
Disaster Cost	$10,000m	$10,000m	$500,000m	$10,000m	$500,000m
Disaster Probability	8.0E-7	8.0E-7	8.0E-7	8.0E-7	8.0E-7
Accident Probability	0.06839	0.02535	0.00768	0.00057	0.00057
Results: Parameter a	2.61167	3.64933	4.86102	-15.97674	-10.61556
Parameter b	1.24067	1.12801	0.69939	2.44772	1.30944
Expected Losses	$0.337m	$0.166m	$1.313m	$0.516m	$5.417m
Subsidy Pre1988	$0.033m	0.028m	$1.158m	$0.239m	5.110m
Subsidy Post1988	$0.003m	$0.003m	$0.959m	$0.003m	$3.242m
Subsidy 2002	$0.005m	$0.005m	$0.963m	$0.014m	$3.416m
Subsidy 2003	$0.005m	$0.004m	$0.956m	$0.012m	$3.357m

The rate of return r is 0.07 and markup π is 0.42. Dollar figures are in millions of 1985 dollars. Expected losses are total expected losses, including all insured and uninsured losses. Industry liability caps are $560m, $6,018m ($9,300m in 2002 dollars), and $6,418m ($10,100m in 2003 dollars) for pre1988, post1988, 2002, and 2003, respectively. Prices are deflated with the PCE deflator.

Figure 3.1: Density Functions

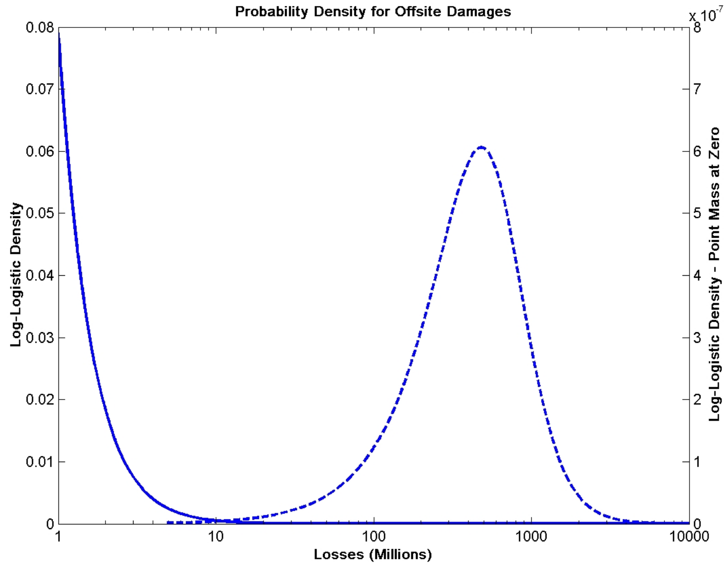
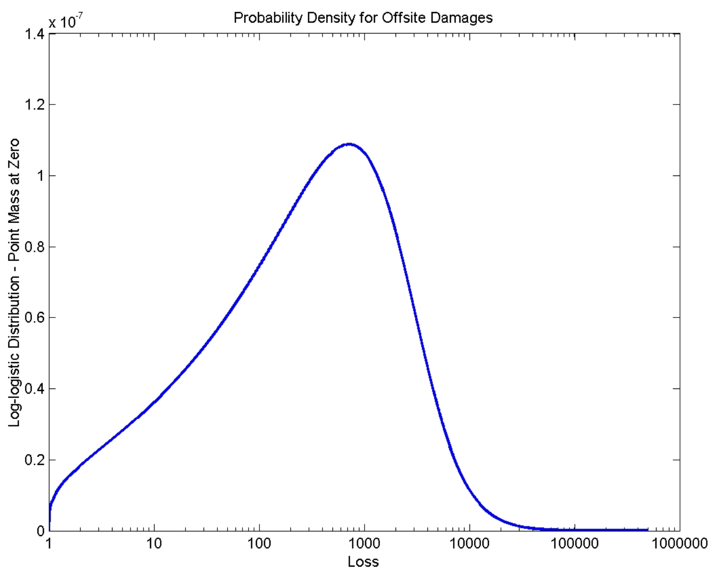


Figure 3.2: Density Functions–Hi Damages



- In Figure 3.1, the corrected DRHH loss function is plotted to the left (solid line), and the cost function for Equation 3.9 is plotted to the right (dashed line). The x-axis is in millions of 1985 dollars.

- In Figure 3.2, the cost function was constructed with worst-case damages of $500,000m. The x-axis covers values between $1m and $1,000,000m in 1985 dollars.

Chapter 4

A Dynamic Programming Approach

This chapter extends greatly our models of regulation and industry economics. We earlier developed the primary features of our stylized world of nuclear power economics by building a static model and using comparative statics to analyze its properties. In reality, of course, dynamics matter in ways that cannot be represented well in a static model. We thus extend our earlier work by adding simple dynamics to our basic static model that will prove sufficient to reveal optimal paths of output, investment, and regulation, and to support more detailed dynamic models in the next chapter.

Many dynamic features do not appear in this chapter. We incorporate some of the omitted features in the following chapter, where we build a numerical version of the dynamic model. The purpose of this chapter instead is to push our analytical model farther in the direction of dynamics. This proves difficult even with our reasonably simple models, and we resort to numerical methods for some of our results.

We employ our model in the calculation of the value to the nuclear power industry of liability limits. We derive measures of the amount the industry would be willing to pay in order to preserve those protections. This extends our work on the subject in Chapter 2 in order to account for the flow of implicit subsidies over time and to account for evolving behavior of firms and regulators.

4.1 Introduction

This work develops dynamic models of the political economy of the nuclear power industry, extending our earlier work with static models. The primary motivations of nuclear power operators and of nuclear industry regulators are considered. Optimal rules are computed to govern behavior of each agent over the life of the industry. These rules take into account the effects of the agents' own actions on the behavior of others. It is assumed that operators' primary motivations are to maximize profits. Operators' choices include whether to operate and how much to invest in maintenance and safety enhancements. Regulators seek to ensure adequate electricity supplies while minimizing costs and expected damage from nuclear accidents. We consider four cases. First, we consider the case in which regulators are benevolent social planners who can guide the economy to the first-best solution. Next, we consider the cases in which regulators employ either regulatory standards for safety enhancements or liability levels for damages. Finally, we consider the case in which regulators govern with both instruments. The model is employed to construct measures of subsidies created by adoption of limited liability levels. These measures are compared to others in the literature.

The models in this chapter are based on our extensions of Shavell's work [57]. In that paper, he derives optimal regulatory policies when firms face liability. However, there are several significant discrepancies between his model and the nuclear power industry. This chapter extends our efforts to eliminate some, but not all, such discrepancies.

In the event of an accident causing damages to third parties, we assume that firms strictly are held liable for all damages. This assumption, while admittedly is too strong, is based on terms of the Price-Anderson Act. This policy specifies minimal levels of insurance that each nuclear power plant operator must carry. It also sets terms for industry self-insurance in addition to the commercial insurance coverage. Operators are exempt from liability for damages in excess of the amount specified in the policy. We assume that operators cannot escape liability for the reason described in the 2003 MIT study [6, p. 81]: "The compensation provision of both the first and second layers of insurance are 'no fault' and not subject to civil liability litigation."

Output matters here. Firms' output decisions are binary: they produce at full capacity if the expected present value of profits is non-negative, and otherwise the firms close. Hence, output does not decline continuously with regulation. In the aggregate, however, output is a decreasing function of regulation. If expected damages are too great, then regulators can force the industry to close. Similarly, if liability or regulation becomes too great, then firms will decide to exit the market. In either case, the benefits of greater safety come at the expense of economic well-being.

This model has multiple periods. The solution is found using finite-horizon dynamic programming techniques, although infinite-horizon techniques also could be applied. We argue that finite-horizon modeling is appropriate for the American nuclear industry, since plants were engineered to operate about 60 years and all existing plants operate under 40 or 60-year licenses, and it is not certain whether a second generation of plants will be politically or economically feasible in the foreseeable future.

We apply the results of this model in two ways. First, we derive the present value to the industry of liability protections. This is the amount of money that the firm would be willing to pay in order to maintain liability protections. In contrast to earlier attempts to quantify these implicit subsidies, we take into account the value of future benefits in addition to current benefits, and we consider in our calculations the net effect of all regulation rather than to focus solely on liability protections. This yields a more accurate picture of the effects of regulation on profits, behavior, and safety. Finally, we discuss the application and extension of this work to cover political matters affecting regulation and industry economics.

4.1.1 Layout of this paper

This chapter develops a model of nuclear power plant operations and industry regulation. First, the model is described, with timings, objective functions for operators and regulators, and derivation of optimal dynamic decision rules. Where it is not possible to derive a complete set of analytical solutions, the results are supplemented with numerical solutions. The key application of the model is the derivation of measures of implicit subsidies created by enforcement of limited liability levels, and we find the present value of these benefits. We also describe techniques of political economy that can extend our work to capture important elements of the industry not captured in our basic model. Finally, limitations are noted and possible extensions are suggested.

4.2 The Model

4.2.1 Timing

This model has two primary groups of players, nuclear industry regulators and power plant operators, who move sequentially in a dynamic game-theoretic framework. Regulators seek to maximize social welfare, and the firms' problem is to maximize profits while satisfying the demands of regulators. It is assumed that a continuum of markets exists, with one nuclear facility per market. No attempt is made to explain the existence of power plants, and prices and demand for electricity are exogenous. Firms are identical, except for the amount of damage that they cause if an accident occurs. We consider a finite number of time periods. When the maximum lifespan has been reached, assuming that the firm survives, the firm incurs any shutdown costs and closes permanently.

At time zero, the level of demand is announced; we assume that this level is fixed throughout time. In the beginning of each period, starting in Period 1, regulators determine the optimal level of liability to impose on the nuclear power industry, and the level is announced. Given this announcement, power plant operators decide an optimal level of investment in safety-enhancing maintenance and similar expenditures. If production yields a higher expected present value than the cost of decommissioning, then firms produce electricity, collect the revenue, and pay operating and investment expenses. Accidents occur at the end of each period with an endogenously determined probability. These accidents cause damage to third parties, for which regulators may hold plant operators liable. If the expected present value of the firm is less than the cost of decommissioning, then operators make no investments and close their plants immediately. If the firm remains in operation at the end of its maximum allowed lifespan, the plant incurs decommissioning costs and closes permanently.

Exposure to liability with corresponding spending on safety, or spending to meet regulatory requirements, reduces profits. We assume that aggregate output may fall with profits, as unprofitable firms exit the market, so that greater safety comes at the expense of output. The model has a continuum of firms that either produce or shut down, depending on whether profits are non-negative. We assume that regulators care about both output and safety, and are cognizant of the effects on output of their own actions. Essentially, we assume a continuum of identical markets, where prices are exogenous. Hence, regulators consider separately consumers' utility in each market. In each, either firms produce at full capacity and consumers receive utility from the product, or firms close and consumers receive a level of utility from zero consumption.

The definition of regulation is narrow, such that policies specify minimal standards for investment in safety-enhancing goods and services. We consider regimes with various combinations of regulation and liability, and we compare social welfare for each.

4.2.2 Definitions

The continuum of (nearly) identical firms are indexed by the level of potential damage, h. In fact, h is the only distinguishing characteristic of the firms. We assume that h is an exact amount. This magnitude of potential damage, known only to the firm, is such that $h \in [a, b]$ where $0 < a < b < \infty$. Regulators do not know potential damages for individual firms, but they do know the distribution of damages $f(h)$, which is nonzero on and only on $[a, b]$. We use a probability distribution $f(h)$ only for convenience, in that it integrates to one and we can use familiar techniques from statistics. More general specifications of $f(h)$ could integrate to any positive value, as it simply specifies the number or measure of firms with potential damages h. Industry capacity and potential output is Q. We assume that all plants have the same capacity. We assume that electricity prices, less unit production costs, are identically equal to one, so that net revenue also equals Q. Firms may invest in goods and services, indexed by x such that $0 \leq x$, to lessen the probability of an accident. The probability of an accident $p(x)$, given the level of investment x, is identical for each firm and depends only on investment. The first derivative of the probability function is negative and the second derivative is positive. (See Dubin and Rothwell [17] for a similar specification.) We assume that p does not change with plant age, thus abstracting from the physical deterioration that tends to leave plants less reliable, and we assume no cumulative effects for investment levels.

Regulators seek to maximize social welfare. A component of the social welfare function is U. For industry output q, where $q \in \{0, Q\}$, $U(q) = q + u(q)$. Hence utility U is a quasilinear utility function, and is determined by the sum of industry net revenue and the benefit to consumers $u(q)$ of consuming q. The numeraire in this utility function is industry revenue. The balance of the social welfare function is in the same units (dollars). Investment and potential damages comprise the balance, as described below. Hence, regulators care about the utility consumers obtain from consumption, industry profits, and potential damages in excess of firms' liability.

Time is indexed by t, beginning with $t = 1$. The maximum possible lifespan is T. If firms operate in Period T, then they must close in Period $T + 1$. We assume that the model parameters are time-invariant; that is, demand, prices, maximum liability, the functions $p(.)$ and $f(.)$, the utility functions, and the values of h and Q for each firm do not vary over time. The endogenous terms of course may vary, including investment, regulation, output, and social welfare.

A matter not pursued fully are the effects of attrition, through accidents, voluntary closure, or forced regulatory shut down, on the capacity of the industry. Note that given a continuum of firms, any positive accident probability will make disasters inevitable each period. In reality, accidents are rare. We thus deviate slightly from rational expectations. We assume that the accident probability p is an *ex ante* measure each period, but no accidents actually occur. In this way, firms and regulators take into account the possibility of accidents when making decisions, but our model does not imply an unreasonably high number of accidents. This matter deserves further attention in future work.

4.2.3 Industry Regulators

Industry regulators seek to balance the need for adequate electricity supplies and the need for safety from nuclear accidents. If there is excess demand without operation of nuclear plants, then neither desire can be satisfied fully without sacrificing the other. We model these conflicting desires with a welfare function such that regulators seek 1) to maximize output to satisfy consumers' demand and 2) to minimize expected losses from accidents.

We consider various regulatory regimes with various combinations of regulation and liability. Hence, regulators have at most one instrument for governing the industry. They choose a minimum level of investment for operators. Whether liability is imposed, and if so the level of liability, is outside the control of the regulators.

We consider only cases in which operators bear either zero liability or liability up to the value of the firm. We do not consider the possibility that regulators will compensate firms for losses, nor do we consider punitive damages.

Similarly, we do not consider the possibility that regulators or consumers will compensate firms for higher levels of investment, in the sort of exchange proposed by Coase. The model could be extended to include such possibilities, but such exchanges have not been observed and thus such possibilities are ignored.

4.2.4 Social Planners

The social planners' problem, in which they seek to maximize social welfare in each market, is to choose each period between closing permanently the plant in that market or to run the plant with a given level of investment. If the plant is decommissioned in Period t, where $t \in \{1, T\}$, then social welfare is

$$\zeta_t^{Close} = U(0) + \frac{\zeta_{t+1}^{Close}}{1+r} = U(0)\frac{1-(\frac{1}{1+r})^{T+2-t}}{1-\frac{1}{1+r}}$$

All plants must close by Period $T+1$, so we have

$$\zeta_{T+1}(h_i) = U(0)$$

In all preceding periods, assuming that plant i was not previously decommissioned, social welfare can be represented as welfare given zero production and consumption plus the difference between welfare with potentially positive production[1] and welfare with zero production. We label the difference in social

[1]We use the adjective "potentially" because social planners will not allow production if expected social welfare is negative. Hence, even if the plant was not shut down in an earlier

welfare between potentially positive and zero production in Period t as $Diff_t$, and claim that it is

$$Diff_t(h) = \max \left\{ \begin{array}{c} 0, \\ \max\limits_{x_t \geq 0} U(Q) - U(0) - x_t - p\left(x_t\right) h + \frac{1-p(x_t)}{1+r} Diff_{t+1}(h) \end{array} \right\}$$

where x is investment in safety enhancements and $p\left(x\right)$ is the probability of an accident. Hence, the difference in welfare is the welfare difference in Period t plus the probability-weighted value of receiving discounted future differences. Note that $Diff_{T+1}(h) = 0$ for all surviving plants. Immediately below, we show that this is the correct specification of such differences.

The social planners' problem in Period t and market i is

$$\begin{aligned} \zeta_t(h_i) &= \max \left\{ \begin{array}{c} U(0) + \frac{\zeta_{i,t+1}^{Close}(h)}{1+r}, \\ \max\limits_{x_{i,t} \geq 0} U(Q) - x_t - p\left(x_t\right) \left[h_i - \frac{\zeta_{t+1}^{Close}(h_i)}{1+r} \right] + \frac{1-p(x_t)}{1+r} \zeta_{t+1}(h_i) \end{array} \right\} \qquad (4.1) \\ &= \zeta_t^{Close} + \max \left\{ \begin{array}{c} 0, \\ \max\limits_{x_t \geq 0} U(Q) - U(0) - x_t - p\left(x_t\right) h_i + \frac{1-p(x_t)}{1+r} Diff_{t+1}(h_i) \end{array} \right\} \\ &= \zeta_t^{Close} + Diff_t(h_i) \end{aligned}$$

for control of plant i with potential losses h_i. We assume that social planners know h_i. Social planners thus know more than the simple regulators considered later, for the regulators know only the distribution $f(h)$. The planner must decide whether to close permanently the plant or to run the plant in the current period. If the plant is closed, then social welfare in the corresponding market is

period so that production may take place, production will be zero if social welfare is negative. For this reason, $Diff_t \geq 0$.

$U(0)$. If the plant operates after investing x_i, then expected damages are $p(x_i)h_i$, and social welfare in the corresponding market is $U(Q) - x_{i,t} - p(x_{i,t})h_i$, plus discounted future welfare.

Again, we see that social welfare may be represented as the sum of utility for zero production and the difference in utility between positive and zero production. Expected future utility is discounted at rate $1/(1+r)$, where r is the interest rate. This rate is chosen for simplicity, so that utility and profits are discounted at the same rate. With probability $p(x_{i,t})$, an accident will occur in market i in period t, and the corresponding plant operator will be liable for damages h_i. The market will receive the discounted value of the finite stream of zero consumption. No accident will occur with probability $1 - p(x_{i,t})$. In this case, the firm moves to the next period and faces a similar optimization problem, until the maximum age of T is reached.

The optimal policy rules for investment may be found by differentiating the social welfare function with respect to investment[2]:

$$1 = -p'(x)\left[h_i + \frac{Diff_{t+1}(h_i)}{1+r}\right] \tag{4.2}$$

For simplicity, we ignore the constraints that are required to ensure that $x \geq 0$, so that maintenance expenditures are irreversible for all probability functions p; this assumption is not restrictive so long as p is sufficiently steep for low investment. Obviously, investment in period $T+1$ will be zero. In all other periods, we see that

[2]Note that the SOC holds: $\frac{\delta \zeta_t(h_i)^2}{\delta^2 x} = -p''(x)\left[h_i + \frac{Diff_{t+1}(h_i)}{1+r}\right] < 0$

$$x_t^{SP}(h_i) \quad = \quad (p')^{-1}\left(\frac{-1}{h_i + \frac{Diff_{t+1}(h_i)}{1+r}}\right)$$

where p'^{-1} is the inverse of the derivative of the probability function. Examination of this function shows that investment increases with potential damages and with potential future relative benefits of production.

To determine the evolution of the level of social welfare, we can focus attention on the evolution of our variable $Diff_t$. Define Δ as the time difference in $Diff$, and denote $p_t \equiv p(x_t)$:

$$\begin{aligned}
\Delta_{t-1} &\equiv Diff_{t-1} - Diff_t \\
&= -(x_{t-1} - x_t) - [p_{t-1} - p_t]\, h \\
&\quad + \left[\frac{1 - p_{t-1}}{1+r}[Diff_t - Diff_{t+1}] - [p_{t-1} - p_t]\, Diff_{t+1}\right] \\
&\quad = -(x_{t-1} - x_t) - [p_{t-1} - p_t]\, h \\
&\quad + \left[\frac{1 - p_{t-1}}{1+r}\Delta_t - [p_{t-1} - p_t]\, Diff_{t+1}\right]
\end{aligned}$$

$Diff$ cannot ever be negative. Note that $Diff_{T+1} = 0$. Note also that if $Diff_T = 0$, then $Diff_t = 0$ for all $t \in [1, T]$. Suppose instead that $Diff_T > 0$. Then

$$\Delta_{T-1} \quad = \quad -(x_{T-1} - x_T) - (p_{T-1} - p_T)\, h + \frac{1 - p_{T-1}}{1+r} Diff_T$$

If $Diff_T > 0$, then with investment at level x_T, utility is sufficiently high that production is optimal. Note that $x_{T-1} = x_T$ is a feasible solution for investment in period $T - 1$. At this rate,

$$\Delta_{T-1} \quad = \quad \frac{1 - p(x_T)}{1+r} Diff_T > 0$$

so that the present value of social welfare is greater in period $T-1$ than in period T. Optimization of investment rules indicates that x_{T-1} will differ from x_T only if the change enhances utility. Hence, we conclude that $Diff_{T-1} > Diff_T > Diff_{T+1} = 0$ for all h, so long as $Diff_T(h) > 0$. In period $T-2$, a feasible level of investment again is $x_{T-2} = x_T$. In this case,

$$\Delta_{T-2} = \frac{1 - p\left(x_{T-2}\right)}{1+r}\left[Diff_{T-1} - Diff_T\right] > 0$$

By similar reasoning, we can show that $Diff_\tau(h)$ is decreasing in $\tau \in [1, T]$ if $Diff_T(h) > 0$. By incorporating this result in the optimal investment rule, we see that optimal investment also decreases in $\tau \in [1, T]$ if $Diff_T(h) > 0$.

We can employ results from the static version of this model by noting that the static version is very similar to the dynamic model in Period T. Conditions that make production preferable and possible in the static model make production feasible and desirable in Period T of this model. The results above extend the arguments to Periods $t < T$ in the dynamic model.

Clearly, social welfare declines with potential damages. Hence, social planners may find it optimal to allow plants with little risk to operate (that is, plants with h close to a), but plants with high risk close (that is, plants with h close to b). We can define a level of potential damages $\tilde{h}_t$ such that social planners are indifferent between closing and operating the plant:

$$\left\{\tilde{h}_t^{SP} :\ argmin_h Diff_t(h) = 0,\ a \leq \tilde{h}_t^{SP} \leq b\right\}$$

We limit the range of $\tilde{h}_t^{SP}$ such that $\tilde{h}_t^{SP} \in [a, b]$. Note that $\tilde{h}_\tau^{SP} = \tilde{h}_T^{SP}$ for all $\tau \in [1, T]$. Expected utility from operations of plant i is non-increasing over time. If ever it is optimal to close a plant before period $T+1$, then it is optimal to close the plant in period 1. Hence, the rule for whether to operate a plant may be determined by considering the decision in period T. Because of this result, we can use the analysis from the preceding static model to learn about $\tilde{h}^{SP}$ (at least the signs of the derivatives, but perhaps not the levels). Plants with $h < \tilde{h}^{SP}$ close in the first period, and remaining plants operate:

$$\begin{aligned} Output_{t,i} &= \begin{cases} 0 & : \quad \tilde{h}^{SP} < h_i \\ Q & : \quad h_i \leq \tilde{h}^{SP} \end{cases} \\ &= \begin{cases} 0 & : \quad h > argmin_h \left\{ Diff_t(h) = 0 \right\} \\ Q & : \quad o.w. \end{cases} \end{aligned}$$

We confirm that social welfare strictly decreases with potential damages, assuming that it is optimal to produce, so long as the first derivative of the probability function p is negative and the second is positive:

$$\frac{\delta \zeta_t^{sp}(h)}{\delta h} = \begin{cases} 0 & : \quad Q_t^{SP} = 0 \\ -p(x_t^{SP}) + \frac{1-p(x_t)}{1+r} \frac{\delta Diff_{t+1}(h)}{\delta h} & : \quad Q_t^{SP} > 0 \end{cases}$$

With the optimal rules derived above, aggregate social welfare in period t is

$$\begin{aligned} \zeta_t^{SP} &= \zeta_t^{Close} + \int_a^b \max \left\{ 0, U(Q) - U(0) - x_t^{SP} - p_t^{SP} h + \frac{1 - p_t^{SP}}{1+r} Diff_{t+1} \right\} f(h) dh \\ &= \zeta_t^{Close} + \int_a^{\tilde{h}^{SP}} \left\{ U(Q) - U(0) - x_t^{SP} - p_t^{SP} h + \frac{1 - p_t^{SP}}{1+r} Diff_{t+1} \right\} f(h) dh \\ &= \zeta_t^{Close} + \int_a^{\tilde{h}^{SP}} Diff_t(h) f(h) dh \end{aligned}$$

Aggregate output in each period is

$$\int_a^{\tilde{h}^{SP}} Q f(h)\, dh = Q \times F\left(\tilde{h}^{SP}\right)$$

where $F(g) = \int_a^g f(h)\, dh$ for $g \in [a, b]$ is the measure of plants that operate.

In summary, we see that aggregate output is constant over time, barring attrition through accidents. Optimal investment and social welfare are non-increasing over time.

4.2.5 Liability Only

We next consider a market in which private firms are permitted to operate without regulatory oversight, but they do face liability. We assume that the maximum level of liability y is given, and may be assumed to be the level of assets or the value of the firm. Alternatively, it may be set to any arbitrary level. In this analysis, we assume that $y \in (0, b]$. By defining y to be the value of the firm, we assume that standard bankruptcy rules apply.

For reasons given in the introduction, we assume that firms are held liable for damages with probability 1. We do not allow the possibility that firms will escape responsibility for damages.

Operators

Power plant operators seek to maximize expected profits in each period. They do so first by determining each period an optimal level of investment in safety improvements and maintenance, given their level of liability and the present expected value of continued operations. If expected profits are greater than decommissioning costs, given the optimal investment level, then operators choose to produce. The per-period level of potential output is given by the level of installed capital, Q. Electricity prices less unit production costs are assumed positive and are normalized to one, and so for positive production levels, Q is the level of output and revenue less operating costs. If profits (revenue less operating and investment costs less expected liability claims plus the present value of expected future profits) are less than decommissioning costs, the plants close immediately and incur shutdown costs. In this version of the model, shutdown costs are assumed zero, so that

$$\Pi_t^{Close} = 0$$

for all $t \in [1, T+1]$. Plants must close by period $T+1$.

The profit maximization problem in period t for firm i with potential damages h_i is specified as

$$\Pi_t^L(h_i) = \max \left\{ \begin{array}{c} 0, \\ \max\limits_{x_t \geq 0} Q - x_t - p_t \min\{h_i, y\} + \frac{1-p_t}{1+r} \Pi_{t+1}(h_i) \end{array} \right\} \quad (4.3)$$

To simplify notation, we denote $p_t \equiv p(x_t(h_i))$. If the firm does not produce, then the firm permanently exits the market with zero profits. If the plant does produce, then the firm earns net revenue Q, less investment x_t and expected liability $p(x)\min\{h, y\}$. The firm also receives expected discounted profits from future periods.

There is no capital investment in this model, and there is no load following. Hence, the firms' output decision is whether to invest and to produce Q units of electricity in the present period or whether to close permanently. We assume that no output is lost when operators invest. Of course, output likely is lost as the result of investment, adding costs in addition to the direct expenditures. The assumption is made solely to simplify the model.

Optimal investment is determined by differentiating Equation 4.3 with respect to investment:[3]

$$\frac{\delta \Pi_t^L(h)}{\delta x} = -1 - \frac{\delta p(x_t)}{\delta x}\left[\min\{h,y\} + \frac{\Pi_{t+1}(h)}{1+r}\right] = 0 \tag{4.4}$$

For simplicity, we ignore the constraints that are required to ensure that $x \geq 0$, so that maintenance expenditures are irreversible for all probability functions p; this assumption is not restrictive so long as p is sufficiently steep for low investment. After simplifying, we have the investment rule as a function of potential damages:

$$x_t^L(h) \;=\; (p')^{-1}\left(\frac{-1}{\min\{h,y\} + \frac{\Pi_{t+1}(h)}{1+r}}\right) \tag{4.5}$$

We see that the optimal investment rule under liability is similar to that under social planning, so long as firms bear full liability. The difference is that the term $(u(Q) - u(0))/(1+r)$ appears in the denominator of the social planning rule, so that $x_t^L < x_t^{SP}$ even for firms that bear full liability. We see also that profits are non-increasing in potential damages:

$$\frac{\delta \Pi_t^L}{\delta h} = \begin{cases} 0 & : \; y \leq h \\ -p(x_t^L) + \frac{1-p\left(x_t^L\right)}{1+r}\frac{\partial \Pi_{t+1}^L}{\partial h} & : \; h < y \end{cases}$$

Using the same reasoning as in the social planning case, we can show that expected discounted profits are non-increasing in the age of the plant. The optimal investment rule thus indicates that investment is non-increasing with age.

[3]Note also that the SOC holds: $\frac{\delta \Pi_t^{L^2}}{\delta^2 x} = -p''(x_t)\left[\min\{h,y\} + \frac{\Pi_{t+1}(h)}{1+r}\right] < 0$ for $h < y$.

We can determine points $\tilde{h}_t^L$, for each period $t \in [1, T]$, such that firms are indifferent between operating and closing.

$$\left\{\tilde{h}_t^L : \ \Pi_t^L(h) = 0, \ a \leq \tilde{h}^L \leq b\right\}$$

We find a result similar to that for social planning: the indifference point does not change over time, so that $\tilde{h}_t^L = \tilde{h}_T^L$ for all periods $t \in \{1, T\}$. This may be seen easily by first finding the value $\tilde{h}_T^L$. At this damage level, profits in T are zero, and so the affected firms' optimization problems in period $T-1$ are identical to the optimization problems in period T. This implies that $x_{T-1}^L\left(\tilde{h}_{T-1}^L\right) = x_T^L\left(\tilde{h}_T^L\right)$, and so $\Pi_{T-1}^L\left(\tilde{h}_T^L\right) = \Pi_T^L\left(\tilde{h}_T^L\right) = 0$. The value $\tilde{h}_T^L$ thus satisfies our conditions for $\tilde{h}_{T-1}^L$, and so we conclude that $\tilde{h}_{T-1}^L = \tilde{h}_T^L$. Similar reasoning extends the argument to all $t \in [1, T]$.

Firms with $h \leq \tilde{h}^L$ produce, and remaining firms close:

$$\begin{aligned} Output_i &= \begin{cases} Q & : \ h_i \leq \tilde{h}^L \\ 0 & : \ \tilde{h}^L < h_i \end{cases} \\ &= \begin{cases} Q & : \ 0 < \Pi_t(h_i) \\ 0 & : \ \Pi_t(h_i) \leq 0 \end{cases} \end{aligned}$$

Because $\tilde{h}^L$ is constant over time, unprofitable firms close in the first period. If no accidents occur, aggregate output will not change over time. Given the infinite number of firms in our model, though, we expect $\int_a^{\tilde{h}^L} p\left(x_t\left(h\right)\right) f\left(h\right) dh$ accidents to occur in period t, and it would be extraordinarily unlikely for no accidents to occur. We thus suppose that p is an *ex ante* measure, but that no accidents occur.

We see that investment increases with potential damages, so long as liability covers those damages:

$$\frac{\delta x_t^L}{\delta h} = \frac{\delta\left((p')^{-1}(h)\right)}{\delta h}\frac{\delta\left(\frac{-1}{\min\{h,y\}}\right)}{\delta h} \geq 0$$

Regulators

Social welfare may be found as under social planning, but now taking the firms' optimal policy functions as given:

$$\begin{aligned}\zeta_t^L &= \int_a^{\tilde{h}^L}\left\{U(Q) - x_t^L - p_t\left[h - \frac{\zeta_{T+1}^{Close}}{1+r}\right] + \frac{1-p_t}{1+r}\zeta_{t+1}^L(h)\right\} f(h)dh \\ &\quad +[1-F(\tilde{h}^L)] \times \zeta_t^{Close}\end{aligned}$$

Aggregate output is

$$\int_a^{\tilde{h}^L} Qf(h)\,dh = Q \times F\left(\tilde{h}^L\right)$$

In summary, we see that under liability only, aggregate output is constant over time, while investment and profits are non-increasing. For all firms that operate, $x_t^L < x_t^{SP}$, so expected damages are greater and social welfare is lower under liability than under social planning unless all firms close in both cases.

4.2.6 Regulation Only

We next consider the case in which firms operate without liability, but regulators impose minimal standards for investment in each period. Ignoring the possibility of direct subsidies, this scenario presents an upper bound for liability limits, measured as the benefits presented to firms by limiting their liability levels.

Operators

The firms' profit functions are specified as

$$\Pi_t^R(h_i) \;=\; \max\left\{0, \max_{s_t \le x}\left\{Q - x + \frac{1-p(x)}{1+r}\Pi_{t+1}\right\}\right\}$$

Given zero liability, firms find it optimal to invest only to improve the likelihood of receiving profits in the future, but they must satisfy current investment requirements. In the last period, when future profits surely are zero, firms prefer to invest nothing. Generally, firms invest either the regulated amount s_t or the optimal level under liability only with $y = 0$:

$$x_t^R \;=\; \max\left\{s_t, (p')^{-1}\left(\frac{-1}{\left(\frac{\Pi_{t+1}(h_i)}{1+r}\right)}\right)\right\}$$

so long as the expected present value of profits is non-negative. For s greater than the sum of current and discounted future revenue, firms close. Otherwise, they operate. Hence, the output rule is:

$$Output_{t,i} = \begin{cases} 0 & : \quad s_t > Q + \dfrac{1-p(x_t^R)}{1+r}\Pi_{t+1} \\ Q & : \quad s_t \le Q + \dfrac{1-p(x_t^R)}{1+r}\Pi_{t+1} \end{cases}$$

Either all firms operate, or all firms close.

Regulators

Regulators take into account the effects of their policies on the decisions made by plant operators. Hence, in effect they choose whether output will be zero or positive. The regulators' optimization problem can be written as the sum of social welfare with zero aggregate output, plus the difference in welfare between positive and zero production for markets in which plants produce. We will derive the difference for the market facing potential damages h, but for now we claim it to be:

$$Diff_t(h) = \max \left\{ \begin{array}{c} 0, \\ U(Q) - U(0) - s_t - p\left(s_t\right) h + \frac{1-p(s_t))}{1+r} Diff_{t+1}(h) \end{array} \right\}$$

Social welfare for markets in which plants are closed can be written as

$$\zeta_t^{Close} = U(0) + \frac{\zeta_{t+1}^{Close}}{1+r} = U(0) \frac{1 - (\frac{1}{1+r})^{T+2-t}}{1 - \frac{1}{1+r}}$$

Hence, we claim that social welfare for individual markets may be written as

$$\zeta_t^R(h) = \zeta_t^{Close} + Diff_t(h)$$

assuming that plants invest no more than the required amount.

To leave the industry viable, it must be that given policy s_t, $\Pi \geq 0$. By solving this profit-function condition for s, we have the upper bound $\bar{s}_t$ defined as $s = argmin_s \{\Pi = 0\}$. We also know that firms will invest no less than x_t^L, given $y = 0$, so there is no reason to consider lesser policies. We thus have the lower bound $\underline{s}_t$, defined as $s_t \geq (p')^{-1} \left(\frac{-1}{\frac{\Pi_{t+1})}{1+r}} \right)$. In the aggregate, social welfare is specified as

$$
\begin{aligned}
\zeta^{R} &= \max \left\{ \begin{array}{c} \zeta_t^{Close}, \\ \max\limits_{\underline{s_t} \le s_t \le \bar{s}_t} \int_a^b \left\{ \begin{array}{c} U(Q) - s - p_t \left[h - \frac{\zeta_{T+1}^{Close}}{1+r} \right] \\ + \frac{1-p_t}{1+r} \zeta_{t+1} \end{array} \right\} f(h) dh \end{array} \right\} \\
&= \zeta_t^{Close} + \max \left\{ \begin{array}{c} 0, \\ \max\limits_{\underline{s_t} \le s_t \le \bar{s}_t} \left\{ \begin{array}{c} U(Q) - U(0) - s_t \\ + \int_a^b \left\{ \begin{array}{c} -p_t h \\ + \frac{1-p_t}{1+r} \left[\zeta_{t+1} - \zeta_{T+1}^{Close} \right] \end{array} \right\} f(h) dh \end{array} \right\} \end{array} \right\} \\
&= \zeta_t^{Close} + \max_{\underline{s_t} \le s_t \le \bar{s}_t} Diff_t \left(E\left(h \right) \right)
\end{aligned} \tag{4.6}
$$

where $p_t \equiv p\left(s_t\right)$. The constraints ensure that regulation leaves the industry viable. We need not consider regulatory levels below the investment levels the industry finds optimal, and we need not consider regulatory levels above that which drives output to zero. Note that the specified lower bound is not defined in period T, and thus should be replaced with zero in that period. More generally, in any case in which $\Pi_{t+1} = 0$, then the constraint becomes $0 \le s_t \le \Pi^{-1}(0)$. We omit such details in the equation for simplicity.

We see that the regulator must set a single minimal standard for investment expenditures for all firms. The regulator cannot impose regulations tailored to individual firms because we assume that h is known only by the firms themselves. In the last line of the optimization problem, we see that the regulators' problem is identical to the social planners' problem for the average firm, with one exception. The exception is that the regulation s must be less than the present value of the firm so that operations for the average firm are profitable. If both regulators and social planners find it optimal for the average firm to operate, but regulators find the constraint binding, then it may be optimal for them to set higher standards but also to subsidize production, so that firms remain profitable. However, we do not consider production subsidies in this paper.

The optimal level of regulation may be found by differentiating the social welfare function given by Equation 4.6:[4]

$$\begin{aligned}\frac{\delta \zeta_t^R}{\delta s_t} &= -1 - \frac{\delta p}{\delta s}\left[E(h) + \frac{Diff_{t+1}(E(h))}{1+r}\right] \leq 0 \qquad (4.7)\\ \Rightarrow s_t^R &= \min\left\{\begin{array}{c} Q + \frac{1-p(s_t^R)}{1+r}\Pi_{t+1}, \\ (p')^{-1}\left(\frac{-1}{E(h)+\frac{Diff_{t+1}(E(h))}{1+r}}\right)\end{array}\right\}\end{aligned}$$

We see that either regulation is set to the optimal level of investment for the average firm under social planning, or investment exhausts profits. Note that $E(h)+\frac{Diff_{t+1}(E(h))}{1+r} > \Pi_{t+1}(E(h))$, so the lower bound on regulation never binds.

We can determine the evolution of optimal regulatory levels by comparing the values of $Diff$ over time. Let Δ_t be the difference between $Diff_{t-1}$ and $Diff_t$:

$$\begin{aligned}\Delta_{t-1} &\equiv Diff_{t-1} - Diff_t \\ &= -\left[s_{t-1} - s_t\right] - \left[p(s_{t-1}) - p(s_t)\right]h \\ &\quad + \left[\frac{1-p(s_{t-1})}{1+r}\Delta_t - \left[p(s_{t-1}) - p(s_t)\right]\frac{Diff_{t+1}}{1+r}\right]\end{aligned}$$

Note that $Diff_{T+1} = 0$. Assume that $Diff_T > 0$. Then

$$\Delta_{T-1} = -\left[s_{T-1} - s_T\right] - \left[p(s_{T-1}) - p(s_T)\right]h + \frac{1-p(s_{T-1})}{1+r}Diff_T$$

Note that for $Diff_T > 0$, s_T led to sufficiently high utility that it was optimal to allow firms to operate. Note that $s_{T-1} = s_T$ is a feasible solution for regulation

[4]Note that the SOC holds: $\frac{\delta \zeta^{R^2}}{\delta^2 s} = -p''(s)\left[E(h) - \frac{Diff_{t+1}(E(h))}{1+r}\right] < 0$s

in period $T-1$. At this rate,

$$\Delta_{T-1} = \frac{1-p\left(s_T\right)}{1+r} Diff_T > 0$$

Optimization of regulatory policies indicates that s_{T-1} will differ from s_T only if the change enhances utility. Hence, we conclude that $Diff_{T-1} > Diff_T > Diff_{T+1} = 0$ for all h. Note also that in period $T-2$, a feasible level of regulation is $s_{T-2} = s_T$. In this case,

$$\Delta_{T-2} = \frac{1-p\left(s_{T-2}\right)}{1+r} \left[Diff_{T-1} - Diff_T\right] > 0$$

By similar reasoning, we can show that $Diff_\tau(h)$ is decreasing in $\tau \in [1,T]$ if $Diff_T(h) > 0$. By incorporating this result in the optimal regulation rule, we see also that regulation is decreasing in $\tau \in [1,T]$ if $Diff_T(h) > 0$.

It is easy to see that if the constraint ever binds, then it always will bind. Consider period T. If the constraint binds, then $s_T = Q < \left(p'^{-1}\right)\left(-1/E\left(h\right)\right)$. However, optimal regulation never will be lower, and so the constraint also must bind in all preceding periods. Because profits are zero in period T, the firms' optimization problem is identical in period $T-1$. By continuing this reasoning, we can extend the argument to period 1.

We can calculate the aggregate level of social welfare under optimal regulation:

$$\begin{aligned}
\zeta_t^R &= \int_a^b \max\left\{\begin{array}{c} \zeta_t^{Close}, \\ U(Q) - U(0) - x_t^R - p_t^R \left[h - \frac{\zeta_{t+1}^{Close}}{1+r}\right] + \frac{1-p_t^R}{1+r}\zeta_{t+1}^R \end{array}\right\} f(h)dh \\
&= \zeta_t^{Close} + Diff_t\left(E(h)\right)
\end{aligned}$$

In summary, aggregate output is constant under regulation apart from losses to accidents, and the values of the firms are non-increasing. Regulation also is non-increasing, as is the social benefit of continued operations.

4.2.7 Liability and Regulation

The final regulatory regime that we consider includes both regulation and liability. As we will see, full analytical results are difficult or impossible to obtain. We instead shall rely on a combination of analytical and numerical solutions to our model.

Operators

Operators again seek to maximize profits, given their level of liability. Their choices concerning investment are constrained by the lower limit set by regulators. Firms either find regulation binding, and thus invest at level s_t, or they do not find the policy binding and so invest as if there were no regulation. In the latter case, firms invest according to the rule derived in Section 4.2.5. If these levels are greater than the mandated level, then the firms set their investment levels accordingly. Otherwise, the firms set their investment levels to the regulatory standard. Next, the firms determine whether, given their investment levels, operations are expected profitable; that is, if the expected present values of operations are greater than exit costs. If so, those firms invest, produce, collect revenue, pay any damage claims up to the level of liability, and continue to the next period if no accidents occur. If firms determine that operations are not expected to be profitable, then those firm exit with zero profits.

We specify the profit function in period $t \in [1, T]$:

$$\Pi_t^{LR}(h_i) = \max \left\{ \begin{array}{c} 0, \\ \max_{0 \leq x} Q - \max\{s_t, x\} - p\left(\max\{s_t, x\}\right) \min\{h_i, y\} \\ + \frac{1-p(\max\{s_t,x\})}{1+r} \Pi_{t+1}^{LR}(h_i) \end{array} \right\}$$

By finding the first-order condition, assuming for now that regulation does not bind, we have

$$\frac{\delta \Pi_t^{LR}(h_i)}{\delta x} = -1 - \frac{\delta p(x)}{\delta x} \left[\min\{h_i, y\} + \frac{\Pi_{t+1}^{LR}(h_i)}{1+r} \right] = 0 \qquad (4.8)$$

Assuming that the irreversibility condition does not bind, we can compute the corresponding investment rule.

$$\begin{aligned} x_t^{LR}(h_i) &= \max \left\{ s_t, (p')^{-1} \left(\frac{-1}{\min\{h_i, y\} + \frac{\Pi_{t+1}^{LR}(h_i)}{1+r}} \right) \right\} && (4.9) \\ &= x_t^L(h_i) \text{ for } \{s_\tau \leq x_\tau^L(h_i) \forall t < \tau \leq T\} && (4.10) \end{aligned}$$

We claim that for non-binding regulatory levels both now and in all future periods, the firms' investment problems are identical to the case in which there is no regulation. However, this claim requires that regulation will not bind in future periods. Otherwise, the present value of profits will be affected, and so while the investment rule remains identical to the liability-only case, the investment level will be lower. It remains to be shown that if regulation does not bind for a firm in period t, then regulation will not bind in future periods.

As we saw earlier, we may find a point $\tilde{h}_t^{LR}(s)$ for which firms with this level of potential damages are indifferent between operating and closing. Now, the indifference point depends on the level of regulation s. The point may be found as:

$$
\left\{ \tilde{h}_t^{\ LR}(s) : \begin{array}{c} Q = \max\left\{s, x_t^{LR}(h)\right\} + p\left(\max\left\{s, x_t^{LR}(h)\right\}\right)\min\left\{h, y\right\} \\ -\frac{1-p\left(\max\left\{s, x_t^{LR}(h)\right\}\right)}{1+r}\Pi_{t+1}^{LR}(h) \end{array} \right\} \quad (4.11)
$$

although we constrain values of $\tilde{h}_t^{LR}(s)$ to the interval $[a, b]$.

To solve the regulators' optimization problem, we must determine how $\tilde{h}_t^{LR}(s)$ changes with the level of regulation s. To determine this, we use the implicit function theorem. First, define

$$
\begin{aligned}
C_t(h,s) &\equiv Q - \max\left\{s, x_t^{LR}(h)\right\} - p\left(\max\left\{s, x_t^{LR}(h)\right\}\right)\min\left\{h, y\right\} \\
&\quad + \frac{1 - p\left(\max\left\{s, x_t^{LR}(h)\right\}\right)}{1+r}\Pi_{t+1}^{LR}(h) \\
&= 0
\end{aligned}
$$

as the combination $\{h, s\}$ that yields zero profits in period t. By differentiating C with respect to h and s, we find

$$
\begin{aligned}
\frac{\delta Ct(h,s)}{\delta h} &= \begin{cases} -p\left(\max\left\{s_t, x_t^L(h)\right\}\right) + \frac{1-p\left(\max\left\{s_t, x_t^L(h)\right\}\right)}{1+r}\frac{\delta \Pi_{t+1}^{LR}(h)}{\partial h}) & : \quad h < y \\ 0 & : \quad y \leq h \end{cases} \\
\frac{\delta C_t(h,s)}{\delta s} &= \begin{cases} -1 - p'(s)\left(\min\left\{h, y\right\} + \frac{\Pi_{t+1}^{LR}(h)}{1+r}\right) & : \quad x^L \leq s \\ 0 & : \quad s < x^L \end{cases}
\end{aligned}
$$

With these equations, we can compute the derivative of $\tilde{h}_t^{\ LR}(s)$ with respect to s in period t:

$$
\begin{aligned}
\frac{\delta \tilde{h}_t^{LR}(s)}{\delta s} &= -\frac{\frac{\delta C_t(h,s)}{\delta s}}{\frac{\delta C_t(h,s)}{\delta h}} \\
&= \begin{cases} -\frac{-1-p'(s)\left(\tilde{h}_t^{LR}(s)+\frac{\Pi_{t+1}^{LR}(\tilde{h}_t^{LR}(s))}{1+r}\right)}{-p(s)+\frac{1-p(s)}{1+r}\frac{\delta \Pi_{t+1}^{LR}(\tilde{h}_t^{LR}(s))}{\partial h}} & : \quad h < y, x^L \leq s \\ 0 & : \quad \text{o.w.} \end{cases} \qquad (4.12)
\end{aligned}
$$

Hence, we see that $\tilde{h}_t^{LR}(s)$ is non-increasing in regulation. We claim that this is so by noting that $\partial C/\partial s$ is zero for $s = x_t^{LR}(\tilde{h}_t^{LR}(s))$, according to the first order condition for profit maximization. For regulation to bind, it must be true that $x_t^L(\tilde{h}_t^{LR}(s)) < s$, and so $\partial C/\partial s$ must be less than zero.

Output is determined according to profitability of operations. Production for firm i may be determined by comparing h_i to $\tilde{h}^{LR}(s)$:

$$
Output_i = \begin{cases} 0 & : \quad \tilde{h}_t^{LR}(s_t) < h_i \\ Q & : \quad \tilde{h}_t^{LR}(s_t) \geq h_i \end{cases}
$$

Aggregate output is

$$
\int_a^{\tilde{h}_t^{LR}(s)} Qf(h)dh = Q \times F(\tilde{h}_t^{LR}(s))
$$

Regulators

Regulators choose a minimal standard for investment in order to maximize social welfare as before. This time, we consider three sets of parameters.

1. $\tilde{h}^L \leq a$

   First, we assume that technology and the market is such that it is privately optimal for all firms to close, even if regulators set the minimal standard to its lowest level ($s = 0$). In this case, given the maximum liability level

y, the only possibility for regulators to foster output is through subsidies; however, we do not consider output subsidies. In this case, we obtain the same solution as in the liability-only case, and social welfare with zero output is

$$\zeta_t^{LR} = \zeta_t^{Close} = U(0)\frac{1-(\frac{1}{1+r})^{T+2-t}}{1-\frac{1}{1+r}} \tag{4.13}$$

2. $a < \tilde{h}^{LR}(s) \leq h(s)$

   In this scenario, at least some firms find it profitable to operate despite liability, but regulation is sufficiently high so that all firms that operate find regulation binding. We define the difference at time t between the social welfare of continued operations and ceasing production in markets facing h:

$$Diff_t(h) = \max\left\{0, \left\{\begin{array}{c} U(Q)-U(0)-s_t \\ -p_t h + \frac{1-p_t}{1+r}Diff_{t+1} \end{array}\right\}\right\} \tag{4.14}$$

   We will derive below lower and upper bounds $\underline{s}$ and $\bar{s}$, respectively. We use this term to define the regulators' objective function:

$$\begin{aligned}
\zeta_t^{LR} &= \max\left\{\begin{array}{c} \zeta_t^{Close}, \\ \max\limits_{\underline{s}\leq s\leq\bar{s}}\int_a^{\tilde{h}_t^{LR}(s)}\left\{\begin{array}{c} U(Q)-s_t \\ -p_t\left[h-\frac{\zeta_{t+1}^{Close}}{1+r}\right] \\ +\frac{1-p_t}{1+r}\zeta_{t+1} \end{array}\right\}f(h)dh \end{array}\right\} \qquad (4.15) \\
&= \zeta_t^{Close} + \max_{\underline{s}\leq s\leq\bar{s}}\int_a^{\tilde{h}_t^{LR}(s)} Diff_t(h)f(h)\,dh \\
&= \zeta_t^{Close} + \max_{\underline{s}\leq s\leq\bar{s}} F\left(\tilde{h}_t^{LR}(s)\right)\times Diff_t\left(E\left(h|h<\tilde{h}_t^{LR}(s^{LR})\right)\right)
\end{aligned}$$

   Regulators choose between forcing the market to close and allowing profitable operations. Regulations are constrained. First, let us define $h_t(s) \equiv$

$\left(x_t^{LR}\right)^{-1}(s)$ as the point of indifference for firms between s and x_t^{LR}. Then any solution to the problem above must satisfy the following constraint:

$$\begin{aligned} \tilde{h}_t^{LR}(s) &\leq h_t(s) \\ \Rightarrow x_t^{LR}(\tilde{h}_t^{LR}(s)) &\leq x_t^{LR}(h_t(s)) \\ &= x_t^{LR}((x_t^{LR})^{-1}(s)) \\ &= s \end{aligned}$$

Regulation must be sufficiently high that all firms that find operations profitable also find regulation binding. At the same time, we assume that regulation is sufficiently low that at least some firms find operations profitable:

$$a < \tilde{h}_t^{LR}(s) \Rightarrow x_t^{LR}(a) < x^{LR}(\tilde{h}_t^{LR}(s))$$

Together, these conditions provide lower and upper bounds for regulation in our optimization problem.

3. $a \leq h_t(s) < \tilde{h_t}^{LR}(s)$

   Finally, we consider the case in which at least some firms operate, and at least some do not find regulation binding. We first define the difference in social welfare between zero and full production in markets with potential damages h:

$$Diff_t(h) \quad = \quad \max \left\{ \begin{array}{c} 0, \\ U(Q) - U(0) - \max\{x_t^{LR}, s\} - p\left(\max\{x_t^{LR}, s\}\right) h \\ + \ \frac{1-p(\max\{x_t^{LR}, s\})}{1+r} Diff_{t+1}(h) \end{array} \right\}$$

   We will derive below lower and upper bounds $\underline{s}$ and $\bar{s}$, respectively. We next specify the aggregate social welfare function and show the validity of the equation above:

$$
\begin{aligned}
\zeta_t^{LR} &= \max\left\{\begin{array}{c} \zeta_t^{Close}, \\ \max_{\underline{s}\leq s\leq\bar{s}} \int_a^{\tilde{h}_t^{LR}(s)} \left\{\begin{array}{c} U(Q)-\max\left\{x_t^{LR},s\right\} \\ -p\left(\max\left\{x_t^{LR},s\right\}\right)\left[h-\frac{\zeta_{T+1}^{Close}}{1+r}\right] \\ +\frac{1-p\left(\max\left\{x_t^{LR},s\right\}\right)}{1+r}\zeta_{t+1} \end{array}\right\} f(h)dh \end{array}\right\} \\
&= \zeta_t^{Close} \\
&\quad +\max\left\{\begin{array}{c} 0, \\ \max_{\underline{s}\leq s\leq\bar{s}} \int_a^{\tilde{h}_t^{LR}(s)} \left\{\begin{array}{c} U(Q)-U(0)-\max\left\{x_t^{LR},s\right\} \\ -p\left(\max\left\{x_t^{LR},s\right\}\right)h \\ +\frac{1-p\left(\max\left\{x_t^{LR},s\right\}\right)}{1+r}\left[\zeta_{t+1}-\zeta_{T+1}^{Close}\right] \end{array}\right\} f(h)dh \end{array}\right\} \\
&= \zeta_t^{Close}+\max_{\underline{s}\leq s\leq\bar{s}}\int_a^{\tilde{h}_t^{LR}(s)} Diff_t(h)f(h)dh \\
&= \zeta_t^{Close}+\max_{\underline{s}\leq s\leq\bar{s}}\int_a^{h_t(s)} Diff_t(h)f\left(h\right)dh \\
&\quad +\int_{h_t(s)}^{\tilde{h}_t^{LR}(s)} Diff_t(h)f\left(h\right)dh
\end{aligned}
$$

As before, regulators choose between forcing markets to close and allowing operations. If any firms find regulation binding, it will be the those with lowest h. To find social welfare, regulators add together the benefits of production for firms investing at the regulated level, plus the benefits of firms investing higher levels, plus the benefits of zero production in markets in which firms close. Policy choices are constrained on the lower end by the lowest voluntary level of investment; we do not consider subsidies, and there is no need to consider $s \in \left[0, x_t^{LR}(a)\right)$. We set an upper bound as:

$$\begin{aligned}
h_t(s) &< \tilde{h}_t^{LR}(s) \\
\Rightarrow x_t^{LR}(h_t(s)) &= x_t^{LR}((x_t^{LR})^{-1}(s)) \\
&= s \\
&< x_t^{LR}(\tilde{h}_t(s))
\end{aligned}$$

At least some firms find it profitable to operate while investing above mandated levels. We define the point of indifference between s and x^{LR} as

$$h_t(s) \equiv \left(x_t^{LR}\right)^{-1}(s)$$

We can find solutions to the objective functions above. First, we solve for the case in which regulation binds for all operating firms (Case 2). By differentiating the difference function with respect to s, we see that

$$\frac{\delta Diff_t^{LR}(h)}{\delta s} = -1 - p'(s_t)\left[h + \frac{Diff_{t+1}^{LR}(h)}{1+r}\right]$$

If we assume that the constraints do not bind, then we can employ this result in the first-order condition for social welfare:

$$\begin{aligned}
\frac{\delta \zeta_t^{LR}}{\delta s} &= \int_a^{\tilde{h}_t^{LR}(s)} \frac{\delta Diff_t^{LR}(h)}{\delta s_t} f(h)dh + \frac{\delta \tilde{h}_t^{LR}}{\delta s} Diff_t^{LR}(\tilde{h}(s)) f\left(\tilde{h}(s)\right) \\
&= \int_a^{\tilde{h}_t^{LR}(s)} \left\{-1 - p'(s_t)\left[h + \frac{Diff_{t+1}^{LR}(h)}{1+r}\right]\right\} f(h)dh \\
&\quad + \frac{\delta \tilde{h}_t^{LR}}{\delta s} f\left(\tilde{h}_t^{LR}(s)\right) Diff_t^{LR}(\tilde{h}(s)) \\
&= 0
\end{aligned}$$

Hence, we see that at the optimum (assuming an interior solution), the cost of additional investment, plus the benefits of lower expected damages and potentially lost future profits, less the net benefits of production from firms that exit the market sum to zero. If the optimum is a corner solution, then s_t^{LR} will result in zero profits for firms with potential damages $h \geq y$.

If we suppose that $\int_a^{\tilde{h}_t^{LR}(s_t)} f(h)dh > 0$, as it will be if this case is relevant, then we can simplify the first order conditions for the second case, and we have

$$\begin{aligned}
\int_a^{\tilde{h}_t^{LR}(s)} f(h)dh &> 0 \qquad (4.16)\\
\Rightarrow 1 &= -p_t' \left[E\left(h | h < \tilde{h}_t^{LR}(s_t^{LR})\right) + \frac{Diff_{t+1}^{LR}(E\left(h|h<\tilde{h}_t^{LR}(s_t^{LR})\right))}{1+r} \right] \\
&\quad + \frac{\delta \tilde{h}_t^{LR}(s_t^{LR})}{\delta s} \frac{f\left(\tilde{h}_t^{LR}(s_t^{LR})\right)}{F\left(\tilde{h}_t^{LR}(s_t^{LR})\right)} Diff_t^{LR}\left(\tilde{h}_t^{LR}(s_t^{LR})\right) \\
&\leq -p_t' \left[E\left(h | h < \tilde{h}_t^{LR}(s_t^{LR})\right) + \frac{Diff_{t+1}^{LR}(E\left(h|h<\tilde{h}_t^{LR}(s_t^{LR})\right))}{1+r} \right]
\end{aligned}$$

Because $\partial \tilde{h}_t^{LR}(s)/\partial s \leq 0$, we know that

$$1 \leq -p_t' \left[E(h | h < \tilde{h}_t^{LR}(s_t^{LR}) + \frac{Diff_{t+1}^{LR}(E\left(h|h<\tilde{h}(s_t^{LR})\right))}{1+r} \right]$$

Thus, we have

$$s_t^{LR} \leq x_t^L \left(E(h | h < \tilde{h}_t^{LR}(s_t^{LR})) \right)$$

If all firms find operations profitable despite facing liability, then this policy rule is identical to that in the case of regulation only. Given the profitability constraint on regulation, and denoting the solution to Equation 4.16 as s_t^*, we have

$$s_t^{LR} = \min \left\{ \begin{array}{c} Q - p\left(s_t^{LR}\right) \tilde{h_t}^{LR}(s_t^{LR}) + \frac{1-p\left(s_t^{LR}\right)}{1+r} \Pi_{t+1}^{LR}(\tilde{h_t}^{LR}(s_t^{LR})), \\ s_t^* \end{array} \right\}$$

The solution s_t^{LR} for this case then is determined as the solution of three equations: s_t^{LR} is determined by the first-order condition (although additional attention must be paid to the constraints), $\tilde{h}_t^{LR}$ is determined by Equation 4.11, and the derivative of $\tilde{h}_t^{LR}$ is given by Equation 4.12.

In similar fashion, we find the optimal level of regulation for the third case first by differentiating the function $Diff_t$ with respect to regulation:

$$\frac{\delta Diff_t^{LR}}{\delta s_t} = -1 - p'(s_t)\left[h + \quad \frac{Diff_{t+1}^{LR}(h)}{1+r} \quad\right]$$

We employ this result in the first-order condition for social welfare, assuming that there is an interior solution:

$$\begin{aligned}
\frac{\delta \zeta_t^{LR}}{\delta s_t} &= \int_a^{h(s)} \frac{\delta Diff_t^{LR}}{\delta s_t} f(h)dh \\
&= \int_a^{h(s)} \left\{-1 - p'(s_t)\left[h + \quad \frac{Diff_{t+1}^{LR}(h)}{1+r} \quad\right]\right\} f(h)dh \\
&= 0
\end{aligned}$$

If any firms find regulation binding, then the following condition holds:

$$\begin{aligned}
\int_a^{h_t(s)} f(h)dh &> 0 \qquad (4.17) \\
\Rightarrow 1 &= -p_t'\left[\frac{\int_a^{h_t(s)}\left[h + \quad \frac{Diff_{t+1}^{LR}(h)}{1+r} \quad\right] f(h)dh}{\int_a^{h_t(s)} f(h)dh}\right] \\
&= -p_t'\left[E\left(h|h < h_t(s_t^{LR})\right) + \quad \frac{Diff_{t+1}^{LR}\left(E\left(h|h<h_t(s_t^{LR})\right)\right)}{1+r} \quad\right] \\
\Rightarrow s_t^{LR} &= x_t^{SP}\left(E\left(h|h < h(s_t^{LR})\right)\right)
\end{aligned}$$

Note, however, that $a = h_t(s)$ in the static case, so that regulation failed to bind for any firm. If the same is true for the dynamic case, then the solution is $s_t^{LR} = x_t^{SP}(a)$.

We conclude that when both regulatory and liability instruments are available to industry regulators, they first must solve the equations above to determine optimal regulatory policies in each case. They then must choose the case yielding the greatest expected welfare given the optimal regulatory policies. We thus specify the level of social welfare in time $t \in [1, T]$ as

$$\zeta_t^{LR} = \max \left\{ \begin{array}{c} \zeta_t^{Close}, \\ \int_a^{\tilde{h}(s^{LR})} \left\{ U(Q) - s^{LR} - p\left(s^{LR}\right) h \right\} f(h) dh \\ +[1 - F(\tilde{h}(s^{LR}))] \times U(0), \\ \int_a^{h(s^{LR})} \left\{ U(Q) - s^{LR} - p\left(s^{LR}\right) h \right\} f(h) dh \\ + \int_{h(s^{LR})}^{\tilde{h}^L} \left\{ U(Q) - x^{LR}(h) - p\left(x^{LR}(h)\right) h \right\} f(h) dh \\ +[1 - F(\tilde{h}^L)] \times U(0) \end{array} \right\}$$

Numerical Results

Finding general analytical solutions in the case of both liability and regulation is quite difficult. Instead, we report here some numerical results. Such results are limited by nature, and depend on additional assumptions.

First, we assume arbitrarily that the distribution $f(h)$ is uniform over h, with $a = 1000$ and $b = 5000$. Second, we specify accident probabilities as $p(x) \equiv \chi^x$, and χ is set to about 0.759. Note that this function satisfies our requirements noted earlier. Utility is specified as $u(Q) = 100 \times \ln(Q + 1)$ and $u(0) = 0$. Remaining parameters are $Q = 100$ and $r = 0.07$. Maximum liability is set to $y = 4,500$ and $y = 1,010$ for low and high liability cases, respectively. Finally, the maximum lifespan is set to $T = 40$.

Results are shown in Figure 4.1, assuming that $y = 1,010$. The figure in the upper-left displays the level of regulation assuming that regulation binds for all firms (the higher level) and that regulation binds for only some firms (the lower graph). For the given assumptions, the optimum is that regulation binds for all. Note that under the alternative, in which regulation binds for only some firms, the optimal level of regulation is identical to the private investment level $x_t^{LR}(a)$; we proved a similar rule in the static case.

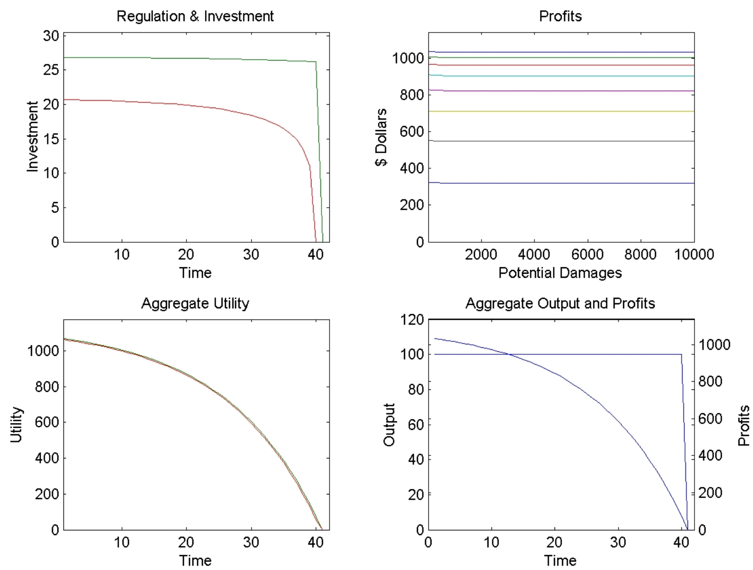
The upper-right figure displays profits, at 5-period intervals, for firms with damages h. Recall that the optimum is for all firms to invest the same amount in each period. The slight downward slope in each graph is because potential damages increase with h, even though the probability of facing such liability is unchanged. Profits, as reported here, actually are the present values of the firms. The present values decline over time, so the uppermost graph is the present value at $t = 1$, and the lowest graph is the result at $t = 40$.

The lower-left figure displays aggregate utility assuming that regulation binds for all firms (the higher graph) and that regulation binds for only some firms (the lower graph). Under the specified parameters, there is little difference, and so the graphs nearly coincide. Note that social welfare appears to converge when there are many remaining time periods.

Finally, the lower-right figure displays aggregate output and aggregate profits over time. Note that aggregate output does not change, assuming that no accidents occur. Note also that profits appear to converge when the potential lifespan of the firm is long.

Two more sets of graphs are displayed in Figures 4.2 and 4.3. Both figures compare results for the regulation-only case to results for both liability and regulation. Figure 4.2 displays results for $y = 4,500$. Note that for periods $t \in [1, 25]$, the optimal level of regulation is such that all firms find it binding. Perhaps surprisingly, it becomes optimal to lower the level of regulation in remaining periods, so that all firms decide for themselves how much to invest. This

Figure 4.1: Model Solutions



seems surprising, since firms have little incentive to invest when time horizons are short. Remember, however, that potential damages are low relative to net revenue and social welfare. Recall from Figure 4.1 that the difference in welfare is small in this case, regardless of whether regulation binds for some or for all firms. A corresponding jump in investment may be seen in the lower-right figure.

A corresponding set of graphs may be seen in Figure 4.3, given the assumption that $y = 1,010$.

4.3 Implicit Subsidies

While typically we define liability y as the value of the firm, making the model conform to standard bankruptcy rules, it could equally well be defined otherwise. In the U.S., liability is established under the Price-Anderson Act. This generally means that liability is less than the value of the firms operating nuclear power

Figure 4.2: Solutions: High Liability

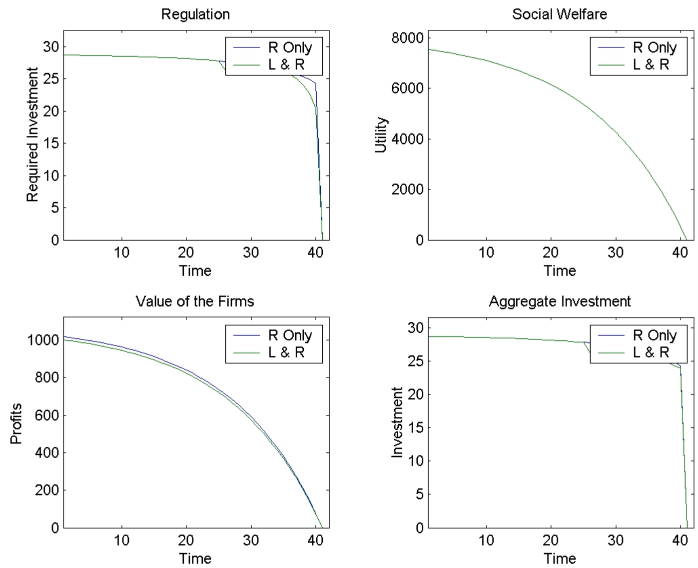
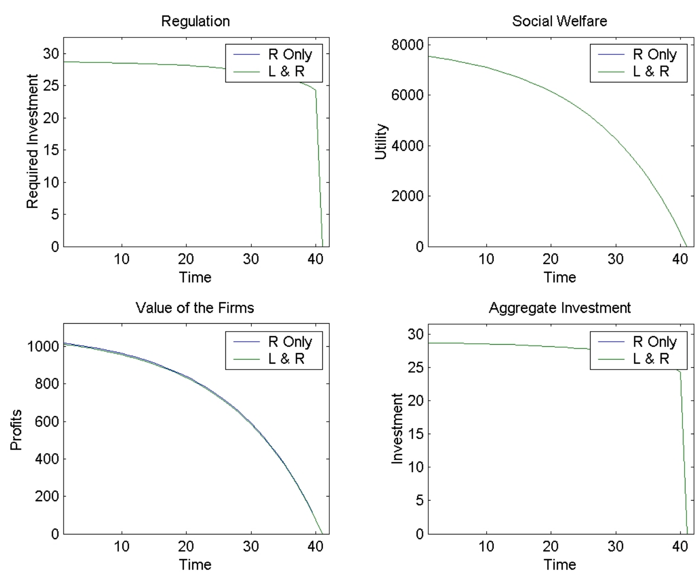


Figure 4.3: Solutions: Low Liability



plants.

Prior to 1988, these levels were set in nominal terms and were adjusted infrequently. Since then, the levels are set in real terms and adjust automatically for general inflation. Still, the liability levels are not linked directly to potential accident costs. One obvious reason for this is the difficulty of establishing the distribution of accident costs, or even to establish an upper bound for these costs. Making cost estimation still more difficult are the great regional differences among plants. Some plants are located in rural settings with relatively low values for surrounding properties, while others are in urban settings with tremendous real estate values. However, commercial insurance companies do assess potential damages for each plant. Factors they consider are the size of the plant, population and property values in the surrounding area, and the probability of an accident at the plant (Dubin and Rothwell [17, 16]). Dubin and Rothwell [17] fail to find that power plants in highly-populated areas respond more quickly to opportunities to improve safety. This may indicate that Price-Anderson protections give too little incentive for operators to minimize risk.

The assumptions in our model regarding potential damages are not satisfactory. A troubling assumption is that operators have complete knowledge of h but that regulators know only the distribution. In reality, it seems that regulators should have an estimate of h that at least approaches the accuracy of the firm's assessment. A better assumption would be that firms have private knowledge of the probability of an accident p, which may be different for each firm. Another troubling assumption is that the potential damage for each firm is a single value. In reality, there is a distribution of potential damages for each plant (Dubin and Rothwell [16], Heyes and Heyes [29]). We might define h_i to be the expected value of potential damages for firm i, and $f(h)$ becomes the distribution of mean values across firms. In this case, all firms might benefit from liability limits, even if their mean damage assessment falls below the limit. We will continue to ignore such problems in the following analysis.

The definition of the value of the firm becomes troublesome when we consider the possibility of catastrophic accidents. Consider the possibility that all assets of a firm are devoted to a single plant. Suppose that the plant is destroyed in an accident. Whether the value of the firm had been defined as the present value of profits or as the value of the firm's capital (see Rothwell [50] for a comparison of the net present value of profits to resale plant prices), the value of the firm is destroyed. For liability laws to be credible and thus to affect investment, the firm must hold other assets or insurance. This problem is less pressing with young firms, because the appeal of future profits make firms more inclined to avoid accidents today and so, at least if we ignore technological problems for young plants, economic incentives make accidents less likely. However, accident probabilities may rise with age in any finite-horizon model, for expected future profits diminish over time. Regardless of the likelihood, accidents are possible at any age, and whether the firm affected would have the means to bear liability remains an important question. Liability-sharing clauses of the Price-Anderson Act partially address the problem.

We could extend our model by allowing regulators to choose a level of liability $\hat{y} \in [0, y]$ to maximize social welfare. In such a model, it is possible that changes in other parameters, as described in the sections above, have been modest, and that the optimal liability level would not have changed much. If so, then it is possible that such a model would be consistent with reality. However, it seems unlikely that regulators choose the liability level to maximize a simple welfare function as presented in this model. Recent difficulties with renewing the Price-Anderson Act, for example, show that political pressures affect significantly the establishment of policies. We will return to the subject of politics in the section below.

In our model, we assume that maximum liability is specified exogenously, and is not under the control of the regulator. If we define y as the value of the firm, which is the maximum liability level under standard bankruptcy law, then we already have analyzed the relevant extremes: the regulation-only case sets liability to zero, and the regulation and liability case sets liability to the full value of the firm. If we define $\hat{y} \in (0, y)$ as the actual level of liability, then we might use the results above to analyze the current regulatory framework. A comparison of results for y and $\hat{y}$ would begin to address the arguments that Price-Anderson should be abandoned. We begin such comparisons below, where we construct measures of the benefits to firms for setting $\hat{y}$ below the full value of the firm. The work follows our work with the static version of this model, and our results extend our findings to the dynamic case.

The benefit to plant owners of liability caps $\hat{y} < y$ can be computed using the operators' profit functions. We must remember that existence of private benefits do not mean necessarily that social welfare suffers, at least given our specification of the welfare function. Despite its negative connotation among industry critics, we nevertheless adopt the common phrase "implicit subsidies" to describe the difference in profits for the two regimes.

We can compute the value of subsidies for a given firm i by comparing profits under two regulatory regimes; we omit the subscript i to simplify the notation.

We compute implicit subsidies generally as

$$S_t = \hat{\Pi}_t - \Pi_t$$

where profits are denoted $\hat{\Pi}$ and Π given liability levels $\hat{y}$ and y, respectively. By making additional assumptions, we can decompose subsidies. In the following equation, we assume that production takes place under both regimes, and we consider the case in which regulation fails to bind for any firm; other assumptions easily can be analyzed with the same framework. We consider two alternative liability rates $\hat{y}$ and y, where $\hat{y} < y < h$ so that $x_t^{LR}(\hat{y}) < x_t^{LR}(y)$ and $p\left(x_t^{LR}(\hat{y})\right) > p\left(x_t^{LR}(y)\right)$. The value of operations is $\hat{\Pi}_t$ and Π_t under policies $\hat{y}$ and y, respectively. The value of subsidies is

$$\begin{aligned}
S_t &= \hat{\Pi}_t - \Pi_t \\
&= \left\{ Q - x_t^{LR}(\hat{y}) - \hat{p}_t \hat{y} + \frac{1-\hat{p}_t}{1+r} \hat{\Pi}_{t+1} \right\} \\
&\quad - \left\{ Q - x_t^{LR}(y) - p_t y + \frac{1-p_t}{1+r} \Pi_{t+1} \right\} \\
&= \left[x_t^{LR}(y) - x_t^{LR}(\hat{y}) \right] + \hat{p}_t \left[y - \hat{y} \right] + \left[p_t - \hat{p}_t \right] y \\
&\quad + \frac{1-\hat{p}_t}{1+r} S_{t+1} + \frac{\Pi_{t+1}}{1+r} \left[p_t - \hat{p}_t \right]
\end{aligned} \tag{4.18}$$

We see then that operators save by spending less on investment goods. Less investment means that the probability of an accident will be higher, but the lower liability level makes the net effect on profits ambiguous. If we are to compute the present value of implicit subsidies, then to this per-period level we add the probability of receiving discounted future subsidies, less the difference in expected future profits caused by higher accident probabilities.

Most other attempts to estimate the benefits of liability caps consider only the second term in the equation above, and only the per-period implicit subsidies are reported. They assume that $y = h$, ignoring standard bankruptcy rules, and that $x^L(\hat{y}) = x^L(y)$. Hence, authors like Dubin and Rothwell [16] essentially estimate subsidies as $p\left(x^L(\hat{y})\right) \times (h - \hat{y})$.

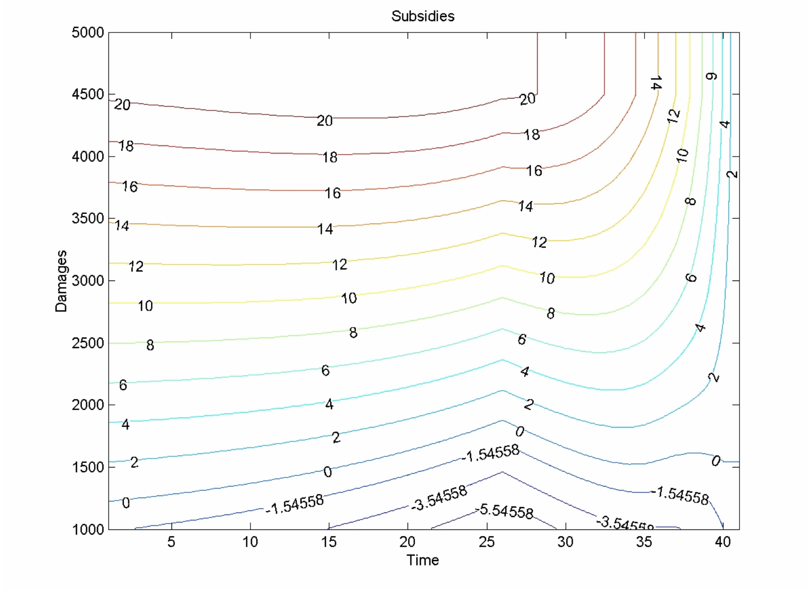
Most debate compares current liability levels, where $\hat{y}$ clearly is less than h, at least in the worst case, with an alternative regime where operators bear full liability (i.e. $y = h$). Such arguments in reality concern whether it is optimal to allow operations, as it commonly is assumed that no plant would operate if forced to shoulder full liability. However, if there is a $\tilde{y}$ such that $\hat{y} < \tilde{y} < h$, and if $\tilde{y}$ is the liability level that leaves firms indifferent between decommissioning and operating, then private benefits are not greater under a $\tilde{y}$ regime than under a regime with full liability h. If we maintain the assumption that exit costs are zero, then $\tilde{\Pi} = 0$. To calculate subsidies, we replace Π in the equation above with $\tilde{\Pi}$

$$\begin{aligned} S_t &= \hat{\Pi}_t - \tilde{\Pi}_t \\ &= \hat{\Pi}_t - 0 \\ &= \hat{\Pi}_t \end{aligned} \tag{4.19}$$

Note that we obtain the same result for any $y > \tilde{y}$, so that subsidies do not increase without bound as potential damages $h > \tilde{y}$ increase. The present value of implicit subsidies are equal to the present value of reported profits less expected liability.

Suppose the full value of a firm is $y = 4,500$, and the enforced maximum liability for the firm is $\hat{y} = 1,010$. We can compute implicit subsidies for this firm by computing the difference in the profit levels reported above. Note that because of the peculiar shift in optimal policies reported in Figure 4.2, the reported

Figure 4.4: Implicit Subsidies



implicit subsidies also will appear peculiar. A contour plot of subsidies is shown in Figure 4.4. Note that implicit subsidies are negative for firms with very low potential damages. These firms actually would prefer higher (though not binding) liability limits with corresponding shifts in regulation. Hence, the value of liability limits to firms is not always so straightforward to compute as many expect.

We do not mean to suggest that calculation of implicit subsidies ever will be easy. Even calculation of the present value of the firm requires some knowledge of accident probabilities, which have proven very difficult to calculate.

Given the years of fighting leading up to the 2005 extension of the Price-Anderson Act, it is clear that the industry strongly values the policy and that critics strongly oppose it. Many critics assume that the industry would disappear without protections. Given calculation of the present value of implicit subsidies, we could gain an idea of the amount that the industry would pay that would leave them indifferent between having or forsaking Price-Anderson. If the cost would leave firms bankrupt, then their critics at least partly are right. If not, then perhaps the benefit is not so great as critics claim. In either case, we should consider not only the effects of Price-Anderson on the value of the firms, but also we should consider the effects of both liability and regulation on safety, and we should consider the overall effect of nuclear power operations on social welfare.

4.4 Political Economy

The 1979 accident at the Three Mile Island (TMI) nuclear power plant made the possibility of a serious accident real to most Americans. While this accident turned out to be relatively minor, and little or no off site damage was caused by escaping radiation, the 1986 accident at Chernobyl truly was catastrophic. Such events led some to adjust upward their assessment of the probability of accidents that would cause harm to third parties, which is represented in this model as an increase in p. (See, for example, Zimmerman [63] and Price [43, p. 58].) In addition, many reassessed their preferences and their willingness to tolerate the risk of nuclear accidents. Suppose that the estimate of expected damages $p(h)\,h$, or more generally the aversion to damages, is scaled upward by parameter α to become $\alpha p(h)\,h$. If operators' assessment of their own potential losses increase, then they willingly increase investment or exit the market. If regulators become more averse to losses, then they may mandate stricter regulations.

The public developed greater concern for safety and relatively less concern for economic well-being following the accidents in the 1970s and 1980s. Consequent pressure on politicians may have caused regulators' preferences to shift similarly.

Such changes may be modeled simply as in the preceding section on decreasing demand.

Alternatively, we can define the parameter α to represent political preferences or public tolerance of nuclear power risks. $\alpha < 0$ indicates a public comprised of thrill-seekers, and $\alpha = 0$ indicates an indifferent population. Increasing positive values of α indicate growing aversion to potential harm. For $\alpha \rightarrow \infty$, consumers reject nuclear power regardless of potential benefits. If we assume $\alpha > 0$, which seems reasonable, then we might ask, what determines the magnitude of the preference parameter. In our model in which each market and each group of consumers are identical, we might assume the parameter exogenous and perform comparative-statics analysis. A slightly more interesting approach would be to assume a range of randomly-distributed preferences. The distribution would be analogous to the real-world distribution of ideological and political persuasions concerning the corporate world, consumer safety, and the natural environment.

Perhaps still more interesting and important cases could be analyzed by extending our model to incorporate dynamics for the level of α. With such a model, tolerance for risk and perception of risk could be based on past performance of plants; of course, this particular application also would require other extensions to our model. If the public had imperfect information concerning the risk posed by the plant in their own market, and if past performance offered a signal of the true risk, then preferences might lean against nuclear operations (high α) following poor performance or misbehavior, and the public might be tolerant of operations (low α) following periods of good performance. Regulators would have political interests leading them to care about the public's perception of risk in addition to economic well-being and their own risk assessments.

Increasing aversion makes it less likely that plants will be allowed to operate, which generally is consistent with the events of the late 1970s and 1980s. The perception of risk appears to have increased following the TMI accident, although there is evidence that it was trending upward throughout the 1970s. In the following years, many plants were closed, investment expenditures increased, and profits fell. However, Zimmerman [63] argues that existing power plants lost little value as a result of TMI once the uncertainty immediately following the accident was resolved. The primary impact of that accident was felt by those building new plants.

Whether the behavior of the public and of regulators is consistent and can be modeled remains an open question. It widely is accepted that regulations were tightened in the late 1970s, and that regulations became tighter still following the TMI accident. In this same period, public opposition to nuclear power became a formidable threat to the industry. Since then, public opposition has dwindled and perhaps regulation has become burdensome. On the other hand, perhaps operators simply improved their behavior and thus simply are avoiding wrath. Clearly, we need to extend our work to consider political factors, but this model provides a good start as we seek to disentangle these factors.

4.5 Conclusion

We constructed a model of liability-bearing firms and regulators and applied it to the nuclear power industry. We considered profit maximization as the primary motivation for firms, and they seek to enhance profits by deciding whether to operate and how much to invest willingly in safety enhancements. We modeled regulators as welfare maximizers that set minimal standards for safety enhancements and accident avoidance measures, which ultimately may determine whether the industry remains viable.

Our solutions for the optimal investment policies indicate that firms have too little incentive to invest, so that investment levels and safety fall short of the first-best solution. This in principle seems to provide some justification for imposition of safety standards, for social welfare otherwise is shown to be lower than it could be. On the other hand, the realities of limited policy instruments make optimal regulatory policies less clear. In simulations of our model, we find support for results analogous to static model implications: in some cases, it in fact is better to set low regulations and simply to let liability guide investment. We do not claim that this case applies to the nuclear power industry. Rather, our model is useful to guide future empirical studies, as well as to provide illumination on a variety of theoretical matters.

We applied our model to derive the present value of implicit subsidies from a model of firms and regulators. This work takes a broader view of the effects on firms of liability limits. We criticize other efforts to identify and quantify implicit subsidies as taking too narrow a view of regulatory effects. Instead, we take into account the effects of liability limits on behavior, and we take into account the effects of regulation. The result yields the full value of liability limits to firms, which should guide future efforts to quantify implicit subsidies and should inform both defendants and critics of Price-Anderson policies.

Chapter 5

A Numerical Model of Nuclear Power Plant Operations

In this chapter, we generalize the dynamic programming model of regulation and the firm developed in the last chapter by adding details and by relaxing some of the restrictive assumptions that were made for sake of simplicity. We combine features of our earlier models of the nuclear power industry and its regulation. We add considerable detail for individual plants. In doing so, we set the stage for the second part of this dissertation. In that second part, we focus directly on the power plants themselves and on the operation of the plants. This is a key chapter, for it ties together nearly every part of the dissertation.

Our model adds many important factors of the nuclear power industry that were left out of previous analytical exercises for sake of feasibility. We add an insurance industry in response to the Price-Anderson clause requiring partial coverage. We specify the level of insurance premiums based on potential damages and the endogenous accident probabilities. We include the potential premium refunds that are specified in the insurance policies. Also included is the liability sharing among all firms required by Price-Anderson.

The model of the firm now includes revenue, operating costs, and decommissioning costs. The output decision now is continuous. Revenue is the product of output and electricity prices, where prices are stochastic and exogenous. Parameters are calibrated or estimated using available data.

We employ the model in two applications. We consider the effects of electricity price growth on the value of firms and on their decisions. We find that the value of the firm predictably falls as price growth rates decline as they did in the mid1980s. We also consider the effects of license extensions that allow older firms to continue operations. We find that the value of all firms increase with such extensions, which first were offered to the industry in the late 1990s.

We thus add significantly to the set of key industry features incorporated in our model, and calibration enhances its realism. The results shed light on the industry in ways that few other models offer, and our work in this chapter provides important guidance for remaining chapters.

In a chapter appendix, we develop a means by which we greatly increase the computational speed and simplify the code of our numerical model. The methodology is useful generally, but we provide an application to show its particular usefulness in finding solutions to calibrated dynamic programming models. We offer evaluations that demonstrate reasonable numerical accuracy and describe ways that the method may be generalized and extended.

5.1 Introduction

When the U.S. government was considering the creation of a private nuclear power industry, they realized that the enormous risks associated with operating a nuclear facility meant that liability would need to be limited in order to ensure viability of the industry. In 1957, the government enacted the Price-Anderson Act which provides liability caps for off site damages. The stated objectives of this policy were 1) to protect the public by ensuring prompt compensation after an accident and 2) to foster the development of the nuclear power industry (Dubin and Rothwell [16]).

Price-Anderson requires that operators purchase private insurance coverage. In 1984, operators paid an average of \$0.4m per year (Brownstein [11]) for coverage of offsite damages between \$1m and \$160m.[1] The insurance companies cover all offsite damages for totals between \$1m and \$160m, and they cover the first \$160m of damage for worse accidents. If plants operate without offsite losses for 10 years, then they are eligible for a 70% refund of paid premiums (Denenberg [15]).[2]

Price-Anderson requires that plant owners equally share liability for damages in excess of private insurance coverage and below an imposed liability cap. Calculation of expected losses above the liability cap, less the amount of industry liability, yields an implicit subsidy per reactor year to power plant operators. Implicit subsidies are the insurance premiums operators are spared for coverage above the liability cap.

Such liability caps eliminated the need for plant operators to protect themselves from possible losses for damages in excess of the liability limit, thus limiting the need to purchase liability insurance. Many argue that by enabling operators to avoid these additional insurance premiums, regulators provide an implicit sub-

[1] Required coverage rose to \$300m by 2003, in current dollars (NEST-DOE [7]).

[2] See [30] for a listing of annual aggregate refunds.

sidy to the industry. While estimates for the value of these subsidies are fairly small (Dubin and Rothwell [16], Heyes and Heyes [28, 29], and Denenberg [15] (note that problems exist in the calculations of Dubin and Rothwell and Heyes and Heyes)), many still argue that the industry would not survive without them. Unfortunately, these estimates are difficult to compute, and little faith should be put in most published estimates (Heyes [26]).

Such protections offered by the government proved insufficient to maintain a healthy nuclear power industry. The 1970's and 1980's proved difficult for the electricity sector. Average annual electricity demand growth exceeded seven percent in the decade or more prior to 1973. Growth rates then fell abruptly to less than three percent. (See, for example, Price [43, p. 107].) Rothwell and Eastman [51] report that from 1979 to 1981, the realized or allowed rate of return was less than the cost of capital for U.S. electric utilities. The need for ever more base load capacity became much less pressing in the 1970s, and the shift in electricity price growth forced increases in efficiency for plants to remain viable. Nelson and Peck [39] show that the reality of weakening demand set in slowly, and that the industry consistently over-estimated future demand growth from the mid1970s to the mid1980s. Price also notes that the industry was slow to react to signs of deteriorating economic conditions.

Many consider the 1979 accident at the Three Mile Island (TMI) plant to be the primary cause of the deterioration of the nuclear power industry. However, there are numerous causes, including falling demand due to increased price growth, slowing income growth, and higher price elasticities (see Nelson and Peck [39]); higher costs (see the EIA report [2]); and greater regulatory hurdles. In fact, the backlog of new orders fell and plants under construction were abandoned even before the TMI accident (Ellis and Zimmerman [18]). Hence, all of these factors should be incorporated in any model claiming to portray the economics of the nuclear power industry. Unfortunately, most models focus only on one, or perhaps a few, such factors. Given the growing interest in resuming construction of nuclear power plants (University of Chicago [8] and MIT [6]), it is important that we improve our understanding of the political economy of nuclear power.

This paper combines a simplified version of the Rust-Rothwell model of nuclear power plant operations [56, 55] with our dynamic model of operations and investment under risk [57]. Power plant operators are assumed to be profit maximizers. They are assumed to be without market power, and thus they observe prices but cannot influence them. Each period, operators choose either to operate or to decommission permanently their plant. If they choose to operate, then they choose a level of investment and a level of capacity utilization. Investment is defined as maintenance and other irreversible expenditures that lower the probability of an accident. If an accident occurs, then an amount of damage known *ex ante* by plant operators will occur. Operators are liable either for the full amount of damage or an announced finite amount, which ever is less. The capacity of each plant is fixed upon construction. Costs are convex in investment and output. The time horizon is finite. The model is solved with dynamic programming techniques.

The solution for the model reports the optimal levels of investment and output based on the age of each plant, the levels of liability faced by each plant, and electricity prices. Optimal levels of investment and output balance the desire to maximize profits by increasing output with the need to limit costs and expected damage payments.

We apply the model in two ways. First, we consider the effects of a structural shift in prices. Such a shift occurred in U.S. electricity markets in the mid1980s. Second, we consider the effects on plants of 20-year extensions to their operating licenses. Such extensions were offered beginning in the late 1990s.

We conclude with development and application of a method to speed calculation of the integral of the approximation of a function $f(x)$, where x is normally distributed. We apply the method to numerical dynamic programming problems. The method is employed in this chapter to increase the speed of finding model solutions, with the added benefit of simplifying our model code.

5.1.1 Layout of this paper

This paper develops a model of nuclear power plant operations. First, the model is described, with timings (i.e., the order of events each period), descriptions of insurance companies and policies, objective functions for the operators, and industry details. We then derive optimal operating and investment policies for the firms. We further describe insurance companies and specify insurance premium calculations. We describe consumers and calculation of social welfare. Next, calibrate the model with available data, and we generate and report numerical solutions and simulations. We then apply the model in two ways. First, we evaluate the effect on profits and behavior of a shift in the structure of electricity prices. Second, we evaluate the response to an increase in the allowed maximum lifetimes of firms. Following the chapter conclusion, an appendix describes a numerical methodology developed for and employed in solving and simulating our model.

5.2 The Model

5.2.1 The Temporal Structure

This model has one primary group of players, nuclear power plant operators, who operate in a dynamic framework. The firms' objectives are to maximize profits. It is assumed that a continuum of markets exists, with one nuclear facility per market. No attempt is made to explain the existence of power plants, and prices and demand for electricity are exogenous. Firms are identical, except for the amount of damage that they cause if an accident occurs. We consider a finite number of time periods. When the maximum lifespan has been reached, assuming that the firm survives, the firm incurs any shutdown costs and closes permanently.

The model also has two secondary groups of agents. First, there is a private insurance company that issues policies, collects premiums, and pays the company's share of damages. Second, there is one or more consumer in each market. These consumers obtain utility through the consumption of electricity. These same consumers bear losses in the event of an accident in cases where the damage exceeds the liability cap.

At time zero, the level of demand is announced; we assume that this level is fixed throughout time and that demand is perfectly inelastic.[3] We assume that demand at least is as high as potential output, so that each firm can produce at

[3]More generally, there may be other generating technologies, e.g. natural gas, that absorb demand fluctuations. Nuclear plants service some or all base load demand, which we assume is perfectly stable. In the absence of nuclear power production, consumption is normalized to zero, though in reality a portion of demand may be met through other generating technologies.

full capacity and sell the amount at the given market price. Prices are modeled as dynamic log-normal autoregressive processes. Before operations begin, a maximum level of liability is imposed on the nuclear power industry, and the level is announced. Given this announcement, each period power plant operators decide an optimal level of investment in safety-enhancing maintenance and similar expenditures. If production yields a higher expected present value than the cost of decommissioning, then firms invest, produce electricity at the optimal utilization rate, collect the revenue, and pay operating and investment expenses. Accidents occur at the end of each period with an endogenously determined probability. These accidents cause damage to third parties, for which regulators may hold plant operators liable. If the expected present value of the firm is less than the cost of decommissioning, then operators make no investments and close their plants immediately. If the firm remains in operation at the end of its maximum lifespan, the plant incurs decommissioning costs and closes permanently.

We also incorporate features of the Price-Anderson Act. First, in each period in which a plant operates, an insurance premium is paid before operations begin. In the event of an accident, the insurance company pays its share of damages at the end of the period. Second, liability in excess of insurance coverage is shared among all operating firms. The shares are assessed and paid at the end of each period.

Exposure to liability with corresponding spending on safety reduces profits. Installation of investment goods makes the production process more difficult, so that output costs are greater with higher investment spending. The model has a continuum of firms that either produce at an optimal utilization rate or shut down permanently, depending on whether the expected present value of profits are greater than decommissioning costs. Essentially, we assume a continuum of identical markets, where prices are exogenous. Each market possesses one firm that either produces goods and delivers them to consumers in the same market who receive utility from consumption of the products, or the firm closes and consumers receive a level of utility from zero consumption.

5.2.2 Definitions

The continuum of (nearly) identical firms is indexed by the level of potential damage, h, that each firm may cause by operating. In fact, h is the only distinguishing characteristic of the firms. We assume that h is an exact amount. This magnitude of potential damage, known only to the firm, is such that $h \in [a, b]$ where $0 < a < b < \infty$. The publicly-known distribution of damages across firms is $f(h)$, which is nonzero on and only on $[a, b]$. We use a probability distribution $f(h)$ only for convenience, in that it integrates to one and we can use familiar techniques from statistics. More general specifications of $f(h)$ could integrate to any positive value, as it simply specifies the number or measure of firms with potential damages h. Firms face liability either for the full level of damages or for a maximum level of damages y, whichever is less. We assume that all plants have the same capacity. Capacity for each plant is Q. Because the measure of plants in the industry is 1, industry capacity and potential output also is Q. This may be seen by integrating over capacity for each plant: $\int_a^b Qf\left(h\right)dh = Q\int_a^b f\left(h\right)dh = Q$. The level of output for a given plant operating at a given capacity utilization rate is denoted q, so that the utilization rate is $q/Q \in [0, 1]$. We also denote aggregate output as q, where in this case $q\left(P\right) = \int_a^b q\left(P, h\right)f\left(h\right)dh$, and where $q\left(P, h\right)$ denotes the optimal plant-level output quantity for given levels of prices and potential damages. The level of expected discounted profits is denoted $\Pi(h, P)$ for individual firms and $\Pi(P)$ for the industry aggregate.

We assume that the logarithms of electricity prices P are normally distributed; we denote the logarithm as $\hat{p}$. Production and investment costs are denoted $C(x, q)$. This function is convex in investment and output. Firms may invest in goods and services, indexed by x such that $0 \leq x$, to lessen the probability of an accident. The probability of an accident $p(x)$, given the level of investment x, is identical for each firm and depends only on investment. The first derivative of the probability function is negative and the second derivative is positive. (See Dubin and Rothwell [17] for a similar specification.) If an accident occurs, then firms are liable for the amount h or the liability cap y, whichever is less. Firms also must clean up on-site damages.

A component of the social welfare function is U. For industry output q, where $q \in [0, Q]$, $U(q) = Pq - C(x, q) + u(q)$. Hence utility U is a quasilinear utility function, and is determined by the sum of industry revenue less operating and investment costs plus the benefit to consumers $u(q)$ of consuming q. The numeraire in this utility function is industry revenue less operating and investment costs. The balance of the social welfare function is potential damages and is in the same units (dollars) as is the numeraire. If a firm exits the market, then the corresponding market receives the present value of the utility stream, given zero output and consumption. Hence, social welfare depends on consumption, industry profits, and potential damages in excess of firms' liability.

Time is indexed by t, beginning with $t = 1$. The maximum possible lifespan is T. If firms operate in Period T, then they must close in Period $T + 1$ and pay decommissioning costs. We assume that all plants begin life at the same time, so that all operating plants are of the same age. While we could generalize this specification, it seems a reasonable simplification since the U.S. essentially has a single generation of commercial nuclear power plants. We assume that the model parameters are time-invariant; that is, demand, price parameters, maximum liability, the functions $p(.)$ and $f(\cdot)$, the utility functions, and the values of h and Q for each firm do not vary over time. The endogenous terms of course may vary, including investment and output, as does the exogenous evolution of prices.

5.2.3 The Firms

We consider markets in which private firms are permitted to operate without regulatory oversight, but they do face liability. We assume that the maximum level of liability y is given, and is assumed to be set to less than the level of assets or the value of the firm and that that $y \in (0, b]$. Alternatively, it could be set to any arbitrary level such that standard bankruptcy rules apply. Instead, we impose terms of the Price-Anderson Act liability protections. As we will see, the values of the firms change over time, and so it seems that perhaps y also should change over time. We do not consider this in the model, nor do we consider optimal values for y.

Power plant operators seek to maximize expected profits in each period. They do so first by determining each period optimal levels of output and investment in safety improvements and maintenance, given their levels of liability, product prices, and the present expected value of continued operations. If expected profits are greater than decommissioning costs, given the optimal investment levels and utilization rates, then operators choose to produce. The per-period level of output is denoted q and is given by the level of installed capital, Q, times the capacity utilization rate. For simplicity, we assume that electricity prices $P = \exp(\hat{p})$ follow a log-normal autoregressive process

$$\hat{p}_t = \gamma + \rho \hat{p}_{t-1} + \varepsilon_t$$

where $\varepsilon \sim N(0, \sigma^2)$. Production and investment costs are given by a convex function. We choose a simple quadratic form to illustrate the problem:

$$C(x, q) = \alpha_1 q + \alpha_2 q^2 + \alpha_3 x + \alpha_4 x^2 + \alpha_5 q x$$

Per-period gross profits thus are $Pq - C(x, q)$. If the values of the firms are less than decommissioning costs, the plants close immediately and incur shutdown costs. In this version of the model, shutdown costs are time invariant, so that

$$\Pi_t^{Close} = Decommissioning$$

for all $t \in [1, T+1]$. Plants must close by period $T+1$.

The Price-Anderson Act requires that operators purchase insurance for specified amounts of off-site damages. In the event of an accident, the insurance covers the first portion of damages. If no accident occurs for 10 years, then the Price-Anderson Act specifies that plant owners are eligible for a refund of up to 70% of their insurance premiums. We specify $Refund_t(P_t, h_i)$ as the amount of refunds received in Period t by plants with h_i. $Refund_\tau = 0$ for $\tau = 1, \ldots, 10$. In subsequent periods, operators receive $Refund_t = Premium_{t-10} \times 0.70$ in periods in which they operate. If instead the plant closes, then we assume that refunds are distributed over the following years. We denote the present value of these refunds as $PDV_t(Refund) = \sum_{\tau=t}^{t+9} \left\{ \left(\frac{1}{1+r}\right)^{\tau-t} Premium_{\tau-10} \right\}$.

Price-Anderson also requires that plants share risk through industry self-insurance. This self-insurance covers damages above the level of insurance coverage and below the liability cap. All plants equally are liable for shares of these damages. The measure of firms bearing liability in Period t is $\int_a^{\tilde{h}_t(P_t)} f_t(h)\,dh$, where $f_t(h)$ is the distribution of plants that have chosen to operate and have survived until Period t. We assume that plants with potential damages $h \leq \tilde{h}_t(P_t)$ will operate, and remaining plants close voluntarily. The amount of liability born by each plant that remains in operation is

$$\begin{aligned} &SharedLiability_t(P_t) \\ &\qquad = \frac{\int_{\max\{a,Coverage\}}^{\tilde{h}_t(P_t)} p(x_t(P_t,h))[min\{h,y\}-Coverage_t(P_t,h)]f_t(h)dh}{\int_a^{\tilde{h}_t(P_t)} f_t(h)dh} \end{aligned} \tag{5.1}$$

The amount of expected damages for which the industry is liable, after private insurance covers damages up to $Coverage_t(P_t, h)$, is seen in the numerator. This amount is shared by all plants that operate; the measure of operating firms is shown in the denominator. Note that the level of shared liability depends only on time and the price level. In this model with its infinite number of firms, the measure of plants experiencing accidents each periods is $\int_a^{\tilde{h}_t(P_t)} p(x_t(P_t,h))\,f_t(h)\,dh$. Even with a constant value for $\tilde{h}_t$, the measure of operating plants thus will fall over time since some will experience accidents. However, we will ignore this detail and assume that the distribution f is independent of time. Since our model is a stylized version of an industry with a finite number of firms, and since accidents are very rare, we hope that this simplification does not impose excessive harm to our results.

The profit maximization problem in Period t for firm i with potential damages

h_i is specified as

$$\Pi_t^L(P_t, h_i) = \max \left\{ \begin{array}{c} \left\{ \begin{array}{c} -Decommissioning \\ +PDV_t\left(Refund\right) \end{array} \right\}, \\ \max_{q_t, x_t \geq 0} \left\{ \begin{array}{c} P_t q_t - C\left(x_t, q_t\right) - p\left(x_t\right) \times Cleanup \\ +\frac{1-p(x_t)}{1+r} E\Pi_{t+1}\left(P_{t+1}, h_i\right) \\ -Premium_t\left(P_t\right) + Refund_t\left(P_t\right) \\ -SharedLiability\left(P_t\right) \end{array} \right\} \end{array} \right\} \tag{5.2}$$

If the expected discounted value of the firm is less than the exit costs plus refunds, then the firm permanently exits the market with zero profits. If the plant does produce, then the firm earns revenue $P \times q$, less operating and investment costs $C\left(x, q\right)$, less expected onsite damages $p\left(x\right) \times Cleanup$, plus expected discounted profits from future periods. The firm pays an insurance premium $Premium$, accepts refunds $Refund$, and bears a share of industry liability $SharedLiability$. Expectations of future profits $E\Pi$ are computed by integrating over prices

$$E\Pi\left(P', h\right) \equiv \int_{-\infty}^{\infty} \Pi\left(P', h\right) \phi(P'|P) dP'$$

where $\phi\left(P' \mid P\right)$ is the density function for future prices given the current price level. We discuss computation of these expectations in the appendix.

Assuming an interior solution and taking as predetermined the functions $Premium$, $Refund$, and $SharedLiability$, the solutions for investment and output may be found by calculating the gradient of Equation 5.2

$$\frac{\delta \Pi_t^L(P_t, h)}{\delta x} = -\frac{\delta C\left(x, q\right)}{\delta x} - \frac{\delta p(x_t)}{\delta x}\left[\; Cleanup + \frac{E\Pi_{t+1}(P_{t+1}, h)}{1+r} \;\right] = 0$$

$$\frac{\delta \Pi_t^L(P_t, h)}{\delta q} = P_t - \frac{\delta C\left(x, q\right)}{\delta q} = 0$$

and elements of the Hessian are

$$\frac{\delta^2 \Pi_t^L\left(P_t,h\right)}{\delta x^2} = -\frac{\delta^2 C\left(x,q\right)}{\delta x^2} - \frac{\delta^2 p(x_t)}{\delta x^2}\left[\ Cleanup + \frac{E\Pi_{t+1}(P_{t+1},h)}{1+r}\ \right]$$
$$\frac{\delta^2 \Pi_t^L\left(P_t,h\right)}{\delta q^2} = -\frac{\delta^2 C\left(x,q\right)}{\delta q^2}$$
$$\frac{\delta^2 \Pi_t^L\left(P_t,h\right)}{\delta x \delta q} = -\frac{\delta^2 C\left(x,q\right)}{\delta x \delta q}$$

The gradient indicates that under optimal policies the marginal cost of an additional unit of investment will equal the marginal reduction in expected cleanup costs and marginal increase in expected profits. Marginal costs include both purchase costs of investment goods and services and lost or more costly production. The second term of the gradient indicates that the marginal revenue will equal marginal costs. For simplicity of notation, we ignore the constraints that are required to ensure that $x \geq 0$, so that maintenance expenditures are irreversible for all probability functions p; imposition of this assumption is not restrictive so long as p is sufficiently steep for low investment. Also, we ignore the constraint that $q \geq 0$.

Note that the level of profits does not depend on potential damages h unless insurance premiums and refunds depend on potential damages. This is true because of liability sharing, and because firms do not take into account their own contribution to the level of shared liability. If premiums do not depend on h, then investment decisions will be independent of h. All firms will invest the same amounts, and these levels will depend only on the age of the firms and the current electricity price.

If we assume that the Hessian is diagonal, so that $\delta^2\Pi/\delta x \delta q = 0$, then we have the investment rule as a function of potential damages:

$$x_t^L(P_t,h) = (p')^{-1}\left(\frac{-\frac{\delta C(x,q)}{\delta x}}{Cleanup + \frac{E\Pi_{t+1}(P_t,h)}{1+r}}\right)$$

where $(p')^{-1}$ is the inverse of the derivative of the probability function. Examination of this function shows that investment increases with potential onsite damages and with potential future relative benefits of production. If we maintain the assumption that the Hessian is diagonal, then the output decision rule is

$$q_t(P_t) = (C')^{-1}(P_t)$$

where $(C')^{-1}$ is the inverse of the derivative of the cost function with respect to output. Solutions for cases in which the Hessian is not diagonal and cases in which the constraints might bind may require numerical computation.

We can determine points $\tilde{h}_t^L(P_t)$, for each period $t \in [1,T]$, such that firms are indifferent between operating and permanently decommissioning:

$$\left\{\tilde{h}_t^L(P_t):\ \Pi_t^L(P_t,h) = 0,\ a \le \tilde{h}^L \le b\right\}$$

Firms with $h \le \tilde{h}^L$ produce, and remaining firms close. Aggregate output is

$$\int_a^{\tilde{h}^L(P_t)} q_t(P_t,h)\, f(h)\, dh$$

5.2.4 The Insurance Company

This model includes a single insurance company that issues insurance policies, collects premiums, and pays a share of off-site damages. Because we know little about the rates and policies of real-world insurers of the nuclear power industry, we will assume that insurers know the distribution of firms $f(h)$, but insurers do not know the level of potential damages for individual firms. This is at odds somewhat with reality; see the NRC [30] document for details.

Insurance premiums are the sum of expected losses, overhead and profit, and the expected discounted value of refunds. We assume that the total amount of premiums collected equals the total amount of damage claims against the insurance company plus costs and profits. We solve such an equation for the premium, given the electricity price:

$$Premium\,(P_t) = \frac{\int_a^{\text{Coverage}} h \times p(x_t(P_\tau,h)) f(h)dh + Coverage \int_{\text{Coverage}}^{b} p(x_t(P_\tau,h)) f(h)dh}{\int_a^b \left\{ 1 - \pi - \dfrac{0.7}{(1+r)^{10}} \prod_{\tau=t}^{10} \int_{-\infty}^{\infty} (1 - p(x_\tau(P_\tau,h))\phi(P_\tau|P_t)dP \right\} f(h)dh}$$

where π is the premium share going to overhead and profits and r is the average yield of investments. The numerator calculates expected damage payments made by the insurance company in the current period. The denominator is the integral of one minus the markup rate minus the discounted level of expected premium refunds. Seventy percent of the premium is refunded following 10 years of safe operations. This amount is discounted at the constant rate r. The probability of 10 consecutive years of safe operations is calculated, given the expected level of future investment which in turn depends on expected electricity prices. The markup $\pi \times Premium$ is overhead, profit, and other expenses.

Because insurers know only the distribution of potential damages, they cannot issue premiums based on the level of potential damages for individual firms. For this reason, refunds in this model also do not depend on h.

5.2.5 The Consumers and Social Welfare

There are an infinite number of consumers, as each of the infinite number of markets has at least one consumer. Each consumer finds electricity consumption desirable. We assume that the group of consumers in each market is identical; in particular, we assume that they have identical preferences.

The utility of zero aggregate consumption in a given market is denoted $U(0)$. In this case, zero need not denote zero consumption, but simply that consumers will not enjoy the fruits of production by the producers in this model. In the case of electricity markets, we consider only electricity produced by nuclear power plants and normalize to zero the production of coal-fired, gas-fired, and other power plants. We assume that nuclear plants produce base-load power, and that it is the other plants that absorb demand fluctuations stemming from variations in price. The present value of a flow of utility from zero consumption from Period t to Period $T+1$ is

$$\zeta_t^{Close} = U(0) + \frac{\zeta_{t+1}^{Close}}{1+r} = U(0)\frac{1-(\frac{1}{1+r})^{T+2-t}}{1-\frac{1}{1+r}}$$

For markets in which plants have been decommissioned, this is the present value of social welfare in Period t. For simplicity, we set the discount factor according to the interest rate. All plants must close by Period $T+1$, so we have

$$\zeta_{T+1}(h_i) = \zeta_{T+1}^{Close} = U(0)$$

Social welfare over all markets may be found for a given price level by taking the firms' optimal policy functions as given:

$$\zeta_t^L(P_t) = \int_a^{\tilde{h}^L(P_t)} \left\{ \begin{array}{c} u(q_t(P_t,h)) + \Pi_t(P_t,h) \\ -p\left(x_t^L(P_t,h)\right)\max\{h-y,0\} \\ +p\left(x_t^L(P_t,h)\right)\frac{\zeta_{T+1}^{Close}}{1+r} \\ +\frac{1-p\left(x_t^L(P_t,h)\right)}{1+r}E\zeta_{t+1}^L(P_{t+1},h) \end{array} \right\} f(h)dh$$
$$+\left[1-F(\tilde{h}^L(P_t))\right]\times\zeta_t^{Close}$$

where $F(g) = \int_a^g f(h)\,dh$ for $g \in [a,b]$ is the measure of plants that operate. The first term on the right-hand side computes the present value of social welfare in markets with operating plants. Social welfare in each of these markets is the sum of consumers' utility and plant profits, less expected damages that are not borne by the firm and its insurance coverage, plus the expected social value of zero consumption, plus the expected present value of future operations. The second term on the right-hand side is the sum of social welfare in markets without operating plants. Expectations of future social welfare $E\zeta$ are computed by integrating over utility

$$E\zeta(P',h) \equiv \int_{-\infty}^{\infty} \zeta(P',h)\,\phi(P'|p)dP'$$

To compute this integral, we proceed as with the computation of expected profits that is described in the appendix.

5.3 Numerical Results

General analytical results are difficult or impossible to calculate for this model, so we evaluate it numerically. We first must specify the functions and parameters that were not specified above.

5.3.1 Calibration

Insurance premiums are set to \$400,000 per reactor per period in 1984 dollars (see Brownstein [11]). We thus ignore variation in premiums based on risk assessments, the population and property values in the areas surrounding plants, and other such factors.[4] We assume that all refunds are 70% of the \$400,000 premiums, or \$280,000; see [30] for a listing of aggregate refunds.

Insurance coverage in 1984 was \$160 million. Shared liability is determined according to Equation 5.1.

The range of potential damages h is $[\$1m, \$10,000m]$, and this range is discretized into 101 equal segments. The liability cap is set to $y = \$660m$.[5] For simplicity, we assume that $f(h)$ is the uniform distribution.[6] Note that we misuse the data, since these values represent the range of potential damages for each plant. In our model, each plant poses damages h, which is a scalar rather than a distribution for particular plants.

We specified above an autoregressive log-normal process for electricity prices. We first set the parameters $\gamma = -0.51$, $\rho = 0.83$, and standard deviation $\sigma = 0.05$, which correspond to relative electricity prices between 1973 and 1985.[7] In the second run, we set the parameters to $\gamma = -0.40$, $\rho = 0.89$, and standard deviation $\sigma = 0.02$, which correspond to relative electricity prices from 1986 to

[4] See, for example, the review of Price-Anderson [30].

[5] These parameters correspond to those in Dubin and Rothwell [16].

[6] Dubin and Rothwell [16] assumed a log-logistic distribution, although their distribution was defined differently.

[7] Prices are from the EIA, are in dollars per kilowatt-hour, and are relative to the GDP implicit price deflator in 1984 prices.

2004. We assume that 50% of the sale price is assigned to power generation and the remaining unit revenue share goes to transmission and other expenses. The truncation points for the log-normal distribution are -5.0 and -1.0. Nineteen Chebychev interpolation nodes are chosen for the approximation and integration of the value function.

As was shown above, we assume that the cost function is a second-order polynomial. Costs per kilowatt of capacity are:

$$49.4 - 7.59q + 0.001q^2 + 2.08x + 0.000002x^2 - 0.00004qx$$

Cost data was taken from the EIA [2]. Total costs are total non-fuel operating costs per kilowatt of capacity and have been converted to 1984 prices. Investment expenditures also have been converted to 1984 prices using the GDP implicit price deflator. Output and capacity data were taken from the EIA website. Potential output is taken to be the level of capacity in 1984, which was 69.7 gigawatts, times the number of hours in a year, so that potential output approximately is 610.6 billion KWh. A linear regression was used to calculate parameters. Constraints were imposed to ensure that the cost function is convex. It is assumed that operating costs are under-reported by 30%, and so the results of this equation are inflated accordingly[8]. Other expenses, such as fuel costs, are not considered.

The maximum number of periods T initially is 40. This corresponds to the number of years that plants initially were licensed to operate. We solve the model a second time to consider implications of possible 20-year license extensions.[9]

[8]See EIA [2] for details.

[9]See Rust and Rothwell [56] for similar analysis.

We set decommissioning costs to \$400m and onsite cleanup following an accident to \$1b.[10] The interest rate is $r = 0.07$. Preferences are specified as $u(q) = 610.6 \log(q+1)$, so that $u(0) = 0$. The probability of an accident is $p(x) = \chi^x$, where χ is chosen so that $p \approx 0.005$ at 1984 investment levels.

Basic Results

The first two figures, Figures 5.1 and 5.2, display parts of the solutions given the parameterizations listed above.

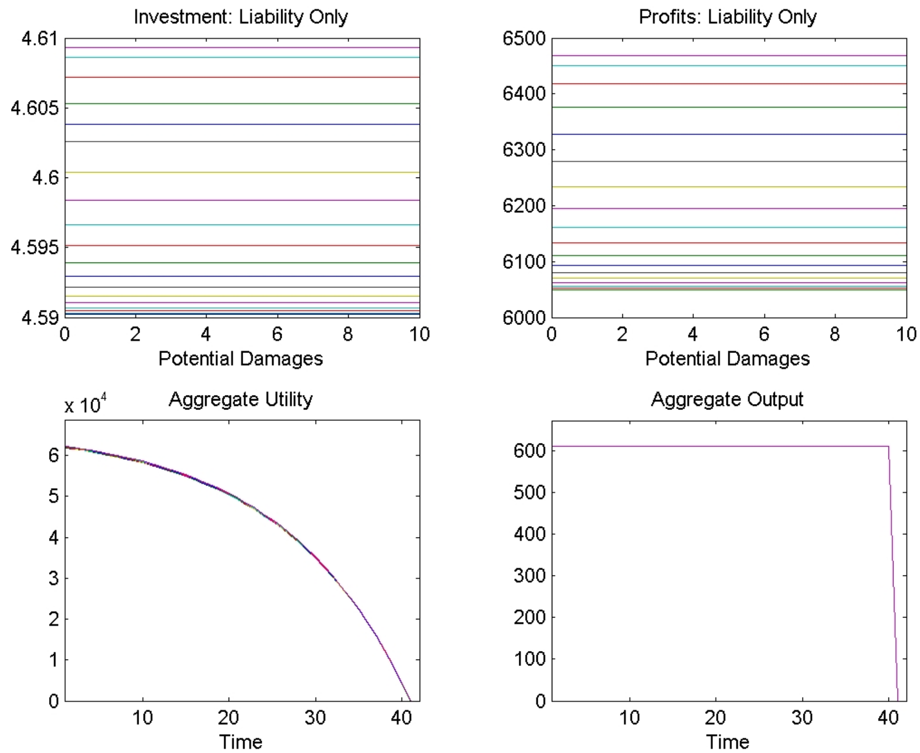
The graph in the upper left corner of the Figure 5.1 displays the level of investment in Period 1 across potential damages. The level of investment is shown for various price levels, with higher prices leading to higher investment levels. Note that investment does not depend on the level of potential damages. This is so because of liability sharing and because we assumed a constant insurance premium despite differing potential damage assessments.

The graph in the upper right corner of the figure displays the expected present discounted value of firms in Period 1 across potential damages. Present values are displayed for various price levels. The present values rise with prices. Note that the values of the firms do not depend on potential damages for the same reasons listed above.

The graph in the lower left displays the aggregate level of social welfare across time. At each point in time, social welfare is displayed for the same set of price levels. Note that social welfare falls over time and increases with prices. Social welfare increases with prices because firms receive higher profits and because

[10] This is the amount cited by Dubin and Rothwell [17] for cleaning up after the Three Mile Island accident in 1979.

Figure 5.1: Dynamic Programming Solutions



we assumed that demand is perfectly inelastic. A more realistic social welfare function would not increase so rapidly with prices, and the positive relationship might actually be counter-factual. With this parameter set, there appears to be little variation in social welfare as the price varies.

The final graph, in the lower right corner, displays aggregate output over time. For this set of parameters, and at the price levels that are graphed, either all plants close or all plants produce in all periods, depending on electricity prices.

Figure 5.2 displays the aggregate present value of firms over time. In each period, the present values are calculated at the same set of price levels. We see that the values of firms fall over time and increases with electricity prices.

Figure 5.2: Aggregate Present Values

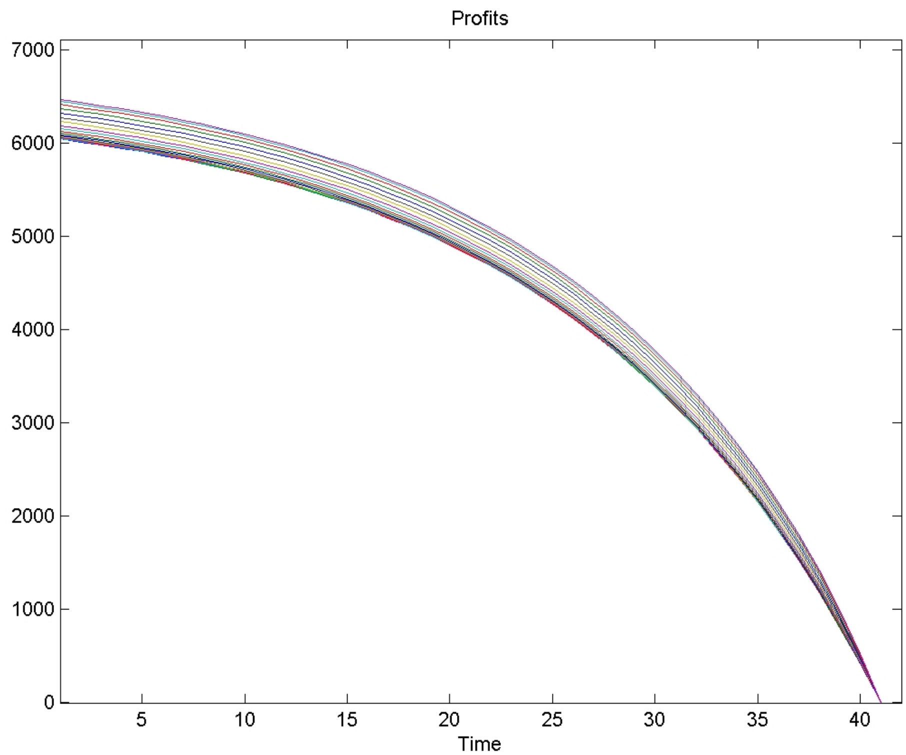
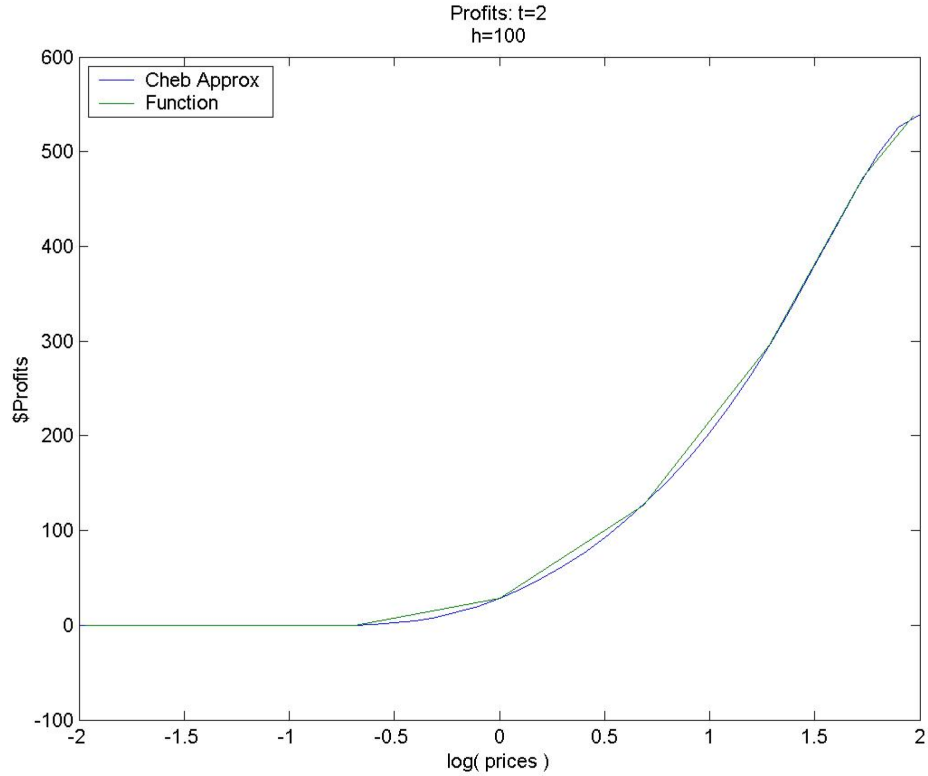
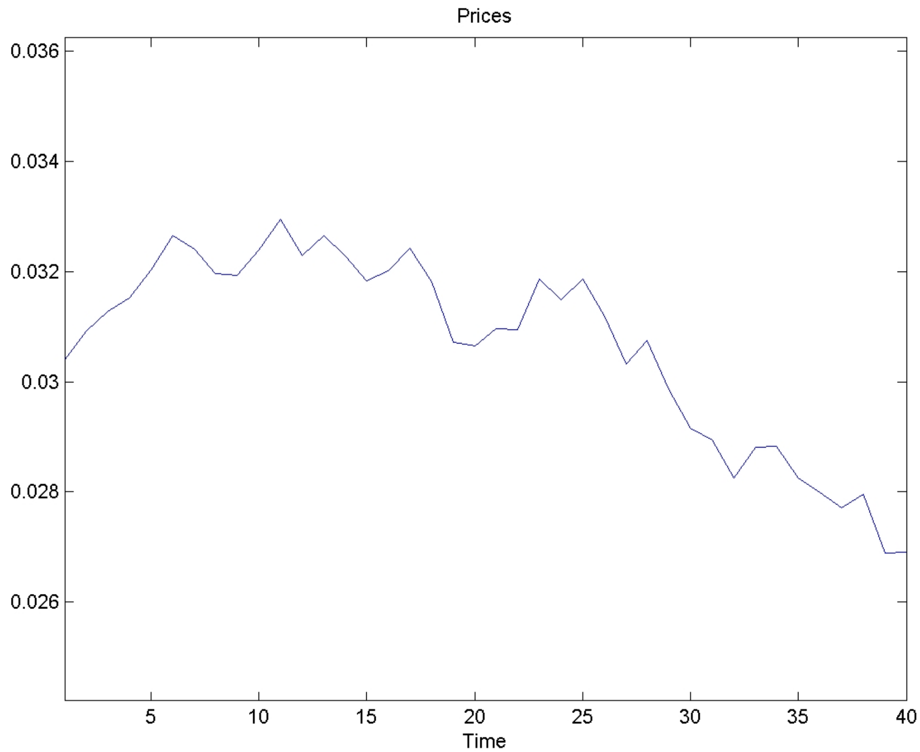


Figure 5.3: Interpolation of Expected Profits



In Figure 5.3, we see expected profits in Period 1 across electricity prices for plants with the lowest level of potential damages. The Chebychev approximation of profits is displayed, along with a finite set of approximation points. Note that despite the non-linearity imposed by the decommissioning rule, in which plants close when the expected present value of the firm falls below decommissioning costs plus refunds, a continuous Chebychev approximation of profits seems appropriate. In contrast, linear splines approximations prove far superior for the investment and output functions because of more extreme nonlinearities. The latter two approximations are necessary for simulations, while the profit function approximation is needed both to solve and to simulate the model. Chebychev interpolation also is used for simulating social welfare levels.

Figure 5.4: Simulated Prices



5.3.2 Simulations

The solutions described above were employed to simulate the behavior of a firm. First, the exogenous price series was simulated, with the price in period 0 initialized to its steady-state level ($\hat{p} = \gamma / (1 - \rho)$). In this case, we calibrated the price equation using post1986 electricity rates. The resulting simulated series is shown in Figure 5.4.

Figure 5.5 displays investment, the present value of the firm, social welfare in the corresponding market, and output. Note that while finite-horizon dynamic programming solutions inherently are nonstationary, investment indeed trends lower but output levels are not trended.

Figure 5.5: Dynamic Programming Simulations

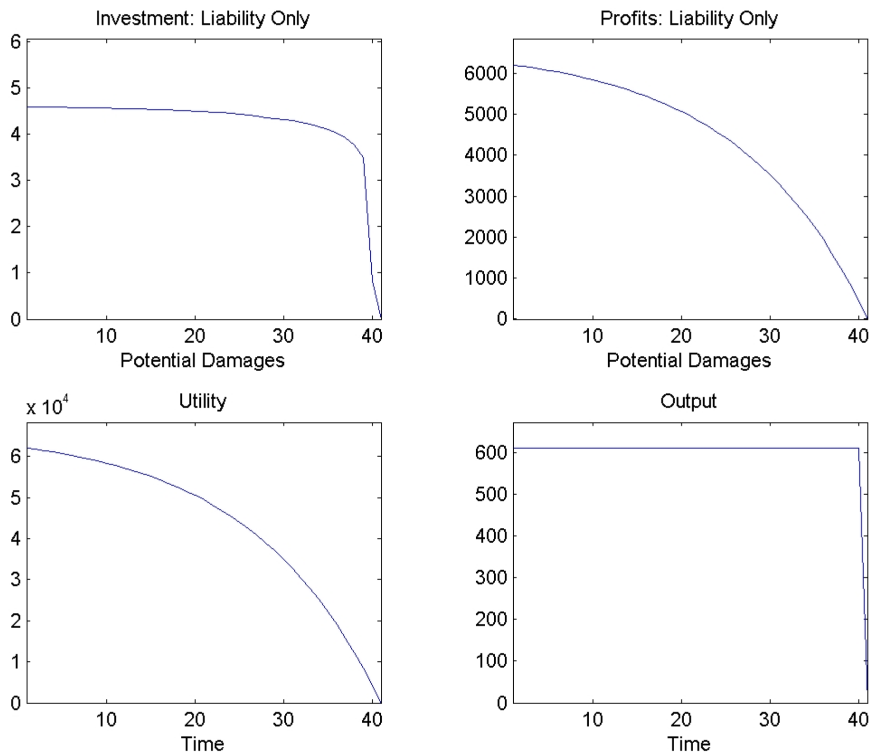


Table 5.1: Correlation Coefficient

	Output	Investment	Prices
Output	1.00	-0.09	0.16
Investment	-0.09	1.00	0.66
Prices	0.16	0.66	1.00

To better understand the properties of the model, and because the data is not trended strongly, we compute the correlation coefficients among output, investment, and prices. These are displayed in Table 5.1. Note that output and investment have a negative correlation, while both output and investment have a positive correlations with prices. We must remember, however, that these statistics are based on a small sample. Simulation of additional data and with alternative parameter specifications could yield significantly different results.

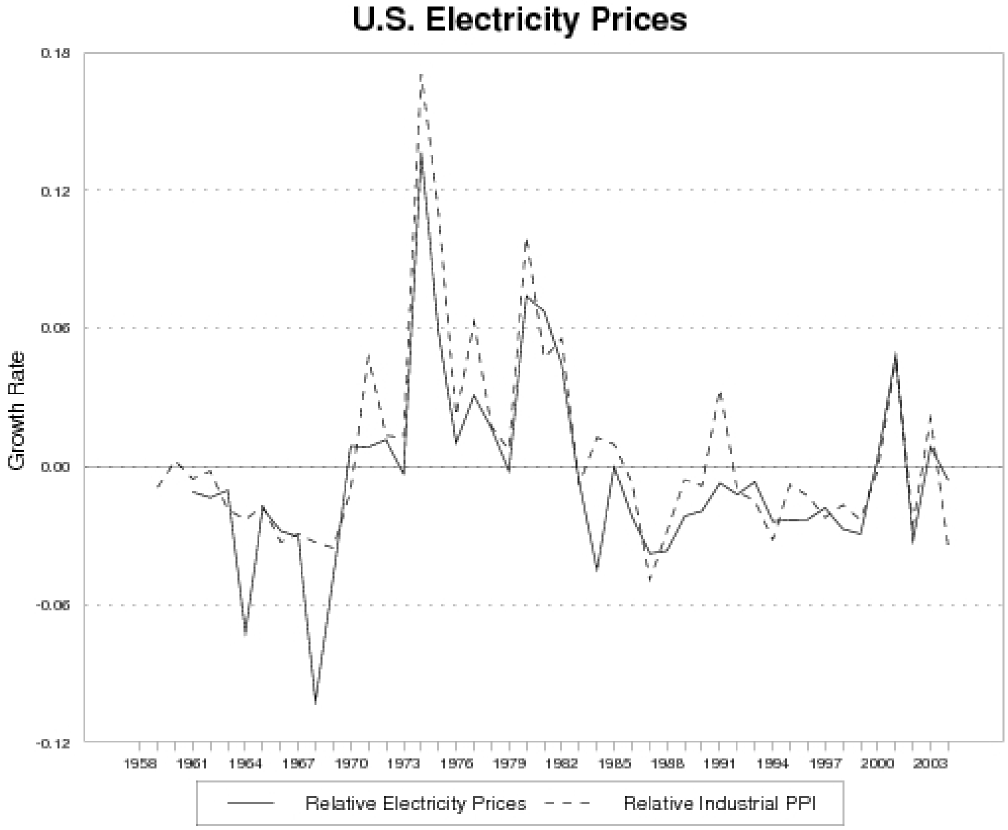
5.4 Applications

We employ the model in two applications. First, we consider the effects of a structural shift in the price parameters. The U.S. electricity sector experienced such a shift in the mid1980s. Second, we consider the effects on plants that are allowed 20-year extensions to their operating licenses. U.S. regulators began offering such extensions in the late 1990s.

5.4.1 Structural Shifts in Prices

Electricity price growth, relative to the GDP price deflator, may be seen in Figure 5.6. Note that price growth consistently was positive in the period from

Figure 5.6: Electricity Prices



about 1973 to 1985. In about 1985, relative price growth became consistently negative. We estimated parameters for the price equation for the two periods; these parameters are listed in the Calibration section above. Various structural stability tests support the graphical evidence for a structural break in the mid1980s. The steady price growth of the 1970s and early 1980s ended, and a long period of gradual decline began.

Rust and Rothwell [55] constructed a detailed model of nuclear power plants. They employed the model in an attempt to detect optimal changes in the operations of power plants due to regulatory reform following the 1979 accident at Three Mile Island. A key simplifying assumption in their model is that electricity prices are constant.

Their model showed that 90% of the present value of operations disappeared in the mid1980s. Much of this was explained by higher operating and maintenance costs, in part due to stricter regulations, increased decommissioning costs, and stricter regulation of prices. Rust and Rothwell also detect an increased likelihood of "prudent" behavior in the era of greater oversight and lower profits. Finally, they observe that plants extended their average times between refueling from 12 to 18 months. Rust and Rothwell conclude that these changes primarily were due to shifts in regulation.

Our model described above is rather abstract, and so despite its calibration using real-world data it is of limited use in performing quantitative analysis. We might hope, however, that the qualitative results seem plausible. We begin by comparing results for 10-year-old plants. This corresponds to a plant that began life in 1975 and was observed in 1985. We use relative price levels of \$0.0498 per KWh, which is close to the 1985 relative electricity price with a 1984 base year.

First, we solve the model using price parameters estimated with 1974-1985 data. We note the solutions at Period 10. We again solve the model, this time using price parameters estimated with 1986-2004 data, and again we observe solutions at Period 10. The differences in plant values roughly correspond to changes a plant might have realized in 1985.

The present value of a 10-year-old plant observing relative prices of \$0.0498 with the high-growth price structure is \$5,766.0 million. The same plant under the low-growth price structure is valued at \$5,710.9 million. The reduction is slight, about 0.96% compared to the 90% result of Rust and Rothwell. On the other hand, the change is in the direction we would expect. Investment declines from \$4.569 million to \$4.564 million. This may be at odds with the increased "prudence" detected by Rust and Rothwell.

We conclude then that some of the changes noted by Rust and Rothwell might be due to demand side shifts and not exclusively to regulatory reforms. Our annual model cannot capture the refueling details that require a high-frequency model like that of Rust and Rothwell. Our model does explain some of the reduction in profits that they discovered. We allowed only demand-side changes, and we did not consider any changes in operating costs, liability levels, or insurance premiums. While in our model the effects of structural shifts are slight, they lead us to suggest that the model of Rust and Rothwell may suffer from their constant-price assumption, and as a result their claimed effects of regulatory reform might be overstated.

5.4.2 Operating License Extensions

Rust and Rothwell [56] build a detailed model of nuclear power plant operations. They apply the model in an investigation of the effects of proposed 20-year extensions to original 40-year operating licenses. They find that the 20-year extensions roughly double the present value of operations.

We replicate the analysis by again modeling a plant that began operations in 1975. This time, we compare the plant values in 1995 under the 40-year licenses with plant values under 60-year licenses. We set the model price to \$0.0358 per KWh, which is close to the actual 1995 relative price. We employ price equation parameters estimated with data from 1986 to 2004.

Under 40-year operating licenses and the noted price, the present value of operations is \$4,858.4 million. Under 60-year licenses, the same plant is worth

$6,111.0 million. While this 25.8% increase is less than the doubling of plant values reported by Rust and Rothwell, the increase also is large and is in the same direction as their findings. Optimal investment increases from $4.49 million to $4.59 million.

We conclude that while the Rust-Rothwell model would improve through relaxation of the constant-price assumption, the change likely would not alter many of their qualitative results.

5.5 Conclusions

We constructed and applied a numerical model of the nuclear power industry. This model provides detail on a number of important features of the American nuclear power industry. Few other works in the literature offer such industry details.

We calculated optimal investment and profits, together with social welfare, for the American markets. We specified details for the insurance market for nuclear liability insurance set up under Price-Anderson policies. Details include specification of insurance premiums, premium refunds, and shared liability. Firms choose investment and capacity utilization levels given current and expected electricity prices, and also they decide when to decommission their plants. They face decommissioning costs, and they face onsite cleanup costs should an accident occur. Output and investment costs are convex.

We find that investment does not vary with the level of damages that firms pose to the public. This is so because of the shared liability specifications of Price-Anderson, and because at least in our model insurance premiums do not vary with potential damages. While our model remains somewhat abstract, and we thus should interpret its results carefully, this suggests that we should consider carefully whether the shared liability clauses yield unintended consequences. On the other hand, it is possible that regulators recognize this problem and tailor their investment requirements accordingly.

We tested our model to determine effects of changes in price structures like those occurring in the 1980s. The model responded predictably, with a fall in firm values corresponding to a reduction in the growth rate of electricity prices. However, the reduction in firm values was very small. This suggests that some, but perhaps very few, of the industry changes noted by Rust and Rothwell may be explained by demand-side changes.

Finally, we tested the response of the model to operating license extensions. The model responded strongly, with a dramatic jump in firm values. This supports the findings of Rust and Rothwell.

This model would benefit from many improvements and extensions. For example, we easily could extend the analysis to consider the effects of capacity uprates; that is, the effects of infrequent discrete increases in potential plant capacities Q. Such changes have become common in the nuclear industry over the past decade. Also, it would be desirable to make electricity prices dependent on output decisions within the nuclear industry. This especially is desirable in the aggregate, since nuclear power presently contributes roughly 20% of U.S. production.

Other possibilities include the allowance of differences across plants for $p(x)$, and to make $f(h)$ a distribution of potential damages for each plant. (See Dubin and Rothwell [17] for a similar specification.) This could improve the plausibility of assumptions regarding private versus public information. Liability limits would affect all plants in all cases. We also might suppose that accident probabilities depend on the utilization rate, so that risk is greater when the plants are run at full capacity.

Rothwell [47] notes the relationship between safety and plant performance. That is, plants with high accident probabilities generally are more troublesome and expensive to operate. Hence, operators have incentives to maintain their plants in order to maximize output and minimize repair costs, even if they face no liability. Dubin and Rothwell [17] find that operators of less-reliable plants moved more quickly to invest in safety equipment. They also report that reliability generally falls with the age of the plant, suggesting that older plants have higher accident probabilities. This correlation between reliability and accident probabilities likely will prove important in any future quantitative analysis and in more detailed theoretical work. Still, we might expect our qualitative results to survive.

5.6 Appendix

5.6.1 Introduction

We have a set of functions of unknown specifications that we have approximated by Chebychev polynomial interpolation. We need to calculate the expected value of these functions given various sets of distribution parameters, assuming that the function argument x is normally distributed. The interpolation is performed over a finite range $[a, b]$, and thus the normal distribution must be truncated at the same end points. The objective is to find an analytical solution for the expected value of $f(x)$ given its Chebychev approximation and the truncated normal distribution such that $x \in [a, b]$.

First, we will set up the problem by defining the probability distribution and the expected value of $f(x)$, and we describe the Chebychev approximation technique. Second, we will show that the expected value of $f(x)$ over [a,b] is a linear combination of the Chebychev coefficients that define the approximation of $f(x)$. The weights in this linear combination in turn are linear combinations of moment integrals of x over domain $[a, b]$, where weights in the latter combination are coefficients of the Chebychev polynomials. Third, we will define an efficient means of computing the moment integrals of $x \sim N(\mu, \sigma^2)$ over interval $[a, b]$ by showing that they are linear combinations of moment integrals for $z \sim N(0, 1)$ when z is integrated over the interval $\left[\frac{a-\mu}{\sigma}, \frac{b-\mu}{\sigma}\right]$. Fourth, we will define a practical algorithm for computing the expected value of $f(x)$ for $x \sim N(\mu, \sigma^2)$. Fifth, we will apply this methodology to the calculation of the expected value function in a dynamic programming problem with one continuous state variable. Finally, we report test results of this method for various functions.

These techniques can be extended to other distributions and interpolation techniques, and they likely can be extended fairly easily to encompass multivariate distributions. The work of describing the error properties for this approximation method, apart from the numerical results reported in the last section, remains to be done.

5.6.2 Definition of the Problem

The Probability Distribution

First, let us specify the distribution. Let $\widetilde{\Phi}(x)$ denote the truncation of the normal cumulative distribution function $\Phi(x)$. Then

$$\widetilde{\Phi}(x) = \frac{\Phi(x) - \Phi(a)}{\Phi(b) - \Phi(a)},$$

for $a \leq x \leq b$, and

$$\widetilde{\phi}(x) \equiv \frac{\partial \widetilde{\Phi}(x)}{\partial x} = \frac{\frac{\partial \Phi(x)}{\partial x}}{\Phi(b) - \Phi(a)} \equiv \frac{\phi(x)}{\Phi(b) - \Phi(a)},$$

where $\widetilde{\phi}$ is the truncated normal PD and ϕ is the normal PDF, and

$$\begin{aligned} \int_a^b \widetilde{\phi}(x)\, \partial x &= \frac{\int_{-\infty}^{\infty} \phi(x)\, \partial x - \int_{-\infty}^{a} \phi(x)\, \partial x - \int_{b}^{\infty} \phi(x)\, \partial x}{\Phi(b) - \Phi(a)} \\ &= \frac{\int_{-\infty}^{b} \phi(x)\, \partial x - \int_{-\infty}^{a} \phi(x)\, \partial x}{\Phi(b) - \Phi(a)} = 1. \end{aligned}$$

The expected value of $f(x)$ over the $[a, b]$ interval given the truncated density function is

$$\int_a^b \widetilde{\phi}(x)\, f(x)\, \partial x = \frac{\int_{-\infty}^{b} \phi(x)\, f(x)\, \partial x - \int_{-\infty}^{a} \phi(x)\, f(x)\, \partial x}{\Phi(b) - \Phi(a)}. \tag{5.3}$$

The Function Approximation

In this appendix, we assume that the function approximation employs Chebychev polynomials, but the techniques developed here can be applied to many sets of polynomials. The Chebychev approximation is made by finding a coefficient vector c that solves the linear system $B \times c = f(x) \Rightarrow c = B^{-1} \times f(x)$, where B is $n \times n$ and c, x, and $f(x)$ are $n \times 1$. x_j is the j^{th} Chebychev interpolation node, where

$$x_j = \cos\left(\frac{\pi\left(j+\frac{1}{2}\right)}{n}\right), j = 0, \ldots, n-1.$$

Chebychev interpolation nodes are specified on the $[-1, 1]$ interval, but any finite domain $[a, b]$ can be mapped into $[-1, 1]$ by $\widetilde{x} = 2\frac{x-a}{b-a} - 1$; hence, we shall ignore this point throughout this paper. B is the basis matrix where elements $B_{i,j}$ is the i^{th} Chebychev polynomial evaluated at the j^{th} Chebychev interpolation node. Chebychev polynomials are specified in trigonometric form as $T_i(x) = \cos(i \times \arccos(x))$ or by the equivalent recursion

$$\begin{aligned} T_0(x) &= 1 \\ T_1(x) &= x \\ &\cdots \\ T_i(x) &= 2xT_{i-1}(x) - T_{i-2}(x). \end{aligned}$$

Define T^C as the lower-triangular matrix of Chebychev polynomial coefficients, in which all elements are zero except

$$
\begin{aligned}
T^C_{0,0} &= 1 \\
T^C_{1,1} &= 1 \\
T^C_{i,j} &= -T^C_{i-2,j}, i > 1, j = 0 \\
T^C_{i,j} &= 2T^C_{i-1,j-1} - T^C_{i-2,j}, i > 1, j > 0
\end{aligned}
$$

for increasing i, j. Then we can write the Chebychev polynomials as $T = T^C \times \overrightarrow{x}$, where the vector $\overrightarrow{x}$ has element $\overrightarrow{x}_i = x^i$ for $i = 0, \ldots, n-1$. Given the coefficient vector c, the approximate value of $f(x)$ for $x \in [a, b]$ may be found by evaluating the first n Chebychev polynomials at x and then evaluating $f(x) \approx c' \times T(x)$ or equivalently by forming $\overrightarrow{x}$ and then evaluating $f(x) \approx c' \times T^C \times \overrightarrow{x}$.

5.6.3 The Expected Value of $f(x)$

Suppose that x is stochastic. For most of this paper, we will assume that x has the truncated normally distribution $N(\mu, \sigma)$ over the domain $[a, b]$, but the contents of this section apply to any distribution for which the first $n-1$ moments exist. Then the expected value of $f(x)$ can be estimated as

$$
\begin{aligned}
\int_a^b \widetilde{\phi}(x) f(x) \partial x &\approx \int_a^b \widetilde{\phi}(x) \left[c' \times T(x)\right] \partial x \qquad (5.4) \\
&= \frac{\int_{-\infty}^{b} \phi(x) \left[c' \times T(x)\right] \partial x - \int_{-\infty}^{a} \phi(x) \left[c' \times T(x)\right] \partial x}{\Phi(b) - \Phi(a)}.
\end{aligned}
$$

Recall that T is a vector of polynomials. Hence, if closed-form solutions exist for the indefinite integrals of moments 0 through $n-1$, then we easily can compute the numerator of Equation 5.4. Closed-form solutions do not exist for the normal distribution. Nevertheless, we will ignore the problem in this section. In the following section, we will describe ways to mitigate the problem.

Let us start with the second integral in the numerator of Equation 5.4; evaluation of the first is done in exactly the same manner. We can write the integral as

$$\int_{-\infty}^{a} \phi(x)\left[c' \times T(x)\right]\partial x = \int_{-\infty}^{a} \phi(x)\left[c'_0 \times T_0(x)\right]\partial x + \int_{-\infty}^{a} \phi(x)\left[c'_1 \times T_1(x)\right]\partial x + \ldots + \int_{-\infty}^{a} \phi(x)\left[c'_{n-1} \times T_{n-1}(x)\right]\partial x$$

for an n^{th}-order Chebychev approximation of $f(x)$. For $n = 5$, the approximate integral is

$$\begin{aligned}\int_{-\infty}^{a} \phi(x)\left[c' \times T(x)\right]\partial x &= c_0 \int_{-\infty}^{a} \phi(x)[1]\partial x + c_1 \int_{-\infty}^{a} \phi(x)[x]\partial x + c_2 \int_{-\infty}^{a} \phi(x)\left[2x^2 - 1\right]\partial x \\ &+ c_3 \int_{-\infty}^{a} \phi(x)\left[4x^3 - 3x\right]\partial x + c_4 \int_{-\infty}^{a} \phi(x)\left[8x^4 - 8x^2 + 1\right]\partial x \\ &= \left[c_0 - c_2 + c_4\right] \int_{-\infty}^{a} \phi(x)\partial x + \left[c_1 - 3c_3\right] \int_{-\infty}^{a} \phi(x)\, x\partial x \\ &+ \left[2c_2 - 8c_4\right] \int_{-\infty}^{a} \phi(x)\, x^2\partial x + 4c_3 \int_{-\infty}^{a} \phi(x)\, x^3\partial x + 8c_4 \int_{-\infty}^{a} \phi(x)\, x^4\partial x\end{aligned}$$

Define $\Delta\Phi$ as the $n \times 1$ vector with elements

$$\Delta\Phi_j = \int_{a}^{b} x^j \phi(x)\partial x, j = 0, \ldots, n-1$$

Again, let T^C be the lower-triangular matrix of Chebychev polynomial coefficients and let vector $\overrightarrow{x}$ have elements $\overrightarrow{x}_i = x^i$. Then

$$\int\limits_{-\infty}^{b} \phi(x)\left[c' \times T^C \times \overrightarrow{x}\right]\partial x - \int\limits_{-\infty}^{a} \phi(x)\left[c' \times T^C \times \overrightarrow{x}\right]\partial x \tag{5.5}$$
$$= c' \times T^C \times \int\limits_{a}^{b} \phi(x)\,\overrightarrow{x}\,\partial x = c' \times T^C \times \Delta\Phi.$$

If we employ this result in the numerator of Equation 5.4, then we see that the expected value of $f(x)$ over $[a, b]$ is a linear combination of the Chebychev coefficients that define the approximation of $f(x)$. The weights in this linear combination in turn are linear combinations of moment integrals of x over domain $[a, b]$, where weights in the latter combination are coefficients of the Chebychev polynomials. We can write the approximate integral as

$$\int\limits_{a}^{b} \widetilde{\phi}(x)\, f(x)\,\partial x \approx c' \times W, \tag{5.6}$$

where vector $W = \frac{T^C \times \Delta\Phi}{\Delta\Phi_0}$.

5.6.4 Efficient Computation of Moment Integrals

If the indefinite integrals exist for the moments of x, then calculation of W in Equation 5.6 is straightforward, and thus estimation of $E[f(x)]$ also is straightforward. We develop here a method for efficiently computing Equation 5.6 for the normal distribution, which has no closed-form indefinite moment integrals. The problem is to find an efficient means of computing $\Delta\Phi = \int_a^b \phi(x)\,\overrightarrow{x}\,\partial x$, where ϕ is the normal density function.

Note that if $x \sim N(\mu, \sigma^2)$, then $z \equiv \frac{x-\mu}{\sigma} \sim N(0, 1)$ has the standard normal distribution. Let ϕ^{STD} denote the standard normal PDF. Let $\Delta\Phi^{STD}$ denote the vector of moments integrals of z, where

$$\Delta\Phi_j^{STD} = \int\limits_{\frac{a-\mu}{\sigma}}^{\frac{b-\mu}{\sigma}} z^j \phi^{STD}(z)\,\partial z, j = 0, \ldots, n-1.$$

Our objective is to find a relationship between $\Delta\Phi^{STD}$ and $\Delta\Phi$. We begin by examining the first several moment integrals of x and z. The CDF of the two are related:

$$\int\limits_{-\infty}^{y} \phi(x)\,\partial x = \int\limits_{-\infty}^{y} \phi^{STD}\left(\frac{x-\mu}{\sigma}\right)\partial x = \int\limits_{-\infty}^{\frac{y-\mu}{\sigma}} \phi^{STD}(z)\,\partial z.$$

According to the Fundamental Theorem of Calculus, the difference of two such equations yields

$$\Delta\Phi_0 = \int\limits_{a}^{b} \phi(x)\,\partial x = \int\limits_{\frac{a-\mu}{\sigma}}^{\frac{b-\mu}{\sigma}} \phi^{STD}(z)\,\partial z = \Delta\Phi_0^{STD}.$$

A similar relationship exists for the first moment integrals:

$$\begin{aligned} \int\limits_{-\infty}^{y} \phi(x)\,x\partial x &= \sigma \int\limits_{-\infty}^{y} \phi^{STD}\left(\frac{x-\mu}{\sigma}\right)\left(\frac{x-\mu}{\sigma}\right)\partial x + \mu \int\limits_{-\infty}^{y} \phi^{STD}\left(\frac{x-\mu}{\sigma}\right)\partial x \\ &= \sigma \int\limits_{-\infty}^{\frac{y-\mu}{\sigma}} \phi^{STD}(z)\,z\partial z + \mu \int\limits_{-\infty}^{\frac{y-\mu}{\sigma}} \phi^{STD}(z)\,\partial z. \end{aligned}$$

Again, the difference of two such equations yields

$$\Delta\Phi_1 = \int\limits_{a}^{b} \phi(x)\,x\partial x = \sigma \int\limits_{\frac{a-\mu}{\sigma}}^{\frac{b-\mu}{\sigma}} \phi^{STD}(z)\,z\partial z + \mu \int\limits_{\frac{a-\mu}{\sigma}}^{\frac{b-\mu}{\sigma}} \phi^{STD}(z)\,\partial z = \sigma\Delta\Phi_1^{STD} + \mu\Delta\Phi_0^{STD}.$$

In similar fashion,the relationship for the second moment integrals can be found:

$$\begin{aligned}
\Delta\Phi_2 &= \int_a^b \phi\left(x\right) x^2 \partial x = \sigma^2 \int_a^b \phi^{STD}\left(\frac{x-\mu}{\sigma}\right)\left(\frac{x-\mu}{\sigma}\right)^2 \partial x \\
&+ 2\mu \int_a^b \phi^{STD}\left(\frac{x-\mu}{\sigma}\right) x\partial x - \mu^2 \int_a^b \phi^{STD}\left(\frac{x-\mu}{\sigma}\right)\partial x \\
&= \sigma^2 \int_{\frac{a-\mu}{\sigma}}^{\frac{b-\mu}{\sigma}} \phi^{STD}\left(z\right) z^2 \partial z + 2\mu \int_a^b \phi^{STD}\left(\frac{x-\mu}{\sigma}\right) x\partial x - \mu^2 \int_{\frac{a-\mu}{\sigma}}^{\frac{b-\mu}{\sigma}} \phi^{STD}\left(z\right)\partial z \\
&= \sigma^2 \Delta\Phi_2^{STD} + 2\mu\Delta\Phi_1 - \mu^2\Delta\Phi_0^{STD} \\
&= \sigma^2 \Delta\Phi_2^{STD} + 2\mu\left[\sigma\Delta\Phi_1^{STD} + \mu\Delta\Phi_0^{STD}\right] - \mu^2\Delta\Phi_0^{STD} \\
&= \sigma^2 \Delta\Phi_2^{STD} + 2\sigma\mu\Delta\Phi_1^{STD} + \mu^2\Delta\Phi_0^{STD}.
\end{aligned}$$

A pattern already has become evident that will allow us easily to relate $\Delta\Phi$ to $\Delta\Phi^{STD}$. The relationship can be written as

$$\Delta\Phi_j = \sum_{k=0}^{j} \frac{j!}{(j-k)!k!}\sigma^{j-k}\mu^k\Delta\Phi_{j-k}^{STD}.$$

Define matrix L as the lower triangular matrix with rows identical to the rows of Pascal's triangle. Define the lower triangular matrices Σ and M as

$$\Sigma = \begin{bmatrix} \sigma^0 & 0 & 0 & \dots \\ \sigma^0 & \sigma^1 & 0 & \\ \sigma^0 & \sigma^1 & \sigma^2 & \\ \dots & & & \dots \end{bmatrix}, \; M = \begin{bmatrix} \mu^0 & 0 & 0 & \dots \\ \mu^1 & \mu^0 & 0 & \\ \mu^2 & \mu^1 & \mu^0 & \\ \dots & & & \dots \end{bmatrix},$$

and define $\circledast$ as the operator that multiplies two $r \times s$ matrices such that $A_{i,j} = B_{i,j} \times C_{i,j}$. Then

$$\Delta\Phi = \left[L \circledast \Sigma \circledast M\right] \times \Delta\Phi^{STD}.$$

Again, closed-form solutions do not exist for $\Delta\Phi^{STD}$. Suppose we formed a Chebychev approximation

$$\int \phi(z)\, z^i \partial z \approx \left[C_i^{STD}\right]' \times T^C \times \overrightarrow{z}, i = 0, \ldots, n-1$$

where T^C again is the lower triangular matrix of Chebychev polynomial coefficients, where C_i^{STD} are the approximation coefficients for the i^{th} moment integral of z, and where element j of vector $\overrightarrow{z}$ is z^j for $j = 0, \ldots, n-1$. If the column i of matrix C^{STD} is C_i^{STD}, then

$$\int \phi(z) \overrightarrow{z} \partial z \approx \left[C^{STD}\right]' \times T^C \times \overrightarrow{z}.$$

Recall that $\Delta\Phi^{STD}$ is the difference of two integrals that differ only in their upper limit of integration. Then for vector $\Delta\overrightarrow{z}$ with elements $\Delta\overrightarrow{z}_i = \left(\frac{b-\mu}{\sigma}\right)^i - \left(\frac{a-\mu}{\sigma}\right)^i, i = 0, \ldots, N-1$,

$$\Delta\Phi^{STD} \approx \left[C^{STD}\right]' \times T^C \times \Delta\overrightarrow{z}.$$

The order of approximation N for $\Delta\Phi^{STD}$ need not be the same as n, the order of approximation for $f(x)$. In the equation above, $\Delta\Phi^{STD}$ is $n \times 1$, T^C is $N \times N$, C^{STD} is $N \times n$, and $\overrightarrow{z}$ is $N \times 1$.

Finally, we have the approximation of $\Delta\Phi$

$$\Delta\Phi \approx [L \circledast \Sigma \circledast M] \times \left[C^{STD}\right]' \times T^C \times \Delta\overrightarrow{z}.$$

Given an approximation domain $[a, b]$ that coincides with the limits of integration for $E[f(x)]$, and given the orders of interpolation n for $f(x)$ and N for the moment integrals of the standard normal variable z, then we have a simple approximation for $\Delta\Phi$ in which only elements Σ, M, and $\Delta\overrightarrow{z}$ may vary. In fact, Σ changes only if σ changes, M changes only with changes in μ, and $\Delta\overrightarrow{z}$

changes with both σ and μ. If we define matrix $Z = \left[C^{STD}\right]' \times T^C$, then the above equation can be written simply as

$$\Delta\Phi \approx [L \circledast \Sigma \circledast M] \times Z \times \Delta\overrightarrow{z}. \tag{5.7}$$

5.6.5 Estimation of $E[f(x)]$ for $x \sim N(\mu, \sigma)$

We finally have the tools required to efficiently estimate $E[f(x)]$ for $x \sim N(\mu, \sigma^2)$. Combine Equations 5.4, 5.5 and 5.7 as follows:

$$\int_a^b \widetilde{\phi}(x) f(x) \partial x \approx \frac{c' \times T^C \times [L \circledast \Sigma \circledast M] \times Z \times \Delta\overrightarrow{z}}{\Phi(b) - \Phi(a)}.$$

Recall that $\Phi(x) = \Phi^{STD}\left(\frac{x-\mu}{\sigma}\right)$. Note that the denominator is $\Phi(b) - \Phi(a) = \Phi^{STD}\left(\frac{b-\mu}{\sigma}\right) - \Phi^{STD}\left(\frac{a-\mu}{\sigma}\right) = \Delta\Phi_0^{STD} \approx \left[C_0^{STD}\right]' \times T^C \times \Delta\overrightarrow{z}$. If $Z_{0,\bullet}$ denotes the first row of Z, then we have finally

$$\int_a^b \widetilde{\phi}(x) f(x) \partial x \approx c' \times \frac{T^C \times [L \circledast \Sigma \circledast M] \times Z \times \Delta\overrightarrow{z}}{Z_{0,\bullet} \times \Delta\overrightarrow{z}}. \tag{5.8}$$

Let vector W represent the fraction in Equation 5.8. Note that for a given domain $[a, b]$, given orders of interpolation n and N, and given distribution parameters μ and σ, W is specified completely, so that it does not depend at all on $f(x)$. Given W, then, calculation of $E[f(x)]$ requires only the inner product of Chebychev approximation coefficients c and W. If function approximations for $f(x)$ and $g(x)$ differ only in their coefficient vectors, then W is identical for both. Given W, evaluation of the expectations requires simply the computation of two inner products. For finite sets of values $\{\mu\}$ and $\{\sigma\}$, we can compute a corresponding finite set of vectors $\{W\}$. Given $\{W\}$, expectations of the set of function $\{f\}$ can be calculated easily given that $E[x] \in \{\mu\}$ and $\sqrt[+]{Var(x)} \in \{\sigma\}$, where the domain of f is $[a, b]$ for all $f \in \{f\}$.

5.6.6 A Dynamic Programming Application

Suppose that we are simulating the operation of a firm using dynamic programming techniques. Each period, the operator of the firm sees the state of his firm and then optimally chooses an action a from the set of possible actions A. We believe that a will be chosen to maximize the expected present discounted value of the firm. Besides the action a, suppose the only relevant condition influencing the value of the firm is the product price; we denote the logarithm of the price as p. Suppose that p is independent of the firm's operations, and that the dynamics of p are summarized adequately as

$$p_{t+1} = \beta p_t + \sigma \varepsilon_{t+1},$$

where $\varepsilon \sim N(0,1)$. If $a(p) \in A$ are the optimally chosen actions, then the value of the firm is defined as

$$V(p_t) = \pi_t(a(p_t)) + \frac{1}{1+r} EV_{t+1}(p_{t+1}), \tag{5.9}$$

where r is the interest rate and π represents profits in the current period given a_t.

Suppose a closed-form representation of V does not exist. Then we might find an approximation $V_t(p) \approx c_t' \times T^C \times \overrightarrow{p}$, where $\overrightarrow{p}_i = p^i$ for all $p \in [a,b]$. The difficulty in evaluation of Equation 5.9 is the computation of EV. Fortunately, we can use the methodology developed above to assist us. We will proceed by relating each part of EV to corresponding parts of earlier equations.

First, we assume that the relevant domain of prices is $\left[e^a, e^b\right]$. We choose orders of approximation n for our function approximation and N for approximation of the standard normal moment integrals.

Second, let p_t be a finite set of points spanning the interval $[a, b]$. The normal vector p_{t+1} has elements corresponding to variable x in preceding sections. For given autoregression parameters β and σ, p_{t+1} has mean βp_t and variance $\sigma^2 \times i_n$, where i_n is an $n \times 1$ vector of ones. From these sets of distribution parameters, a set of vectors $\{W\}$ can be constructed according to Equation 5.8.

Third, we begin to solve the model by recursively evaluating Equation 5.9. For final period τ, $EV_{\tau+1} = 0$. Hence, $V_\tau = \pi_\tau$. Given π_τ, for which a is chosen optimally, we can find approximation coefficients c_τ such that $V_\tau(p_j) = \pi_\tau(a(p_j)) \approx c'_\tau \times T^C \times \overrightarrow{p_j}$, where $[\overrightarrow{p_j}]_i = (p_j)^i$ and where p_j is the j^{th} element of p_τ. Next, we proceed to period $\tau - 1$. This time, EV is not zero, assuming π_τ is not zero. EV_τ is defined as

$$\int_a^b \widetilde{\phi}(p_\tau|p_{\tau-1}) V(p_\tau) \partial p = \int_a^b \frac{\phi^{STD}\left(\frac{p_\tau - \beta p_{\tau-1}}{\sigma}\right)}{\Phi^{STD}\left(\frac{b-\beta p_{\tau-1}}{\sigma}\right) - \Phi^{STD}\left(\frac{a-\beta p_{\tau-1}}{\sigma}\right)} V(p_\tau) \partial p.$$

If we replace the function V with its approximations, then we have

$$\int_a^b \widetilde{\phi}(p_\tau|p_{\tau-1,i}) V(p_\tau) \partial p \approx c'_\tau \times T^C \times \int_a^b \frac{\phi^{STD}\left(\frac{p_\tau - \beta p_{\tau-1}}{\sigma}\right) \times \overrightarrow{p_i}}{\Phi^{STD}\left(\frac{b-\beta p_{\tau-1}}{\sigma}\right) - \Phi^{STD}\left(\frac{a-\beta p_{\tau-1}}{\sigma}\right)} \partial p, i = 1, \ldots, n.$$

This equation has the same form as Equation 5.4. Given calculation of $\{W\}$ in the second step, we can calculate this integral for element i of vector EV_τ as $c'_\tau \times W^{\{i\}}$.

5.6.7 Evaluation

This section summarizes tests of the methodology using known functions. Approximations of known functions are made. The integrals of these function approximations, weighted by the truncated normal density function, are computed according to the methodology developed above. The integrals are computed using Simpson's method, which performs function interpolation of the probability-weighted function using quadratic splines.[11] Calculations are performed repeatedly with constant variances but allowing the mean to vary. The integrals computed with the new method are compared to estimates computed with Simpson's method.

The order of approximation for the moments of the normal distribution is 50, and we form an approximation of the normal distribution over seven standard deviations. The order of approximation for the function $f(x)$ is 10. The domain for the function, which corresponds to the non-zero interval for the truncated normal distribution, is $[0, 100]$. We calculate the integrals repeatedly while allowing the mean of the normal distribution to vary across the same interval. The standard deviation is 10. The number of quadrature points for Simpson's method is 500,001.

The approximate integrals are displayed below, along with the relative errors. Note that the errors are relative to the results using Simpson's method, which itself contains approximation errors. The function employed in Figure 5.7 is $f(x) = x$, and the function employed in Figure 5.8 is $f(x) = x^2$.

Note that these polynomial functions can be approximated very well using Chebychev techniques. Chebychev approximation is less precise for functions such as $f(x) = \sqrt{x}$. Hence, integration of the weighted approximation of $f(x)$ also is less precise. Figure 5.9 displays results.

It likely is possible to alter the spacing of the interpolation nodes to improve

[11] Simpson's method was chosen for ease of implementation. Other methods may be substituted without much difficulty, and they may provide a better baseline for comparison.

Figure 5.7: Expected Values of a Linear Function

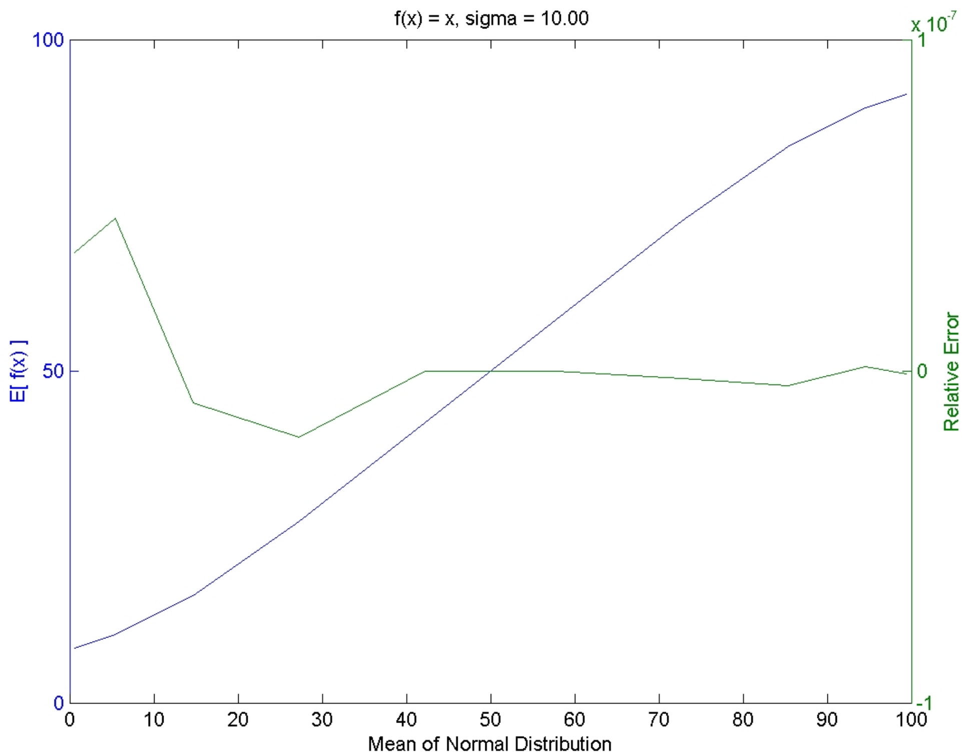


Figure 5.8: Expected Values of a Quadratic Function

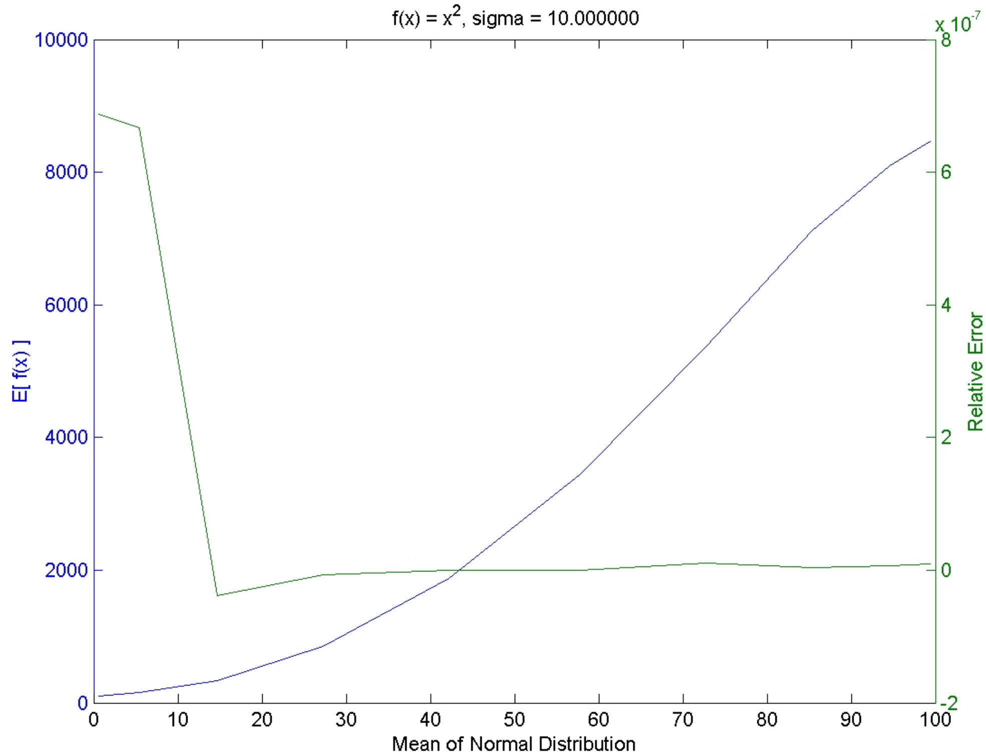
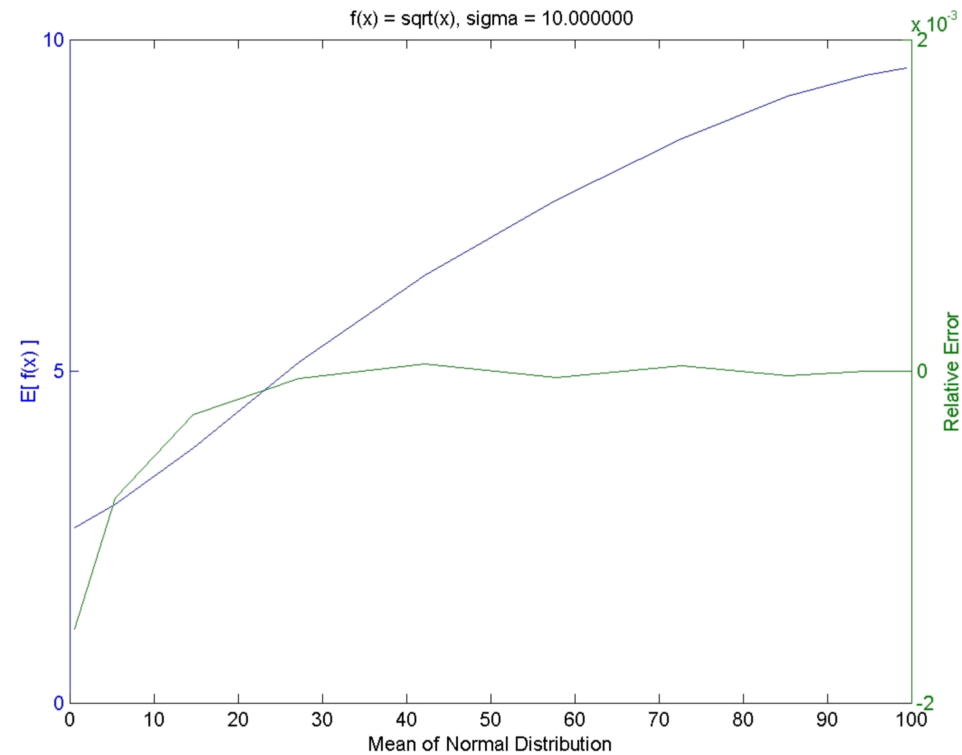


Figure 5.9: Expected Values of a Square Root Function



the fit of the function approximations. Typically, performance of interpolation techniques improves by increasing the density of nodes in areas where the function exhibits greatest curvature. In the case of the square root function, approximation error likely would decrease by putting relatively more nodes near zero, and relatively less in the upper end of the domain.

A number of generalizations of these method are possible. They include adoption of distributions other than the normal distribution, and approximation methods other than Chebychev. Especially useful would be to extend the technique to multiple dimensions.

Chapter 6

Conclusion for Part 1

At the beginning of this section, we posed several questions. Should operators of nuclear power plants continue to run their plants given the current economic circumstances and regulatory policies? Should regulators adopt a conciliatory stance to feed the economic desires of producers and consumers, or should they enforce hard-line standards to lessen the risks of nuclear accidents? What are the effects of liability limits on the decisions of plant operators, and what is the economic benefit to plant owners?

The preceding four chapters shed some light on these questions, and they provide a framework in which to analyze other questions related to liability limits and nuclear power. Our models in Chapter 2 illustrated basic economic principles that suggest plant operators will have greater incentive to produce when demand and prices are high, and when regulatory costs are low. We didn't fully answer the question regarding whether plants should be allowed to operate. We did, however, demonstrate the tradeoffs between economic well-being and safety, where increasing wealth and consumption requires acceptance of risk. We saw that liability limits indeed affect the profitability of power plant operations, by making them more inclined to produce and less inclined to invest, and thus liability limits affect the optimal decisions of plant operators. The effects on decisions aren't necessarily bad from the perspective of consumers who place high value on consumption relative to expected losses from an accident. Such consumers would prefer limited liability, if it is required to maintain profitability for firms, in order to obtain consumption goods. We saw that in some cases, it may be optimal to increase profits by imposing liability limits, but to force firms to spend the funds on safety enhancements. We extended the concept of what constitutes implicit subsidies and we derived theoretical support for their definition, but we showed that existing perceptions of implicit subsidies may exaggerate their true levels.

In Chapter 3, we reviewed the attempts of others to define and measure implicit subsidies. We reveal and correct several errors in published calculations. We further show that the class of models currently employed are inconsistent with the stated facts. In particular, existing models imply that insurers believe that claims will be filed frequently. According to the stated facts, claims should be filed only after serious accidents. In the following exercise, we take the facts seriously and offer several alternative models that eliminate this troubling implication. The results suggest that implicit subsidies may be far lower than reported. On the other hand, we show evidence that the stated facts might be misleading, and we provide data that should be incorporated to extend our understanding of Price-Anderson and its effects of the industry.

In Chapter 4, we extend the static model of Chapter 2 to a multiperiod framework. We found some reason to fear that too little incentive is given to firms posing the greatest threat to invest in safety measures. This problem comes through the liability sharing clause of the Price-Anderson Act. On the other hand, regulators already may have addressed the problem by adopting policies and instruments capable of forcing those firms to invest more. Also, our distribution of potential harm is rather artificial, and all plants pose risk of great harm to the public, and so perhaps regulators simply impose strong safety standards for all plants. We again apply our model in the study of implicit subsidies. The dynamic framework allows us to calculate the expected present value of current and future subsidies, taking into account the endogenous investment problem and its effect on risk. This effort is unique, and should guide future efforts to quantify the value of liability limits to the industry.

In Chapter 5, we extend the dynamic model developed in Chapter 4 by adding a number of industry details. In particular, we add many details to describe nuclear power plant operations, and we define the insurance industry and other means of dealing with liability established under Price-Anderson. We calibrate and employ the model to simulate the effects on the industry of two historical events. First, we simulate the sharp drop in electricity prices that was observed in 1985. Second, we simulate the extensions of 40-year operating licenses to 60 years that became available in the late 1990s. The model produces satisfactory qualitative results. In the first case, results suggest that existing firm models should be extended to incorporate electricity price growth. The second case provides qualitative and quantitative support for earlier findings that license extensions add greatly to the value of firms. Finally, we develop a means to speed computation in numerical dynamic programming models. The method was employed in our work to speed calculations and to simplify code.

We have presented a picture of the nuclear power industry and its regulation.

Our analysis remains rather abstract, so that in many cases the details correspond only vaguely to the actual economic agents and the environment in which they operate. In the next section we will present a closer look at the real world by constructing and reviewing industry data. We then will provide a detailed look at a key agent of our earlier models, the nuclear power plant operator.

Part II

U.S. Nuclear Power Plant Operators

Chapter 7

Introduction to Part II

How has the nuclear industry fared in the past 15 years? Have the factors that contributed to the struggles of the 1970s and 1980s been mitigated? Have nuclear power plant operators learned from earlier experiences?

In the first section, we looked at the overall nuclear power industry and sought greater understanding of it by building a series of increasingly detailed models of its primary features. In this section, we take a look at the history of the industry by reviewing first data on the aggregate and regional electricity markets and then cost and operating data for individual sites and plants. We then turn from simple observation of the markets and operator behavior to a model of operators in an attempt to explain their behavior and to decipher the nature of their decisionmaking.

In Chapter 8, we review aggregate and regional electricity prices. We see that relative prices climbed rapidly from about 1973 to the mid1980s. At that point, relative prices began a slow decline, marked by dramatically increased seasonal volatility. Structural stability tests confirm graphical evidence of significant changes in the price structure. Surely these changes affect significantly the profitability of power plants and have corresponding effects on decisions of operators. We attempt to confirm these effects in our model of power plant operators. Among various effects of these price changes that we might expect to see reflected in operator behavior, we list two. First, the increase in seasonal volatility should increase the incentive to refuel, repair, and inspect plants when demand is lowest. Thus, we expect operators to exhibit an increased tendency to refuel in the spring and fall, and to limit down time so that they are back in service when high price levels resume. Second, we expect the reduction in price growth to force stricter adherence to optimal policies and cost minimization. Other authors observed this increase in operator discipline and explained it as a reaction to heightened regulatory standards and enforcement. Our arguments do not negate their claims but simply offer alternative explanations to present a fuller picture of the industry.

In Chapter 9, we turn attention first to operating data. These data describe conditions and events at individual nuclear power plants. We have a large data set, covering nearly every commercial American plant over the past 30 years. The story told by these data is dramatic. We see that the industry that struggled terribly two decades ago improved greatly. Apparently, optimal methods were learned and now are applied rigorously, aided by regulatory reforms. Average operating spells are longer, refueling spells are shorter, and temporary shutdowns appear less frequently. Great improvements in efficiency and output would seem to indicate that profitability should have improved.

We next turn to financial data in an attempt to verify these impressions. Writers a decade ago reported what they believed to be the beginning of new trends. Runaway cost growth in the 1980s seemed to be slowing. We extend the data by seven years, and it confirms their suspicions. Operating and maintenance, fuel, and capital additions costs have ceased their upward climb in real terms, and in fact unit costs seem to be falling.

Improvements on the cost side matter little if revenues weakened still more. We find evidence that real electricity prices have been falling. Have improvements in productivity been sufficient to keep income at healthy levels? Unfortunately, we lack revenue data, for while operators are required to report costs, revenue information remains proprietary. Our attempts to construct revenue data are crude, yet they tell a plausible tale. It seems that revenues have climbed steadily, even as costs have fallen. Corresponding attempts to construct profit information indicate that following ten years of losses in the 1980s and early 1990s profits are positive and rising.

Finally, in Chapter 10 we construct a model of power plant operators. The model employs our set of monthly plant-level operating data and our monthly price data. We attempt to capture basic properties of the fuel cycle and similar information that determine the evolution and conditions of the plant. Given this set of information, operators choose actions to maximize the present value of profits. While our model is similar to earlier efforts, we offer several important extensions. First, we include price data to capture the effects on operator behavior of price growth. Second, we incorporate the possibility of severe accidents and the liability faced by operators. In addition, our extended data set allows us to understand better the nature of power plant operations in the post Three Mile Island industry. We apply the model primarily in two ways. First, we test the model for structural stability, given the structural shift in electricity prices. Other authors found similar models unstable, but they assumed no electricity price growth. Our model suggests that the changes in behavior observed by others resulted significantly from weakening demand and other changes in electricity prices. Our second application measures the benefit to firms of possible license extensions from 40 to 60 years. The U.S. Nuclear Regulatory Agency began accepting applications for these extensions in the late 1990s, and a number of plants so far have received them. We find that plants should be willing to invest significantly in upgrades in order to obtain extensions, for the extensions improve significantly the value of the firms. We also offer historical simulations and forecasts under various assumptions for a plant of particular interest, the Three Mile Island nuclear power plant.

Chapter 11 concludes the dissertation.

Chapter 8

Price and Demand Data

In the following work, we analyze the U.S. electricity markets over the past 45 years. We begin by examining aggregate electricity prices, both at monthly and annual frequencies. We build univariate models of electricity prices and test them for stability. We then review and model monthly regional electricity price levels. Finally, we examine trends in annual aggregate electricity demand. In both the price and demand data, we find evidence of significant market instability in the 1970s and 1980s.

The analysis is intended to support structural economic modeling applications that employ the data reviewed here. We thus are interested in whether the structural models of prices are adequate and sufficiently flexible to represent the data. In general, we find that apart from occasional structural shifts, simple models are sufficient to provide reasonable first-order representations of the data.

8.1 Price Data

8.1.1 U.S. Electricity Prices

This section analyzes the properties of aggregate U.S. producer prices for electricity. We develop simple models and test for structural stability of electricity prices. The employed aggregate data is the Producer Price Index for industrial electricity rates. It is monthly from January, 1958 to June, 2004; is not seasonally adjusted; and was obtained from the Bureau of Labor Statistics [59]. First, unit root tests are performed to determine necessary transformations. Second, a simple ARMAX model is estimated and tested for structural stability. We then examine regional industrial electricity prices and test the adequacy of a very simple model that will be suitable for use in a dynamic programming model.

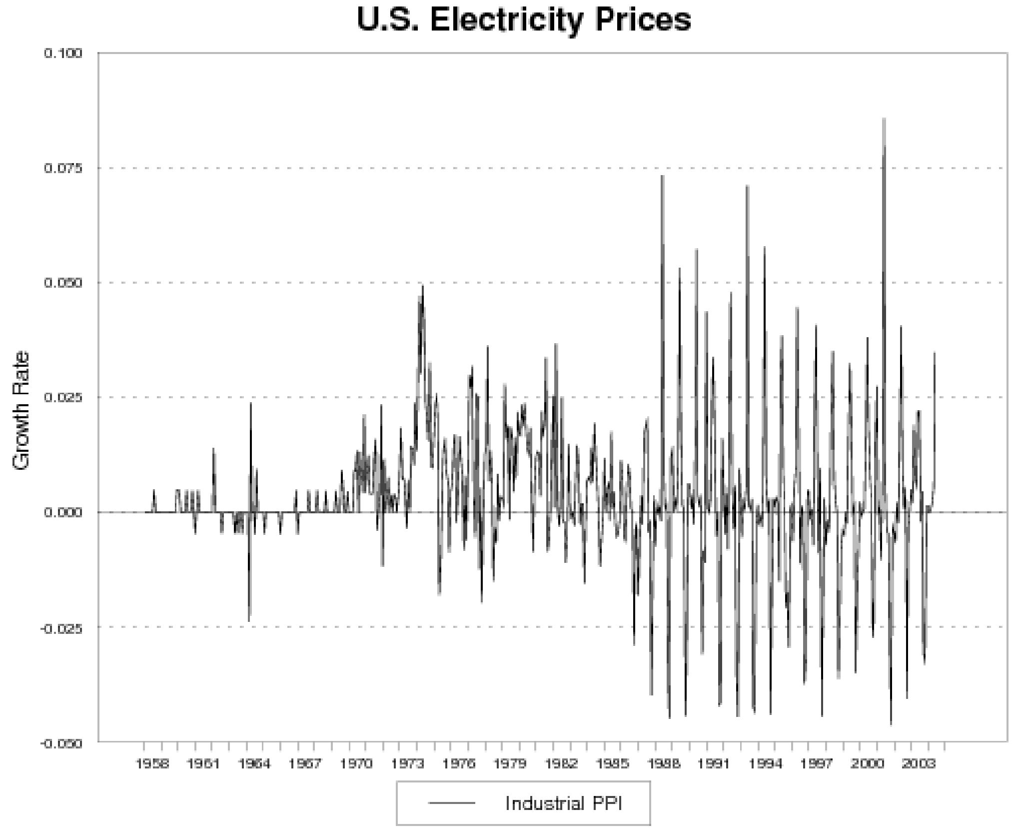
Analysis

Industrial electricity prices were very stable throughout the late 1950s and the 1960s. This may be seen in the monthly growth rates displayed in Figure 8.1.[1] They became more volatile and grew fairly rapidly through the 1970s. Growth especially was high in 1974 and 1979–80.[2] Nominal prices generally continued to climb since then, but the trend slowed abruptly in the mid1980s. As the trend shifted, prices developed a pronounced seasonal pattern. Davis, et al point out that the falling relative prices were not a new trend but the resumption of the

[1]See Davis, et al [14], Section 2, for additional details and references on the history of electricity prices.

[2]Davis, et al [14] list several reasons for the rapid price increases. They include technological problems, economic instability that made planning difficult, high fossil fuel costs, and heightened environmental and safety regulations.

Figure 8.1: Producer Price Index



historical norm. They list a series of regulatory reforms passed in the late 1970s that took effect over the following years as part of the reason for such changes.

Descriptive statistics for nominal industrial electricity prices are presented in Table 8.1. Note that the statistics are for monthly growth rates; the rates have not been annualized. We see that prices grew slowly in the late 1950s through early 1970s, at about 0.1% per month, and that volatility was quite low. Between 1973 and 1985, the average growth rate increased by a factor of 9, and volatility also increased substantially. Between 1986 and 2004, growth rates fell to slightly below the average rate in the 1960s. However, volatility increased well beyond that seen in the 1970s. This time the nature of the volatility was quite different. As may be seen in Figure 8.1 and as we will see later in regression estimates, recent volatility primarily is in the form of seasonal cycles. This stands in contrast to earlier periods in which seasonal fluctuations were dominated by persistent changes. Table 8.1 also displays statistics for the entire sample period and for the period following the energy crisis of 1973. The wide swings in average growth rates seems to suggest that there may have been a structural shift in the mid1980s, and perhaps another in 1973. This possibility will be tested in the following sections.

Table 8.1: Descriptive Statistics for Aggregate Electricity Prices

PPI Growth Rates	Mean	Standard Error	Observations
1959:1–1972:12	0.146%	0.0051	168
1973:1–1985:12	0.927%	0.0127	156
1986:1–2004:6	0.126%	0.0210	222
1959:1–2004:6	0.361%	0.0157	546
1973:1–2004:6	0.457%	0.0185	378

Unit Root Testing

Augmented Dickey-Fuller unit root tests, with lag lengths selected by BIC, were used to test whether the data, in growth rates, were suitable for use in estimating an ARIMA model. Results may be seen in Table 8.2, where (**) indicates rejection of the unit root null hypothesis at the 1% significance level for all sample periods. These results should be viewed with scepticism given the apparently contradictory graphical evidence noted above. Note that the BIC statistic, which is known to be overly parsimonious in small samples, indicates inclusion of only

Table 8.2: Unit Root Tests: Industrial Electricity Prices

	1959:1–1985:12	1986:1–2004:6	1959:1–2004:6
Lag Length	1	15	15
t-Test	-7.6078 **	-3.5423**	-3.6351**
z-Test	-117.1824**	-188.1705**	-42.8321**

one lag is optimal in the first sample; the AIC statistic indicates that 14 lags should be employed, which perhaps is more reasonable. Because rigorous analysis of the price series is not necessary for the present work, we will accept the results and proceed with estimation of an ARMAX model.

ARMAX Models

Graphical analysis of autocorrelations and partial autocorrelations support the impressions given by the unit root tests, namely that we must proceed cautiously with the assumption that the growth rates of prices are stationary. Other tests that are not reported here suggest that seasonal differencing may be appropriate. To maintain the simplest possible models, we avoid seasonal differencing and instead employ seasonal dummy variables. The following model,[3] with one AR and one moving average term in addition to seasonal dummy variables, seems to fit the data fairly well, although certain qualifications are necessary:

$$(1-L)^D y_t = \alpha + \frac{(\omega_0 + \omega_1 L + \cdots + \omega_n L^n)}{(1 - \delta_1 L - \cdots s - \delta_m L^m)} X_t + \frac{(1 + \theta_1 L + \cdots + \theta_q L^q)}{(1 - \phi_1 L - \cdots - \phi_p L^p)} u_t \quad (8.1)$$

[3]The following equation and table summarize similar text found in the RATS Reference Manual [20].

where:

y_t	is the dependent variable
u_t	is the series of residuals
q	is the number of MA coefficients
θ_q	is the MA coefficient at lag q
p	is the number of AR coefficients
ϕ_p	is the AR coefficient at lag p
α	is a constant
D	is the number of differences
X_t	are exogenous variables
n	is the number of lags for X
ω_n	is the coefficient on X at lag n
m	is the number of denominator lags for X
δ_m	is the denominator coefficient at lag m.

In this analysis, y_t is the logarithm of the electricity producer price index, the number of differences D is one, and the number of moving average terms (q) and autoregressive terms (p) both are one. The exogenous variable vector X is composed of monthly dummy variables; the number of lags (n) and denominator lags (m) both are zero. Results for the model are presented in Table 8.3 for two sub-periods and the entire data range. An ARIMA (1,1,1) with monthly dummy variables was selected as a compromise between the three sample periods. The model seems to fit the data fairly well in the sample period from January, 1986 to June, 2004. The R^2 value is high and the Ljung-Box statistic indicates that the residuals are white noise.[4] The model fits the data considerably less

[4]Greene [21] notes that some econometricians claim that the Ljung-Box statistic is not appropriate for models with lagged dependent variables. Nevertheless, it supports the results

well for the first sample period and for the entire sample. The apparent serial correlation remaining in the residuals is disturbing. Other aspects of the results, however, are plausible. Note, in particular, that the dummy variable parameters are large and significant in the later sample period; this is expected given the obvious qualities of the data evident in the graphs. The dummy variables seem to contribute little in the early sample period, in which little seasonal variation is evident.

Because this is not a formal analysis of electricity prices, we will proceed with the present model despite concerns about its adequacy. A standard Chow test for structural stability yields the value $F(3{,}518) = 167.05$, which is significant at the 1% level. Though our conclusions must be qualified, these results support the strong graphical evidence that a structural shift occurred in electricity prices sometime in the mid1980s. At this point, we will forgo attempts to pin down a precise date for the shift.

This result will be employed in the review of previous models of electricity markets and in the design of new models. Clearly, any such model needs to account for market instability. Dynamic programming models suffer the curse of dimensionality, such that the addition of variables adds greatly to the computational burden. Incorporation of price variables into a dynamic programming model thus requires a very simple forecasting equation with few stochastic terms on the right-hand side. Simplicity is sufficiently critical that we must accept certain short-comings that ordinarily would be troubling. We thus develop an AR1 model of the logarithm of electricity prices with monthly dummies. The single stochastic explanatory term satisfies our demand for simplicity. The work

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of graphical analysis of the residuals using correlograms.

presented here simply suggests the adequacy of such a model. The results are displayed in Table 8.4. The data and predicted values are plotted in Figure 8.2. The models appear, at first glance, to fit the data quite well. Closer examination reveals persistence in the error terms. Still, given the limitations of estimating dynamic programming models, it appears worthwhile to pursue an AR1 model in log-levels. We will explore the matter further with panel data in the following section.

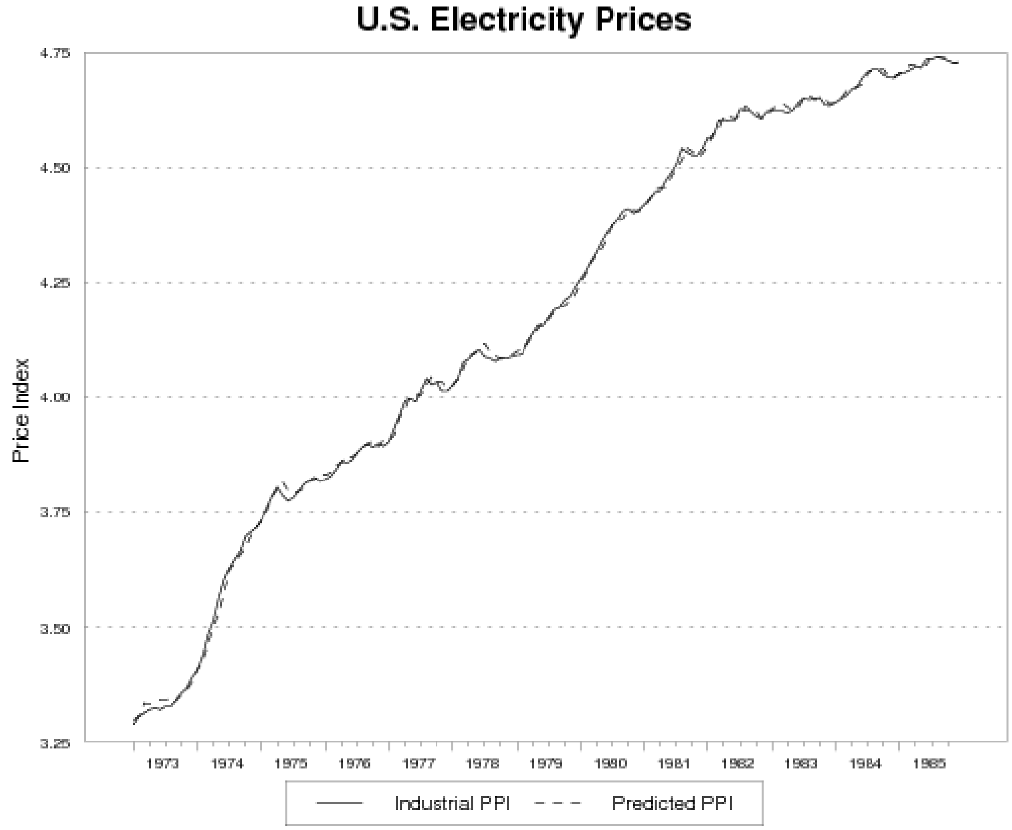
8.1.2 Regional Electricity Prices

Regional industrial electricity price indexes are displayed in Figures 8.3 through 8.5, together with the aggregate U.S. electricity PPI. The data were obtained from the BLS [59] and are shown in growth rates. While certainly there are regional differences, a few basic features are evident across regions and in the aggregate data. First, the fairly steep upward trend that persisted throughout the 1970s and early 1980s slowed abruptly. Nominal prices have grown slowly since then. Second, at about the same time that the structural shift occurred, prices gained a prominent seasonal pattern in at least most regions.

A simple AR1 model was estimated with the regional price data in logarithms for two periods: January, 1973 to December, 1985 and January, 1986 to December, 2003. No allowance was made for regional differences. The validity of this assumption was tested. Regression results are displayed in Table 8.5. Analysis of variance results for the residuals in the first and second sample periods are summarized in Table 8.6.

Once again, caution is in order because of doubts about the specification of these models. With caution in mind, these results indicate that there are no

Figure 8.2: Aggregate Price Estimation



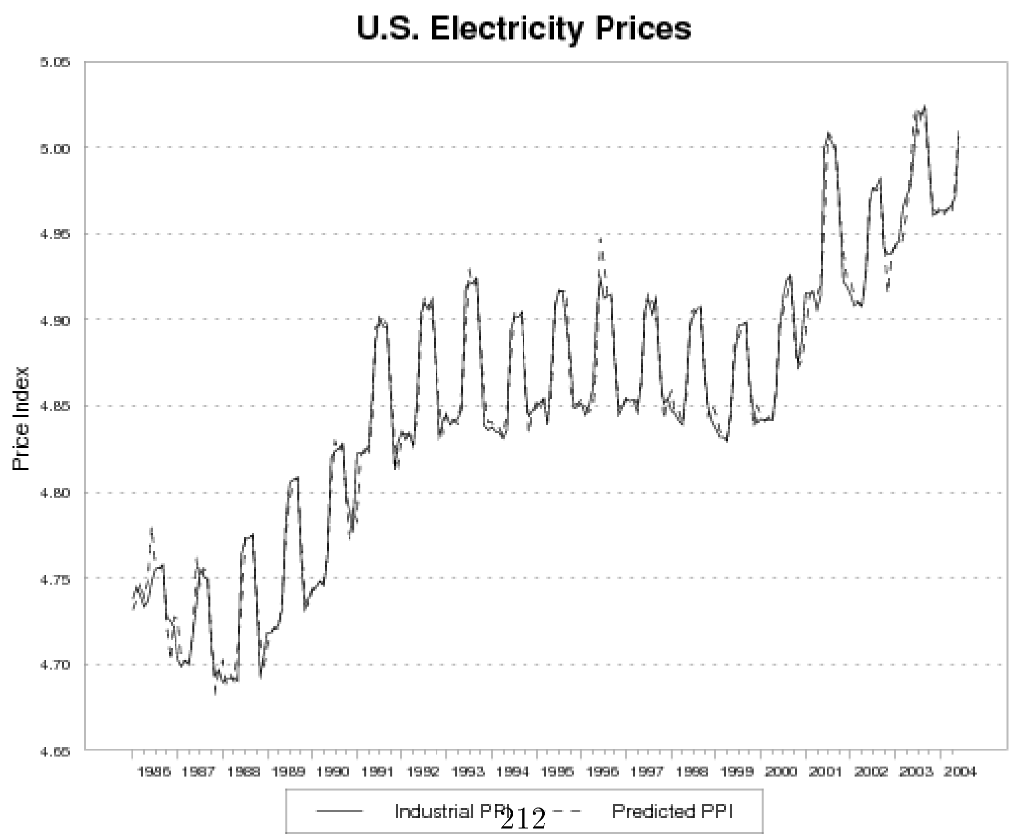


Figure 8.3: Regional Electricity Prices

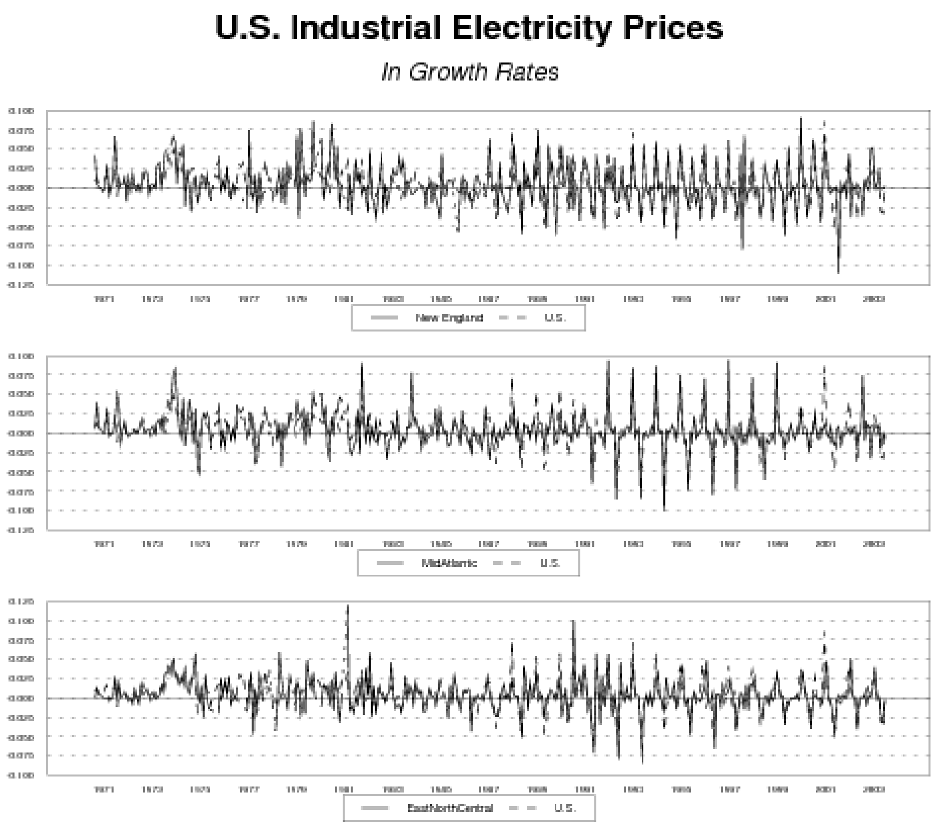


Figure 8.4: Regional Electricity Prices

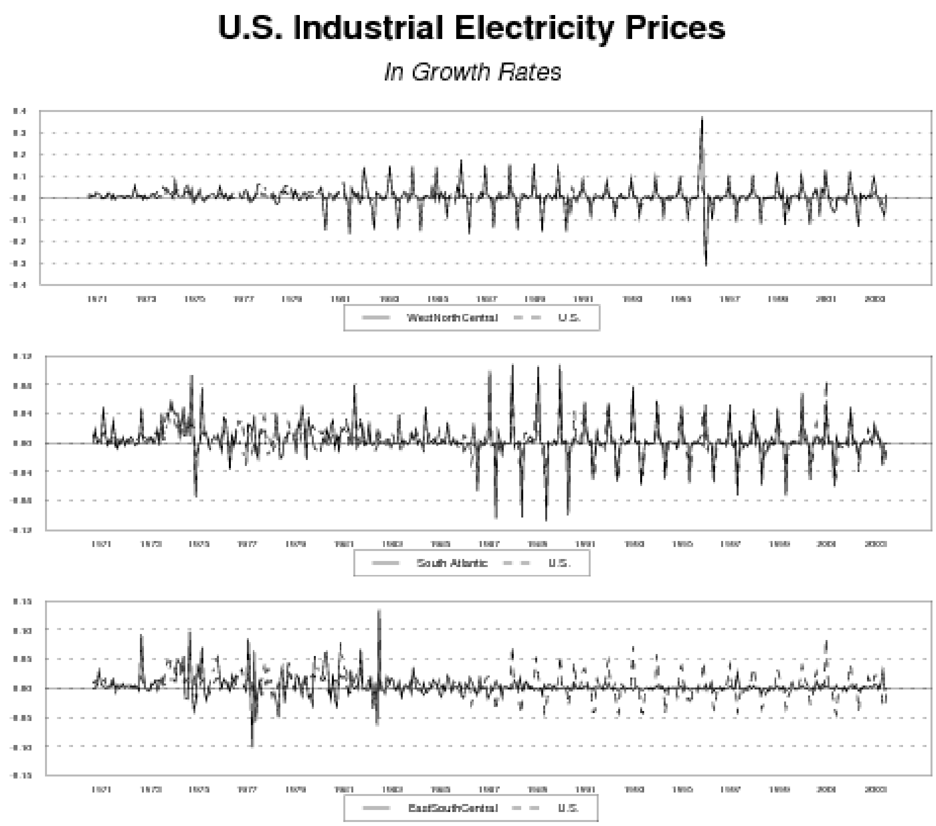
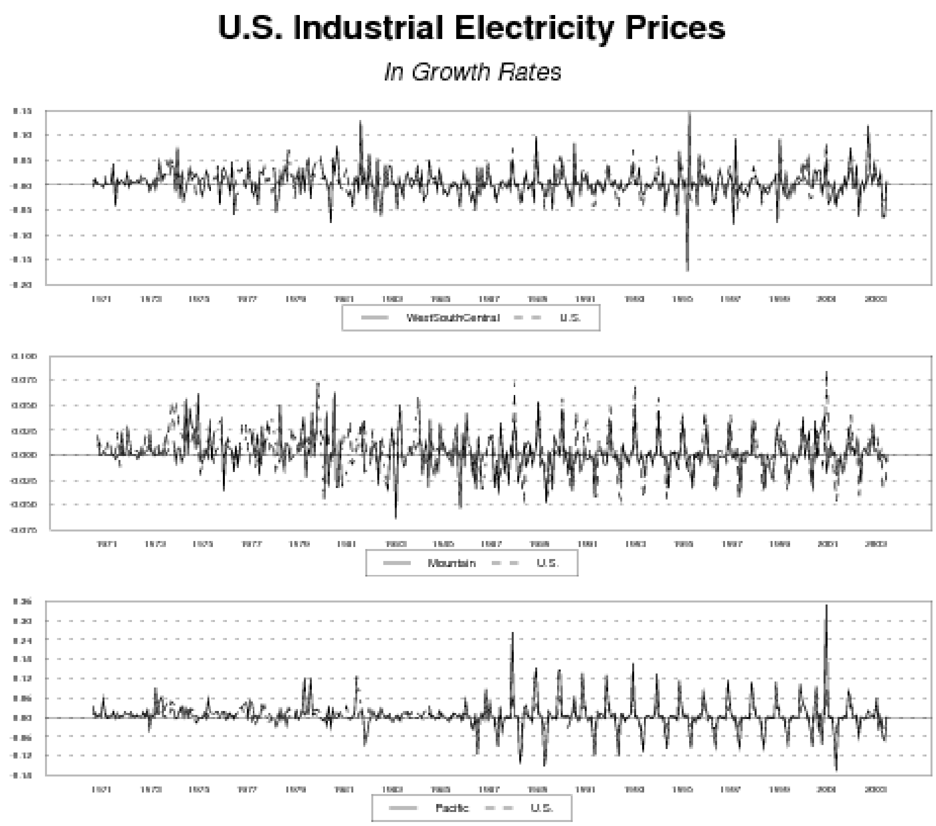


Figure 8.5: Regional Electricity Prices



significant first-order differences across regions evident in the regression residuals. The result holds for both sample periods. The result is important if the regression equation is to be incorporated into a dynamic programming model, for it means that we do not need to add state variables to account for regional distinctions. A check of second-order characteristics of the residuals indicates that we should not be too comfortable with the model:

	χ^2
1973:1–1985:12	667.267**
1986:1–2003:12	747.257**

The chi-square test for equal variances indicates that there are significant differences in variance among the residuals. We might suspect other second-order problems as well. In particular, significant serial correlation likely persists, as was evident in the graphical results for aggregate data.

8.2 Electricity Demand

We do not conduct extensive analysis of electricity demand. We do, however, briefly consider changes in the demand structure to gain a better understanding of the industry. First, we examine data plots for total electricity output, real Gross Domestic Product, and annual aggregate electricity prices relative to the GDP deflator. Summary statistics also are reported. Next, we estimate a relatively simple model of electricity demand. The structural demand equation is borrowed from Nelson and Peck [39]. Finally, we examine the regression results for signs of market instability.

Figure 8.6 displays annual growth rates for electricity production and real GDP from 1949 to 2004. The graph shows that electricity output growth exceeded real GDP growth from 1949 to 1972. After 1973, output and real GDP grew at similar rates, with lower average electricity demand growth. In both periods, real GDP and output are highly correlated. Figure 8.7 displays growth rates of relative prices, measured both as the overall annual electricity price average (from EIA [19]) and as the annualized industrial electricity PPI (from BLS [59]). Except for a period of high relative price growth in the 1970s and early 1980s, relative electricity prices generally have been falling slightly since 1959.

The statistics reported in Table 8.8 confirm that output growth exceeded GDP growth before 1973 by about 3 percent per year. In 1973, output growth fell from an average of 7 percent to 2.6 percent, while real GDP growth fell from 4.2 percent to 3 percent. Relative price growth also increased dramatically, from 1.6 percent to 11 percent per year. After 1985, energy markets became considerably more stable. Electricity output growth remained largely unchanged at 2.5 percent. Real GDP growth recovered somewhat to an average of 3.0 percent per year. Electricity price growth rates fell to about their earlier average of 1.4 percent. Statistics also are displayed for two longer periods.

While it is difficult to determine precise times for slowing of electricity prices and of demand in the mid1980s, it appears that output slowed before or at about the same time that price growth fell. Because prices were heavily regulated until recently, perhaps the possible lag between weakening demand and price reductions was due to sluggish response by price regulators. The high fossil

Figure 8.6: Output and Real GDP Growth

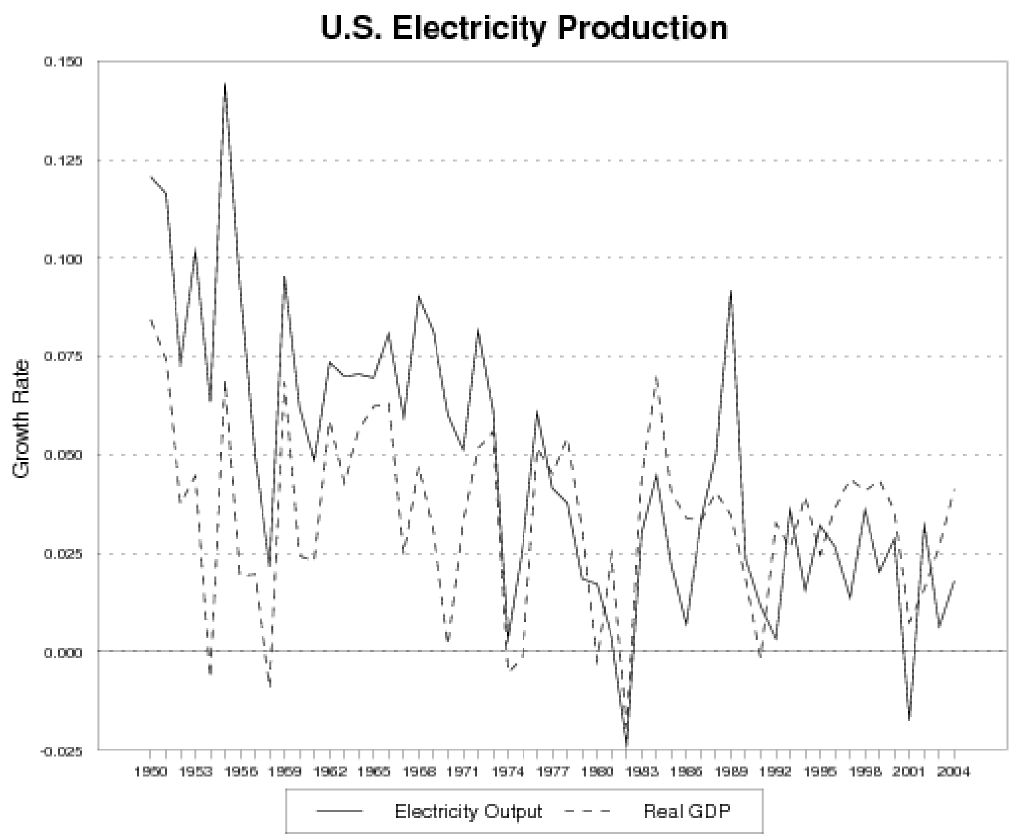
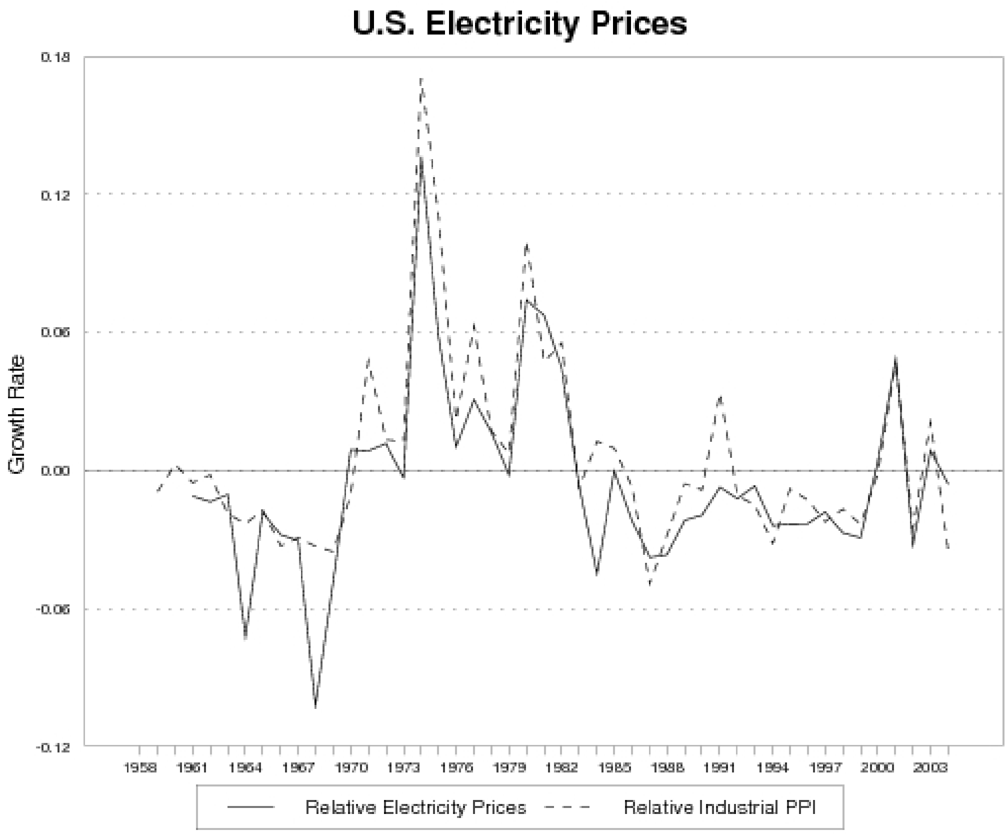


Figure 8.7: Relative Electricity Prices



fuel prices of the 1970s were beginning to moderate by the mid1980s, so that production costs dropped accordingly. Ellis and Zimmerman [18] note that many baseload power plants that were under construction, both coal and nuclear, were cancelled as supply exceeded demand requirements. As surplus capacity grew to high levels, the excess capacity perhaps gave regulators sufficient ability to effectively reign in price growth in the 1980s. Davis, et al [14] provide historical details of electricity prices.

We estimate the relationship between output, prices, and GDP using the model of Nelson and Peck [39]. We test this model for structural stability. We do not use formal methods to determine the date of possible structural changes. Instead, we simply adopt the 1985–1986 date employed in the tests for price stability. The test equation is

$$q_t = \beta_0 + \left(\beta_1 / \left(1 - \beta_2 L\right)\right) p_t + \beta_3 x_t + u_t$$

where

$$u_t = \gamma u_{t-1} + e_t,$$

and where q is electricity output, p is the relative price of electricity, and where x is real GDP. Estimation is performed using growth rates of each variable. Results are shown in Table 8.9.

The model seems to fit the data very well in the first period but not so well in the second. The Ljung-Box statistic does not reveal evidence of serial correlation in the residuals. There is evidence of serial correlation in the results for the full sample. The Chow test statistic is F(3,34) = 7.17, which is significant at the 1 percent level. We thus conclude that the demand structure shifted in the mid1980s. Regression results are plotted in Figures 8.8 to 8.10.

Figure 8.8: Demand Regression Results: Sample 1

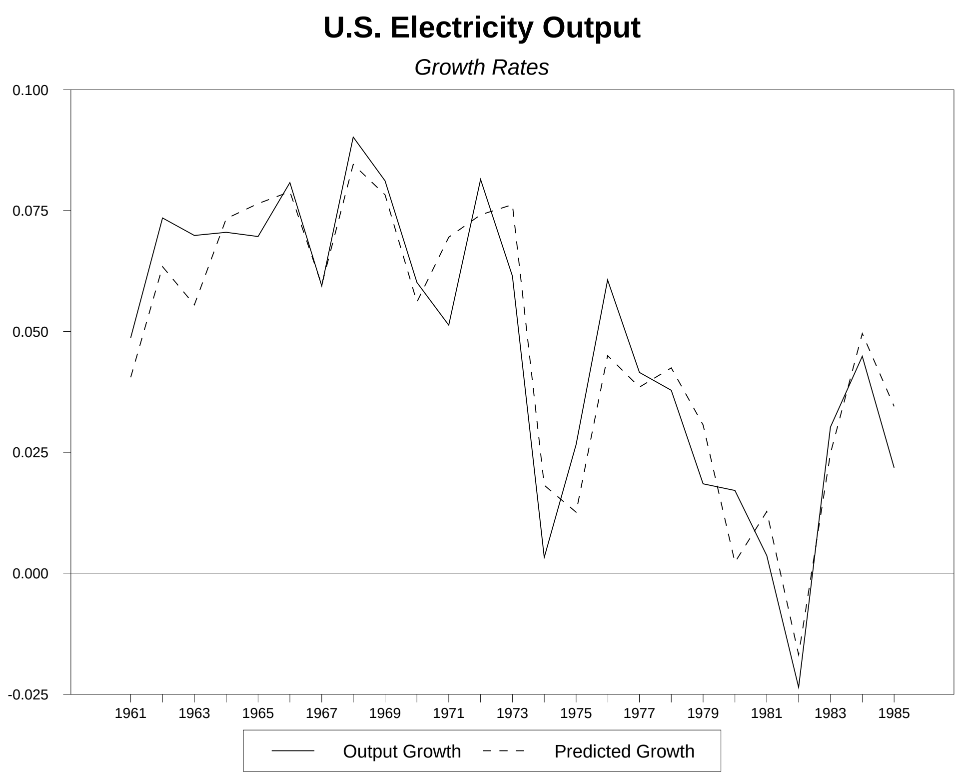


Figure 8.9: Demand Regression Results: Sample 2

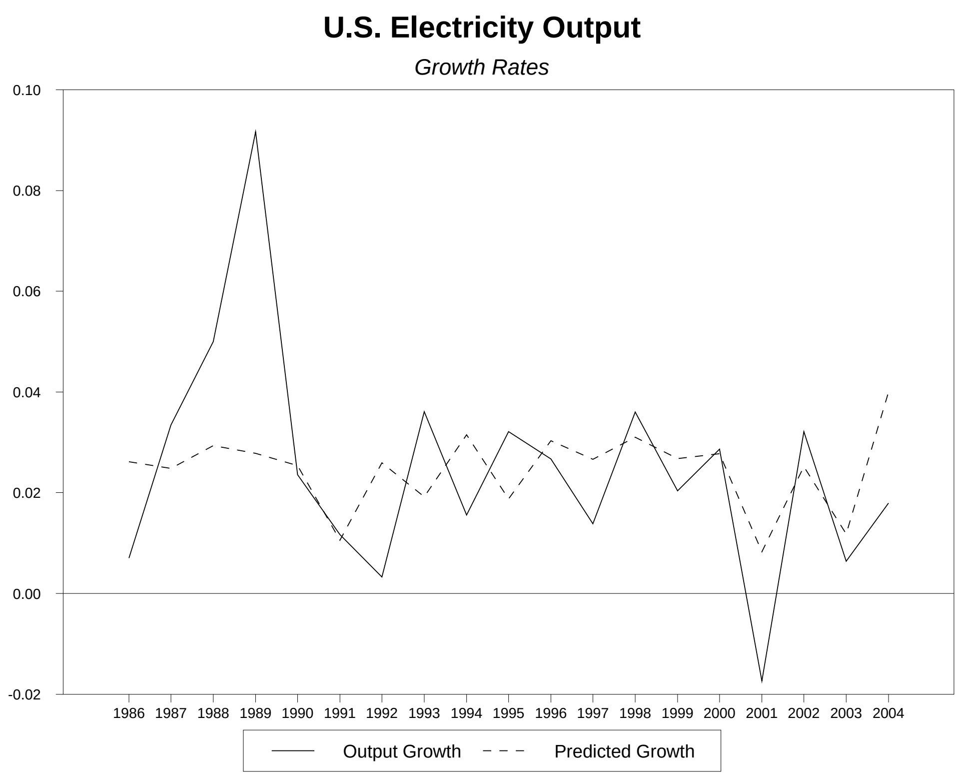
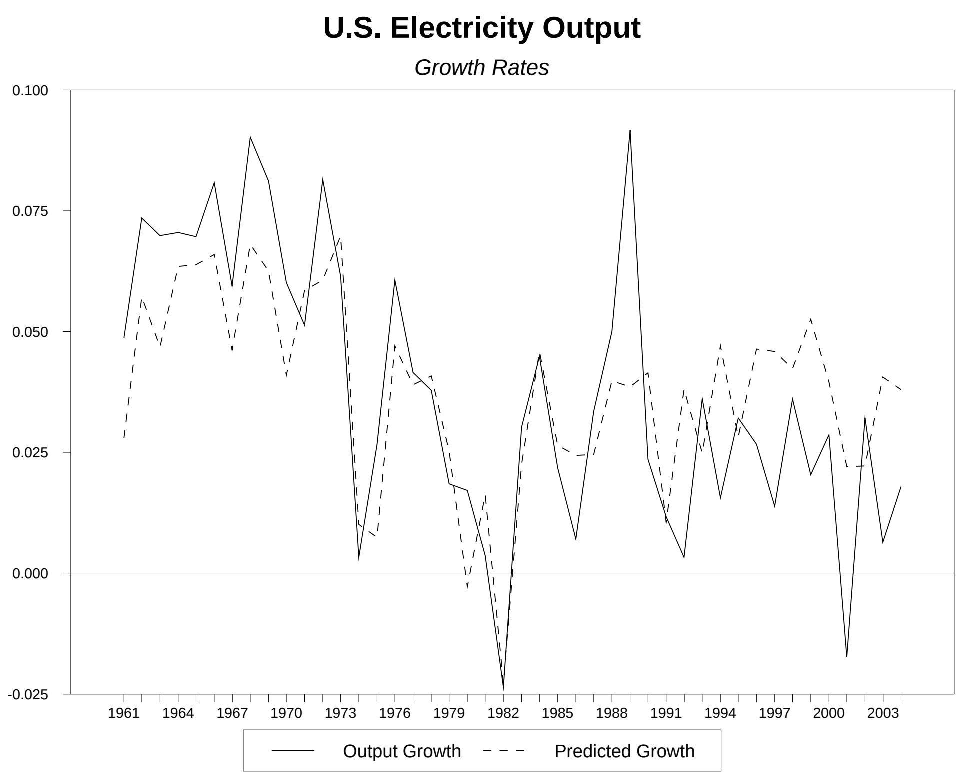


Figure 8.10: Demand Regression Results: Full Sample



8.3 Conclusion

We have seen that the electricity industry has undergone dramatic changes in the past several decades. Price growth was slow until the early 1970s, then high until the mid1980s, and then slow again but seasonally volatile. Demand growth was very high until 1973. Between 1973 and the late 1980s, output growth swung widely, but on average growth was much slower than in the 1950s and 1960s. Since 1990, output growth has been moderate and quite stable.

The analysis in this paper supports the adequacy of a crude price equation, when we are willing to trade satisfactory second-order characteristics for simplicity. It seems that a logarithmic AR1 model of regional electricity prices, with seasonal dummies, will provide first-order estimates satisfactory for use in a dynamic programming model.

We also provide evidence of a structural shift in electricity prices around 1986. Rust and Rothwell [55] constructed a dynamic programming model of nuclear power plants. In order to simplify the model, they assumed that electricity price growth was zero over the estimation period. They estimated the parameters of the model over two subperiods: 1975-1979 and 1984-1993. They conclude that the model parameters significantly differ across the sample periods, so that optimal behavior and plant values also changed significantly. They assume that much of the differences can be explained by changes in the regulatory environment following the 1979 accident at the Three Mile Island nuclear power plant. The results in this chapter, however, indicate that the simplifying assumptions in the dynamic programming model may affect their results. We show that price growth certainly was not zero, and that the price structures in the Rust-Rothwell subperiods differ significantly. These differences are not captured in the structure of the Rust-Rothwell model, and so the changes in price structure likely affect the parameter estimates. To what extent their results would change if their model included non-constant prices remains to be shown in Chapter 10.

Table 8.3: Aggregate Price Regression Results

	1959:2–1985:12	1986:1–2004:6	1959:01–2004:6
Constant	0.00517*	0.00201	0.00394*
AR{1}	0.92600**	0.19637	0.33357*
MA{1}	-0.70004**	-0.34111	0.00077
January	-0.00019	0.00275	0.00077
February	0.00232	-0.00321	-0.00011
March	0.00493*	-0.00003	0.00273
April	0.00264	-0.00391	-0.00021
May	0.00007	0.01362**	0.00552*
June	-0.00020	0.04060**	0.01651**
July	0.00195	0.00787*	0.00428
August	0.00108	-0.00250	-0.00042
September	-0.00238	-0.00120	-0.00198
October	-0.00295	-0.03772	-0.01693**
November	-0.00527*	-0.02820**	-0.01452**
SEE	0.0087	0.0100	0.0128
Centered R^2	0.315	0.786	0.348
Degrees of Freedom	309	208	532
Ljung-Box Q	61.25**	27.15	431.39**

Table 8.4: AR1 Results for Aggregate Prices

	1973:1–1985:12	1986:1–2004:6
Constant	0.03201**	0.00383
AR{1}	0.99207**	0.99381**
December	0.00714	0.02822**
January	0.01154**	0.03071**
February	0.01327**	0.02483**
March	0.02157**	0.02801**
April	0.01404**	0.02415**
May	0.01038*	0.04166**
June	0.01015*	0.06874**
July	0.01382*	0.03614**
August	0.01171**	0.02590**
September	0.00486	0.02721**
October	0.00519	-0.00930**
SEE	0.0113	0.0101
Centered R^2	0.999	0.986
Degrees of Freedom	156	209

Table 8.5: Regression Results: Regional Prices

	1973:1–1985:12	1986:1–2003:
Constant	0.02218**	0.01702**
AR{1}	0.99258**	0.99264**
January	0.01510**	0.01963**
February	0.01597**	0.02075**
March	0.01368**	0.01849**
April	0.01517**	0.01929**
May	0.01284**	0.01698**
June	0.01652**	0.02685**
July	0.03562**	0.04622**
August	0.02058**	0.02499**
September	0.01429**	0.01940**
October	0.01197**	0.01663**
November	-0.00631**	-0.00501**
SEE	0.0281	0.0302
Centered R^2	0.997	0.997
Degrees of Freedom	3093	3174

Table 8.6: ANOVA

Sample Period	Source	Sum of Sq	DoF	Mean Sq	F-Stat	Signif
1/1973–12/1985	INDIV	0.002	8	0.0003	0.335	0.953
	ERROR	2.435	3097	0.0008		
	TOTAL	2.437	3105			
1/1986–12/2003	INDIV	0.001	8	0.0002	0.194	0.992
	ERROR	3.005	3313	0.0009		
	TOTAL	3.007	3321			

Table 8.8: Output and Real GDP Growth

		59–72	73–85	86–04	59–04	73–04
	Obs.	14	13	20	46	32
Prices	Mean	1.668%	11.227%	1.435%	4.219%	5.334%
	StdErr	0.02913	0.06816	0.02570	0.06106	0.06807
GDP	Mean	4.203%	2.987%	3.076%	3.373%	3.010%
	StErr	0.01958	0.02829	0.01245	0.02045	0.02004
Output	Mean	7.103%	2.647%	2.455%	3.930%	2.541%
	StdErr	0.01386	0.02165	0.02165	0.02926	0.02255

Table 8.9: Electricity Demand

	1961–1985	1986–2004	1961–2004
Constant	0.02649**	0.01168	0.01344
GDPR	0.57446**	0.39454	0.62775**
P	-0.14166**	-0.07661	-0.09022**
d_P{1}	0.87532**	-1.09229	0.92469**
MA{1}	0.06216	0.08780	0.26467
SEE	0.011	0.023	0.21
Centered R^2	0.877	0.141	0.523
Degrees of Freedom	20	14	39
Ljung-Box Q	1.549	3.110	30.022**

Chapter 9

Operations and Financial Data

9.1 Introduction

This chapter analyzes the history the U.S. nuclear power industry as revealed in available data. The work assembles two primary forms of data. First, monthly operating data is constructed from 1975 through 2003. Second, cost data is collected from 1961 through 2000. Available price data, which was described in the previous chapter, is combined with annual output data to construct revenue and profits. Finally, the two data sets are combined to make possible future analysis of the relationship between costs, plant conditions, and operators' decisions.

The monthly, plant level operating data include information on output, the primary type of activity performed at the plant, conditions at the plant, and whether problems occur. The annual, site level cost data include information on operating and maintenance costs, fuel costs, and capital additions costs, in addition to capacity and output.

Monthly output data is combined with price data and additional information in an attempt to construct annual revenue and ultimately profit estimates. The process is difficult and we assume the results contain significant error. Still, few if any others have published such attempts, and the results seem plausible despite remaining problems.

Both data sets reveal clearly that while the 1980s were troubled times for the nuclear power industry, the 1990s and recent years have seen dramatic improvements. Evidence of such improvements include stable or falling unit costs, soaring productivity and reliability, and climbing profits. Recent activity data reveal operators following policies, which presumably are optimal, far more strictly than in the past. We suppose that these changes in behavior are the results of forced re-optimization in the face of soaring costs, learning, and regulatory reform. We will employ this operating data and revisit these questions in Chapter 10.

9.2 Operating Data

9.2.1 Introduction

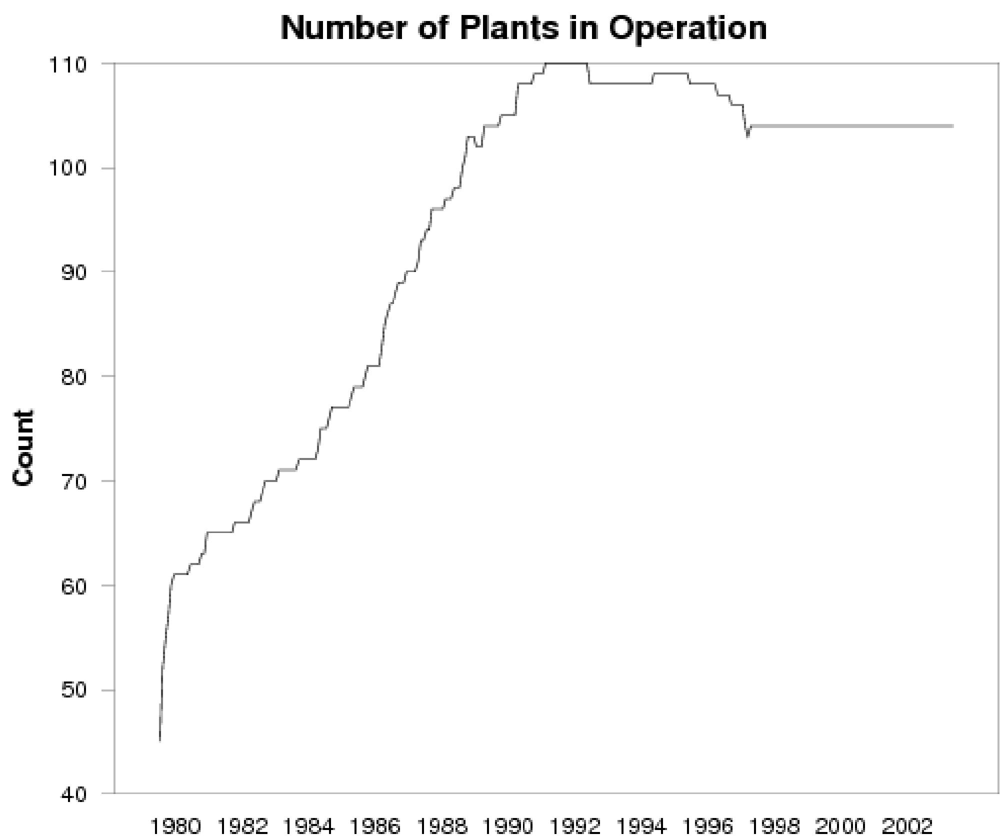
The operating data comprise an unbalanced panel spanning the months from April, 1979 to December, 2003.[1] One hundred sixteen plants are represented in the sample, with a total of 27,385 reactor-month observations. The number of plants in the sample is plotted over time in Figure 9.1. In the latter years, all 104 of the operational American reactors are represented in the sample.

The work updates the data set constructed by Rust and Rothwell [54, 56, 55].[2] Their data ended in December, 1994. The data in this set extend their

[1]For the next chapter, we merge this data with an earlier set to span the months from January, 1975 to December, 2003.

[2]The data used to construct our data set were provided in 2006 by Geoffrey Rothwell of

Figure 9.1: Number of Plants in Operation



panel by 108 months. More important than this number itself is that data for these months reveal whether trends that appeared to begin in the Rust-Rothwell sample have continued. These apparent trends include increased output and plant availability, improved reliability, and moderating costs.

9.2.2 Reliability and Performance

Of great concern to all, whether for environmental, public health, or economic reasons, is the reliability of nuclear power plants. While the data in this set reveal nothing directly about the safety of nuclear power, the likelihood of serious accidents may be correlated with the reliability statistics that can be constructed with these data. Our primary interests, however, are the economic implications of reliability.

Figure 9.2 plots monthly average availability factors from 1980 to 2003. The availability factor is the fraction of time in a month that a plant operates. Clearly, there is a strong seasonal pattern, primarily because operators prefer to repair and refuel in the spring and fall. Monthly averages rose from about 60% in the 1980s to about 80% by 2000.

The capacity factor, or availability factor, distribution over all periods is displayed in Figure 9.3. Plants at 0% utilization may be closed for refueling, repairs, because they are entering a stage of permanent decommissioning work, or for other reasons. Nearly 25% of months are classified with a capacity factor of zero. Few months are spent at low but positive levels. The frequency grows with the capacity factor, with roughly 60% of months spent at 100% capacity.

Figure 9.4 reports the same information by decade. Several trends are appar-

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Stanford University.

Figure 9.2: Trend in Availability Factors

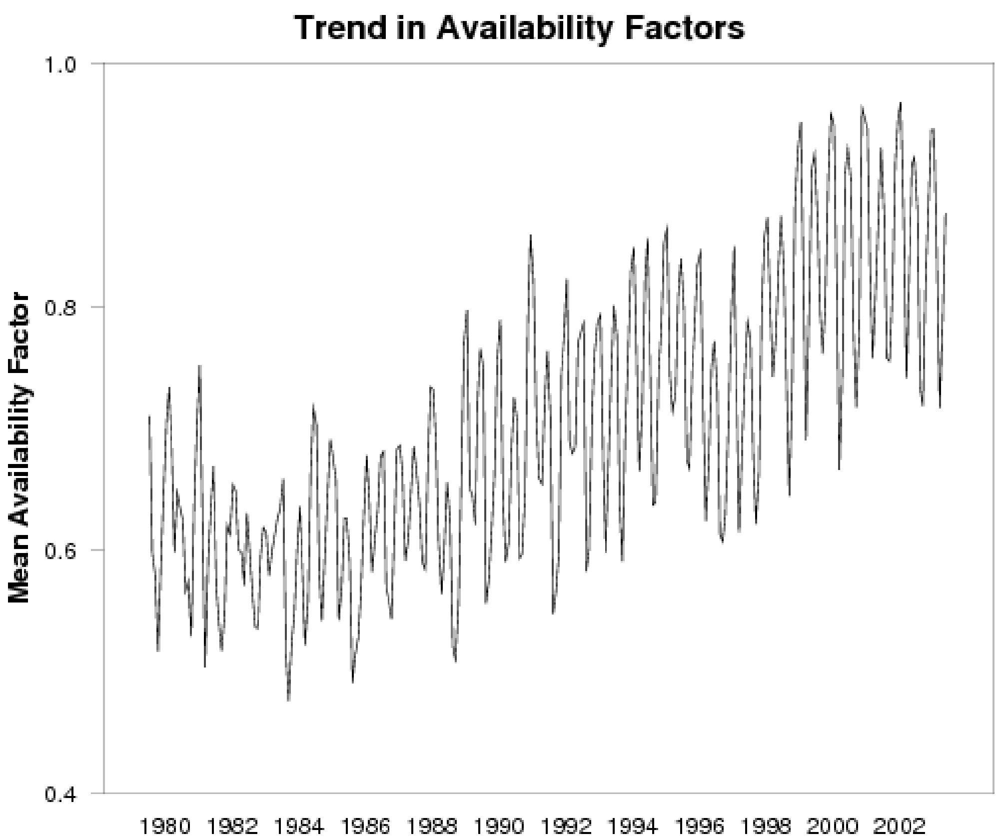


Figure 9.3: Capacity Factor Distribution

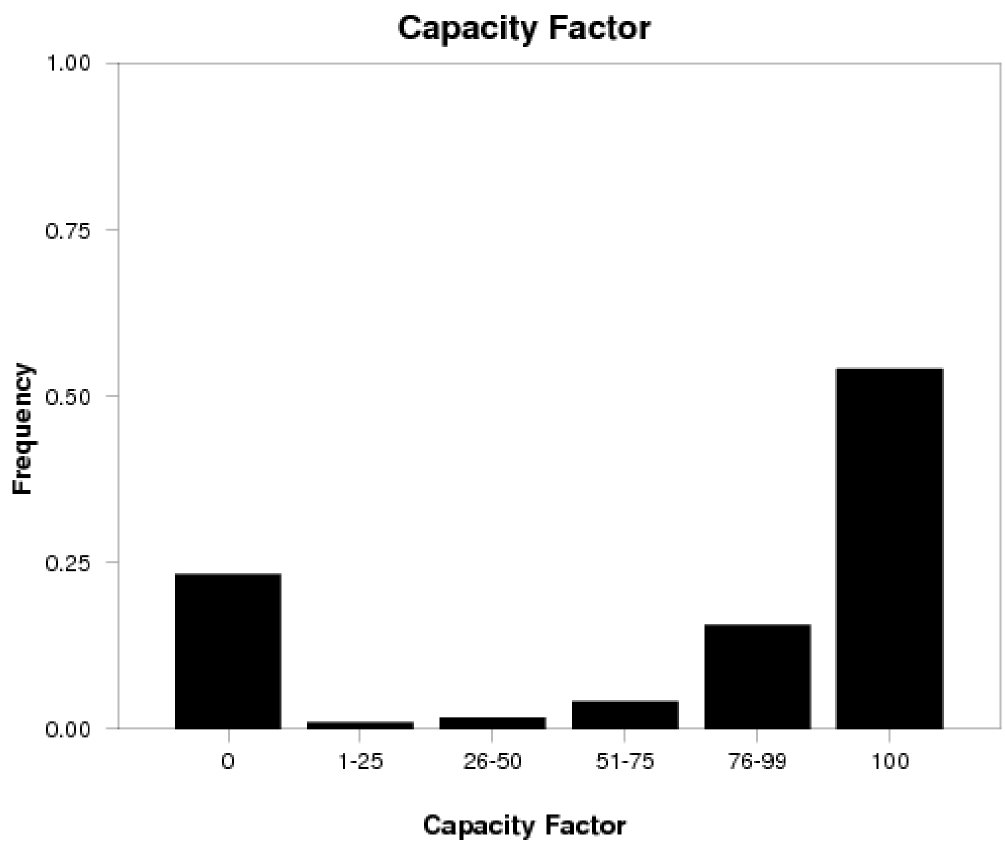
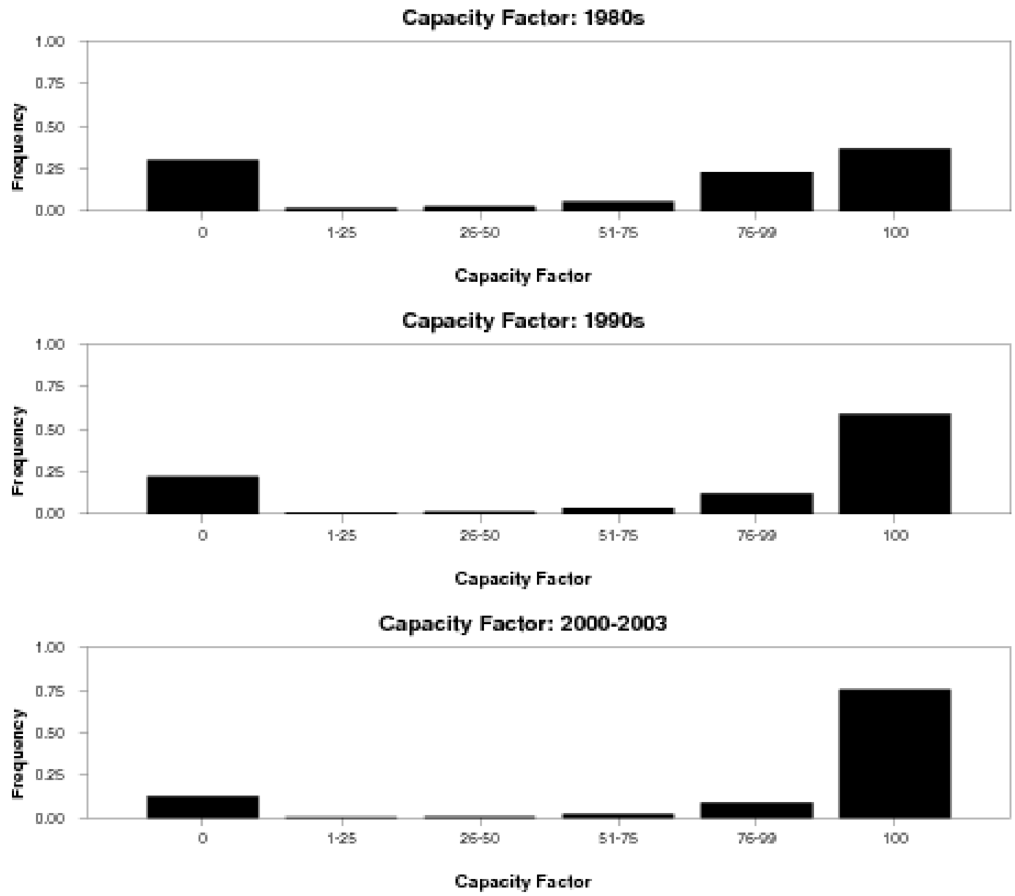


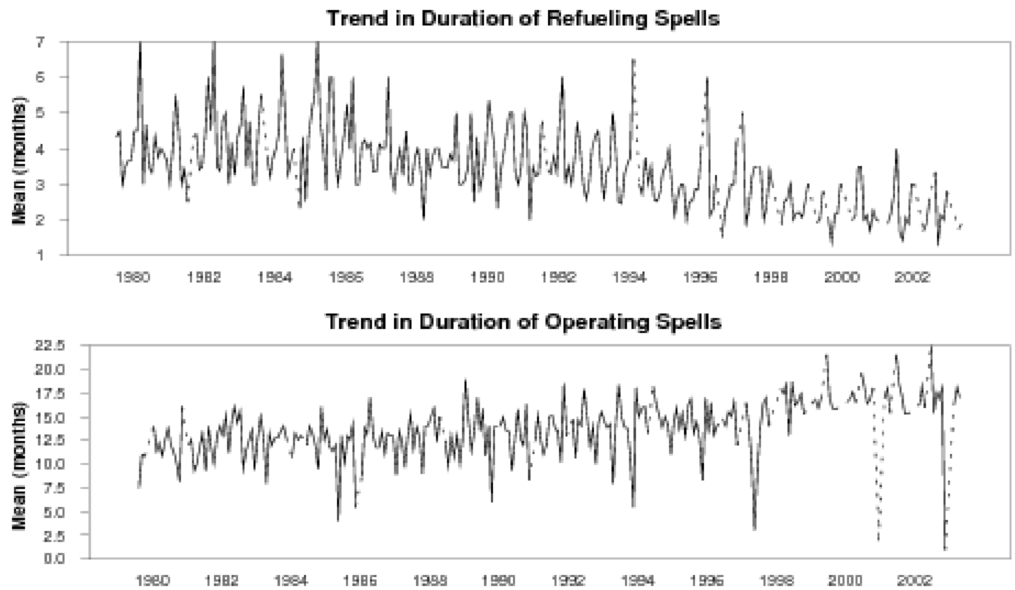
Figure 9.4: Capacity Factors by Decade



ent. First, the amount of time that plants are not operating falls significantly. Even more significant is the increase in time spent at full capacity. Time spent at intermediate levels of production fall, as probability mass shifts toward the endpoints.

Figure 9.5 reports the average lengths of operating and refueling spells that end at given dates. The average number of months required to refuel plants averaged about four to five months throughout the 1980s. The average declined to two or three months by 2000. Remember, however, that repairs often are made during refueling spells. Many repairs and retrofits were required in the

Figure 9.5: Length of Operating and Refueling Spells



tumultuous 1980s. Some of the observed pattern may be explained accordingly.

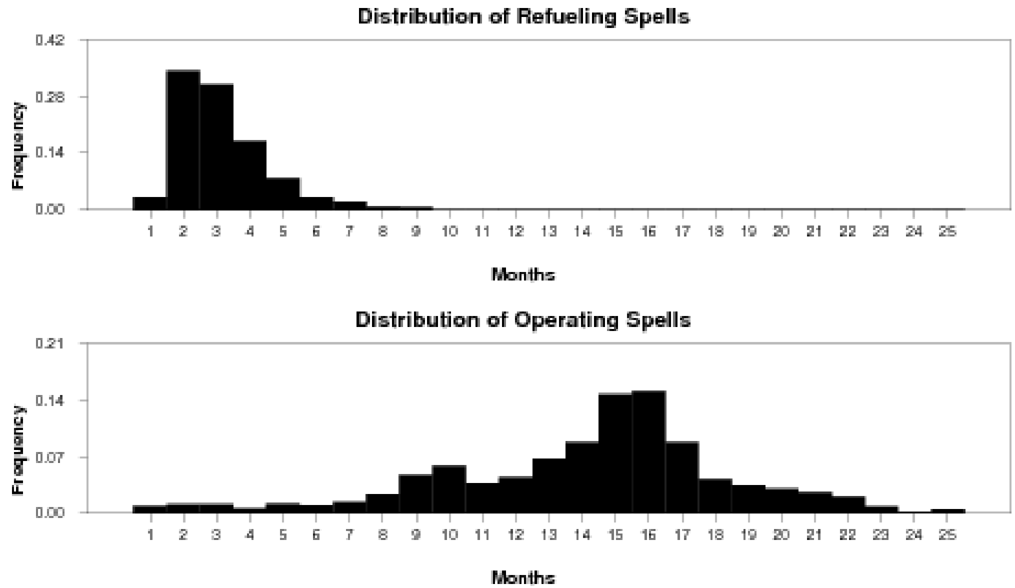
The figure also displays the average length of operating spells. Just as refueling spells shortened over the sample period, operating spells grew from 10 or 12 months on average to perhaps 18 months. This pattern was reported in Rust and Rothwell [55], and we see that the pattern also held in the following nine years.

Figure 9.6 displays the frequency distributions of refueling and operating spells. The mode of the refueling distribution is two months, but the upper tail maintains significant probability through nine months.

The mode of the operating spell distribution is 16 months, but significant probability mass is distributed widely about the mode. Still, roughly one-third of operating spells last 15 or 16 months. A second mode is evident at 10 months.

We examine the distribution of refueling spells by subperiods in Figure 9.7.

Figure 9.6: Distributions of Refueling and Operating Spells



Note that the mode falls from three months in 1980-1992 to 2 months in 1993-2003. Probability mass at the mode increases from about 40% to nearly 60%. This may indicate that fewer repairs, retrofits, and inspections are required in the latter period, and it also may indicate that sufficient learning took place by the mid1990s to allow consistently brief refueling spells. With the increased seasonal volatility in electricity prices, we also suppose that there is increased incentive to limit refueling to months with the lowest prices.

Figure 9.8 displays similar distributions by sub-period for operating spells. Rust and Rothwell reported that a sample ending in 1979 revealed average operating spells of 12 months. In their 1984-1993 sub-period, they report average operating spells of 18 months. In the first graph in the figure, we see that the mode for the 1980-1992 sub-period is 15 months. In the second sub-period, from 1993-2003, the data is clustered much more tightly about the mode of 16 months.

Figure 9.7: Refueling Spell Distributions

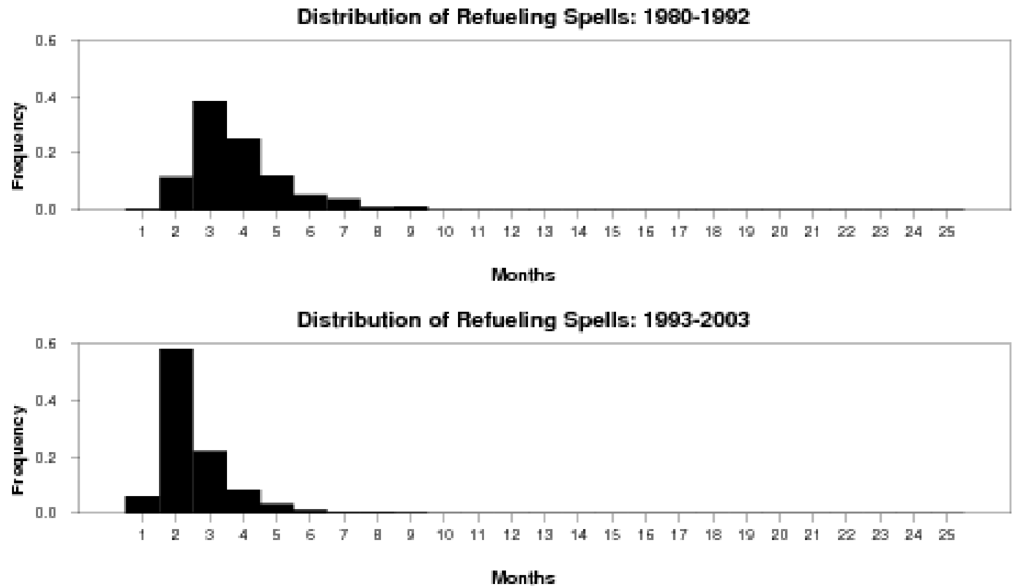


Figure 9.8: Distribution of Operating Spells

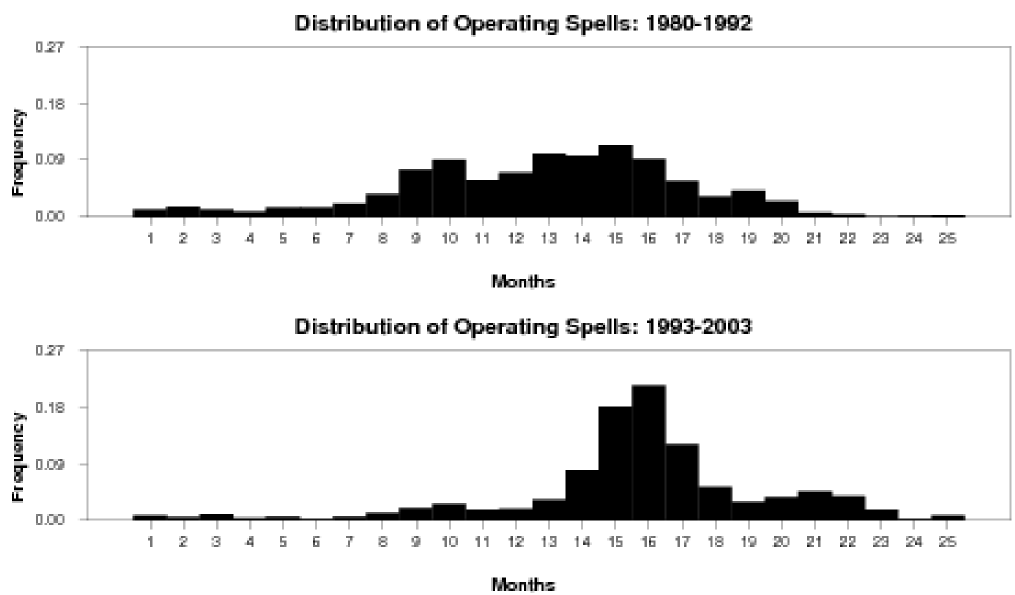


Table 9.1: Spell Table

	Full Sample	1980-1989	1990-1999	2000-2003
% of time operating	76.695	69.911	77.824	87.132
% of time at 0% capacity	07.982	11.597	07.582	01.841
% of time refueling	15.278	18.460	14.525	11.027
Total Reactor/Months	27385	9339	12847	4888

Table 9.1 reports the percentage of time spent operating, at zero capacity, time refueling, and the number of observations per sub-sample. The percentage of time spent operating climbs from 70% in the 1980s to 87% after 2000. The time spent shut down declines from 12% in the 1980s to about 2%, and the time spent refueling falls from 18% to 11%.

Figure 9.9 reports the effect of the duration of operating spells on availability factors. In the early months of an operating spell, reliability increases to a peak of nearly 90% after about eight months. Availability then gradually declines to about 20% after 24 months.

Finally, we consider the probability that an operating plant will be forced to shut down one or more times in a given month. In Figure 9.10, we see that the probability is about 25% that a plant will be forced to shut down in the first month of an operating spell. The outage rate falls to roughly 10% by the twentieth month of operation.[3]

We consider the effects of age on average outage rates in Figure 9.11. Note an apparent "bathtub" shape of the probability distribution. Young plants face

[3]Erratic patters in the data for months 20 to 25 likely are due to the small number of observations. Plants usually are refueled before the operating spell reaches 20 months.

Figure 9.9: Effect of Duration on Availability Factors

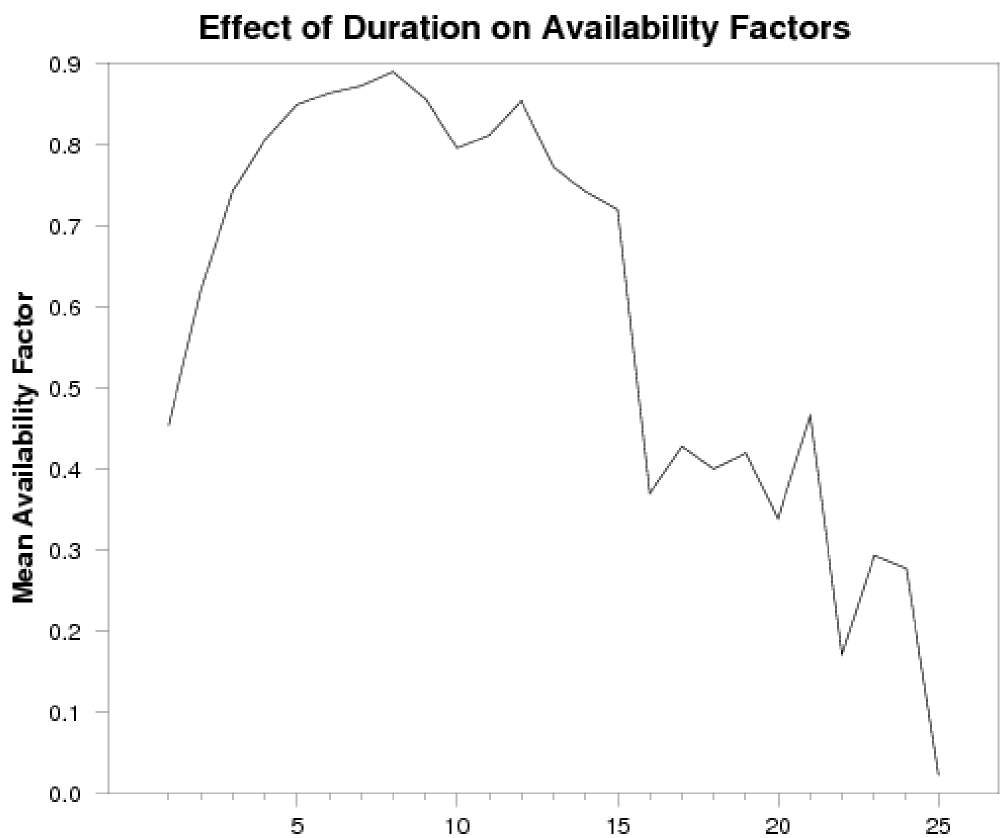


Figure 9.10: Outage Rates vs Duration

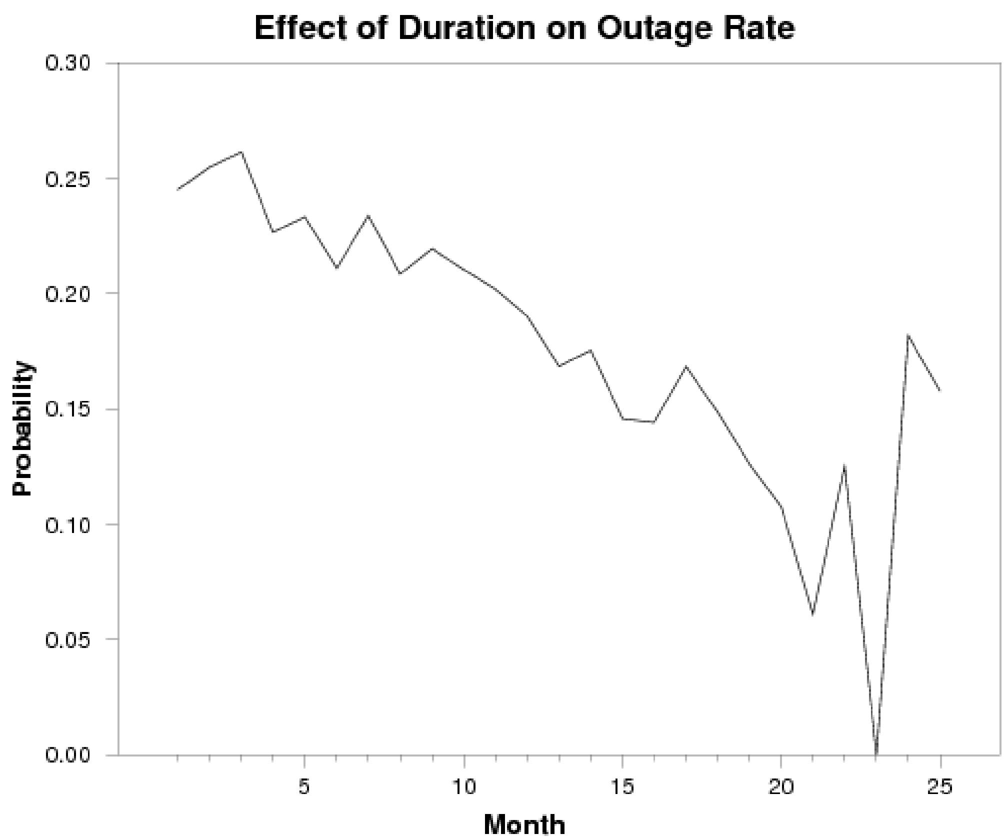
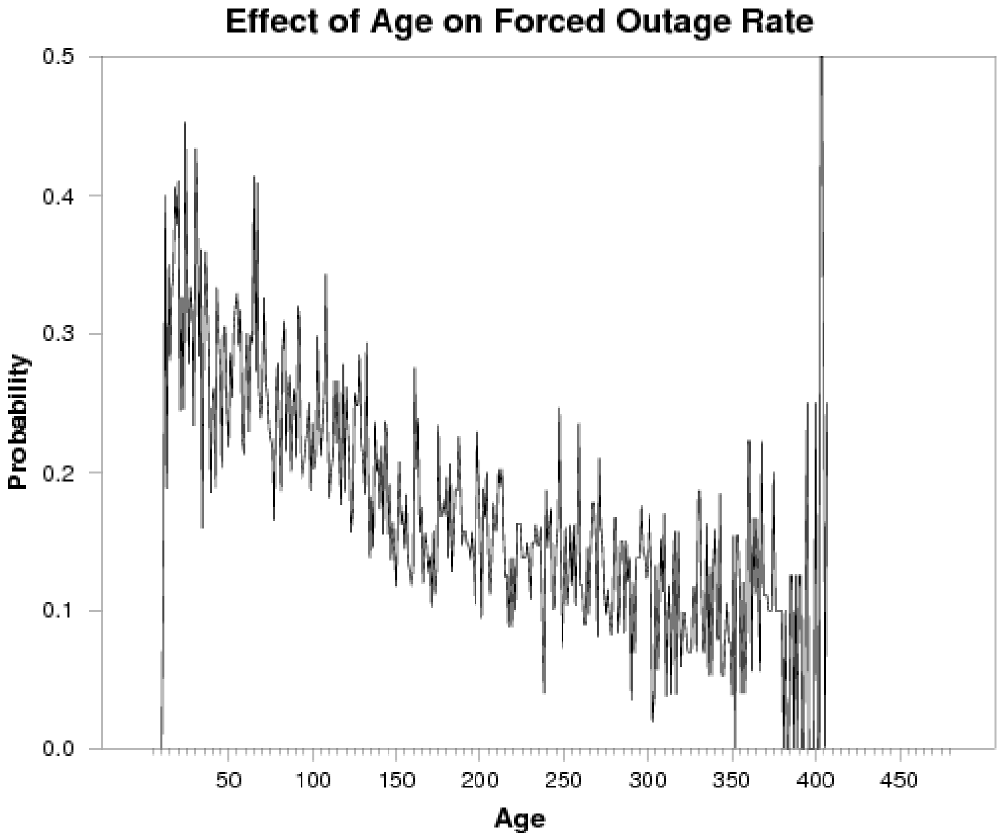


Figure 9.11: Outage Rates vs Age



forced outage rates of perhaps 30%. The average falls roughly to 12% for plants of age 300 months. While the statistics are less reliable for older plants, since we have relatively few observations for them, it appears that the probability ceases its decline by that point, and perhaps the probability of forced outages begins to grow as plants pass 300 months. Rust and Rothwell suspected that this pattern would be revealed, but their panel was too short to reveal it.

9.3 Cost Data

The cost data were collected from the Federal Energy Regulatory Commission's Form 1, "Annual Report of Major Utilities, Licensees and Others," Schedule 402.[4] The data set include three series of accounting data: operations and maintenance costs, fuel costs, and capital additions expenditures,[5] as well as annual output figures.

These cost data are available annually for each site with a functioning commercial plant. Sites have between one and three functioning reactors. The full data set is an unbalanced panel with 1,751 observations, covering 74 sites for the years 1961 to 2000.

The cost data essentially are accounting data and do not necessarily correspond nicely to economic concepts of the same names.[6] Nonfuel operating costs that are considered expenses are categorized as operating and maintenance costs. Nonfuel costs that are capitalized are considered capital additions expenditures. Categorization of these costs depends, to some degree, on the discretion of the plant owners and of regulators. Such discretionary practices differ across owners and regions, thus introducing potentially nonrandom errors into our data.

The operating data described above is based on monthly data for each plant (i.e. reactor). In order to merge the data sets, a mapping of monthly, plant-level data to annual, site-level data was established. Unfortunately, some data is lost due to differences in coverage. Observations were included in the merged data set only if all 12 months of operating data for each plant on the site were

[4]The data were provided by Geoffrey Rothwell at Stanford University.

[5]See the EIA analysis [2] for further details.

[6]See the EIA cost analysis [2], Chapter 2, for more details.

available. The resulting merged data set covers the years 1980 to 2000, with 73 sites and 1,229 observations.[7]

Figure 9.12 displays average plant capacity, in megawatt-hours, in our data set and the average computed from aggregate data reported by the EIA. Our data account for most of the capacity of a typical plant in the 1990s, but fail to account for significant capacity in the 1980s. This might indicate that our data are at variance with that of the EIA, or it might indicate that large plants are not represented adequately in our matched sample. Our average capacity figures are based on the capacity ratings assigned to plants when they opened. To account for changes in capacity ratings over time, we add aggregate capacity uprates to constructed capacity totals. These changes account for some, but not all, of the differences in recent years. The second graph displays the number of plants in operation. Most plants are found in our sample by 1990, but many do not appear in our matched data set in the 1980s.

Figure 9.13 displays the number of sites in the data set with one, two, or three plants. Note that the number of single-plant sites peaked roughly in 1991 and then began to decline. This is explained, in part, by construction of additional plants on existing sites. For the same reason, we see the numbers of two- and three-unit sites growing into the mid1990s.

The first graph in Figure 9.14 displays aggregate capacity. While our data accounts for most of the actual capacity starting in the early 1990s, the gap is wider between our data and the actual total in the 1980s. We again consider the effects of capacity uprates, which have become increasingly important in recent years. The second graph displays a histogram of capacity by site. Note that a

[7] We have data to extend the merged set back to 1975.

Figure 9.12: Industry Size

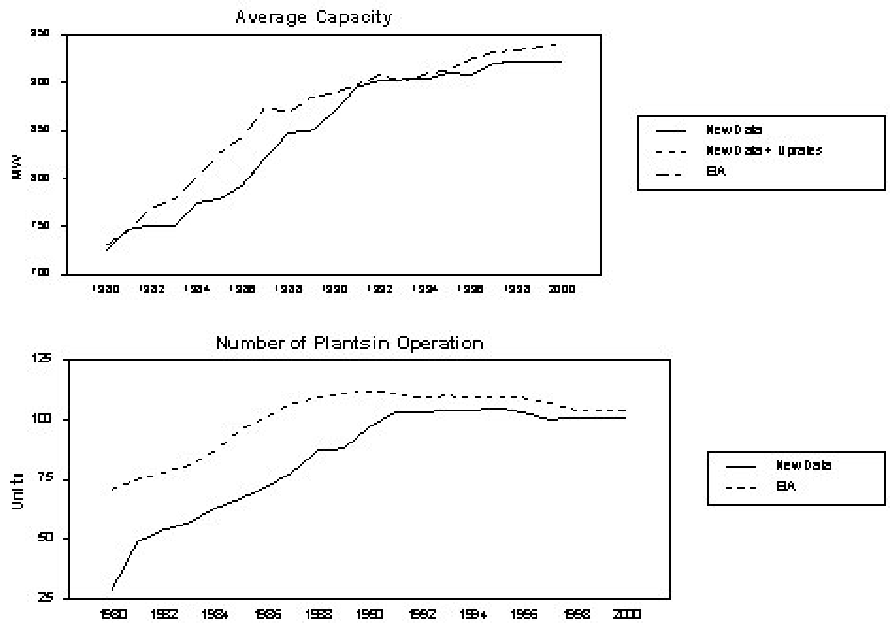


Figure 9.13: Number of Plants per Site

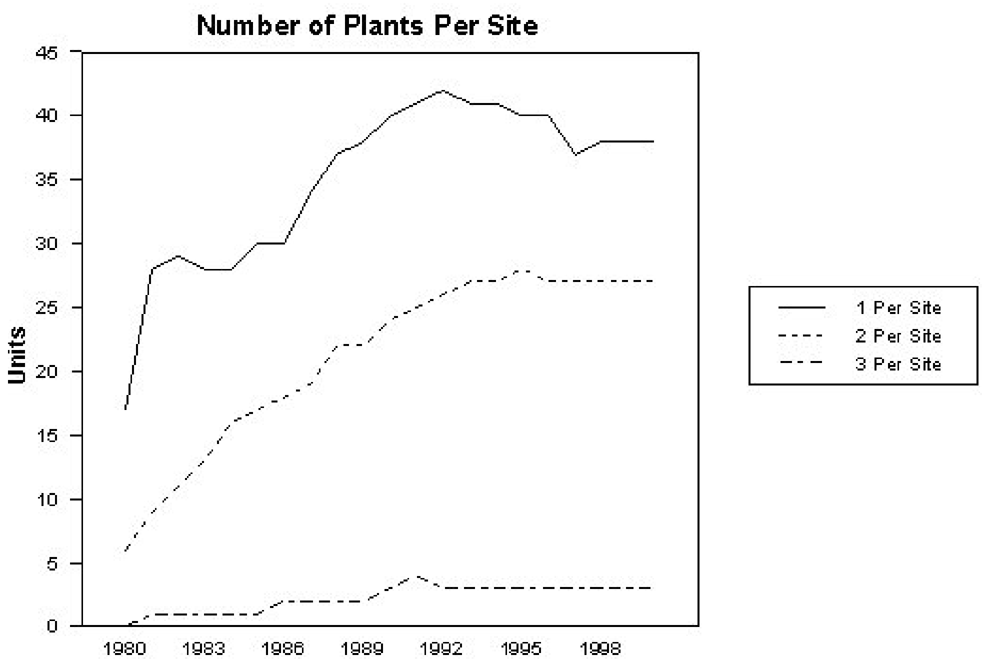
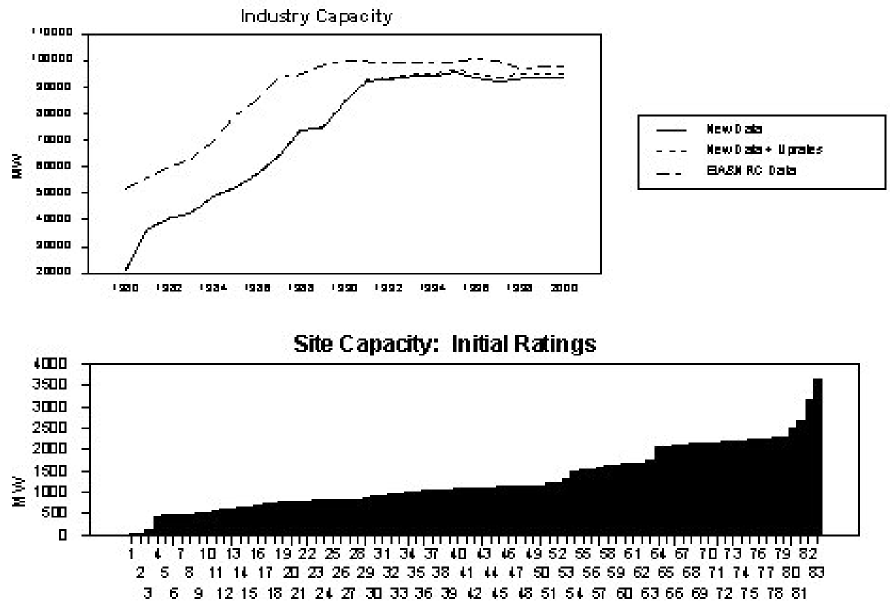


Figure 9.14: Site Capacity

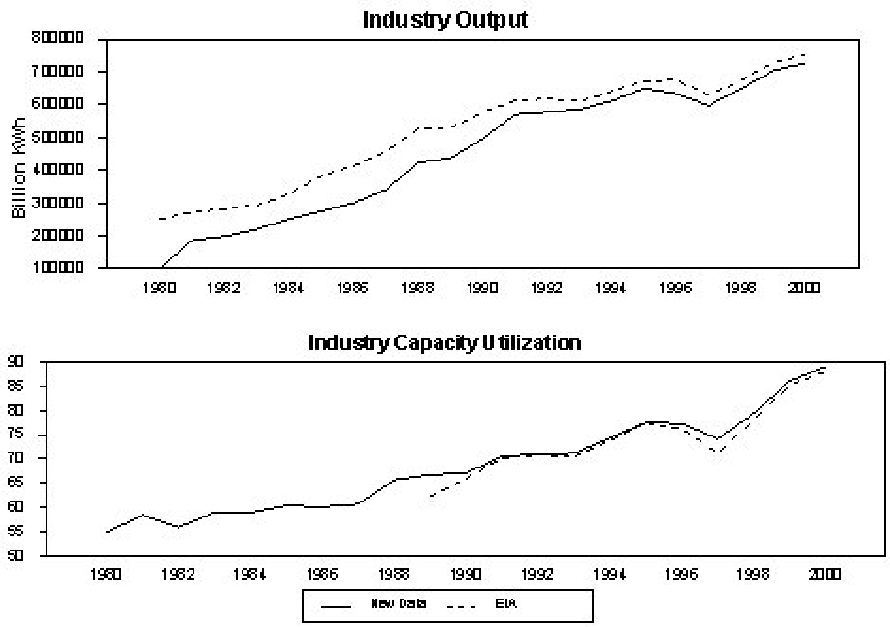


single site might be represented more than once, if a plant was added or removed from operation.

We consider two reasons for these gaps between our capacity totals and the actual levels. First, as noted previously, our capacity data do not account for capacity uprates, where plants may be upgraded in order to produce more power than was possible originally. The aggregate additional capacity was added to our aggregate capacity data and is displayed in the first graphs of Figures 9.12 and 9.14. However, the additional capacity does little to bridge the gap.

A more important explanation is that the matching process typically leads to the elimination of data near the beginning and end of reactors' lives. Many reactors began or ended operation in the 1980s, and fewer opened and closed in the 1990s. This likely accounts for much of the differences.

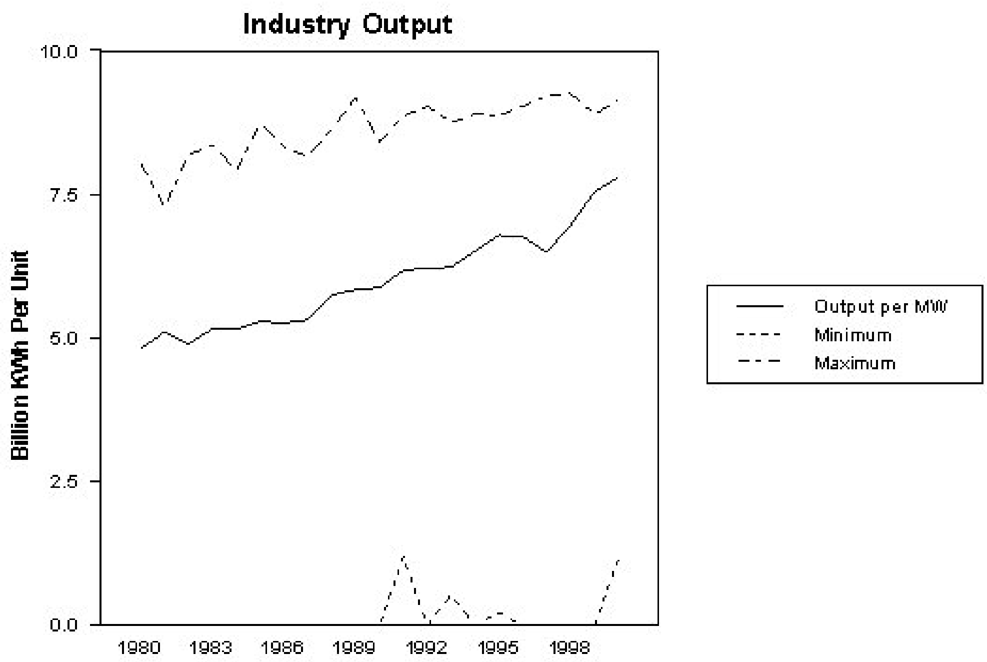
Figure 9.15: Industry Output



Similar characteristics are evident in our aggregate output data when compared to EIA figures. These data are compared in Figure 9.15. We account for most industry output only after 1990. On the other hand, our capacity utilization data (measured as potential output to actual output) closely matches the EIA data; this may be seen in the second graph. Figure 9.16 displays average output per megawatt (MW) of capacity, and it also displays the minimum and maximum across plants of output per MW.

Clearly, there are differences between our aggregates and the totals reported elsewhere. It remains to be established, however, whether our data are representative of the industry or whether other problems remain. The following three sections present operations and maintenance costs, fuel costs, and capital additions expenditures.

Figure 9.16: Output Distribution

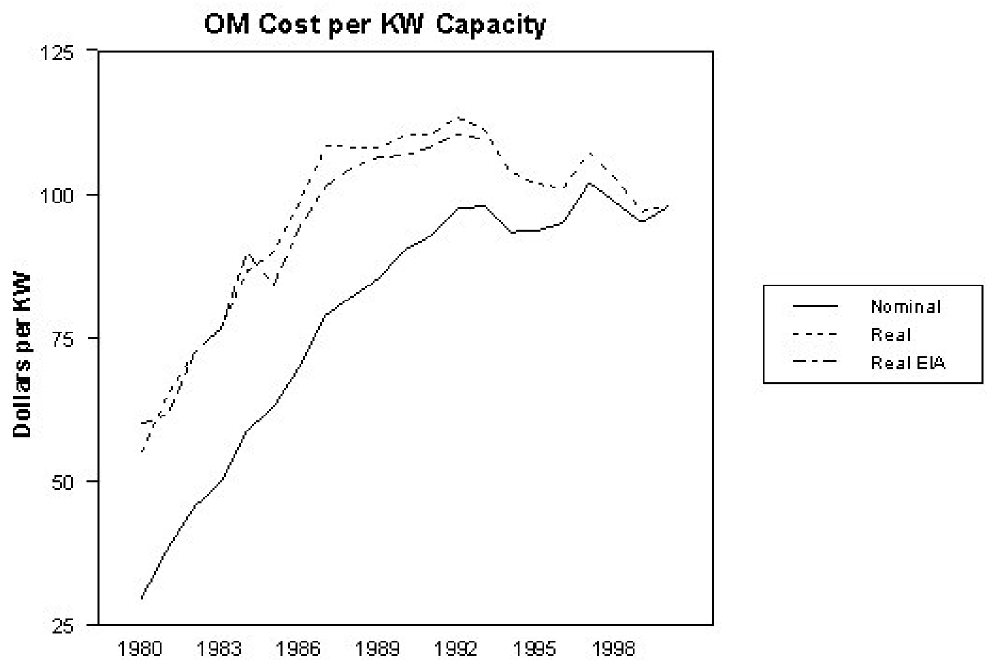


9.3.1 Operating and Maintenance Costs

Average operating and maintenance costs per kilowatt of capacity are displayed in Figure 9.17. Real costs are very similar to those reported by the EIA in 1995. Costs grew rapidly in the 1980s and into the early 1990s. Since then, costs have leveled in nominal terms and have fallen in real terms. The EIA [2] reports efforts by the NRC to improve efficiency in order to maintain its safety standards but at lower costs. In addition to learning by power plant operators, such efforts may explain the slowing and eventual reversal of cost growth.

Figure 9.18 displays average real operating and maintenance costs per kilowatt (KW) of plant capacity. In addition, it shows the minimum and maximum costs across sites per KW of capacity. Note that the best-performing sites had moderate cost growth. The worst-performing plants experienced rapid

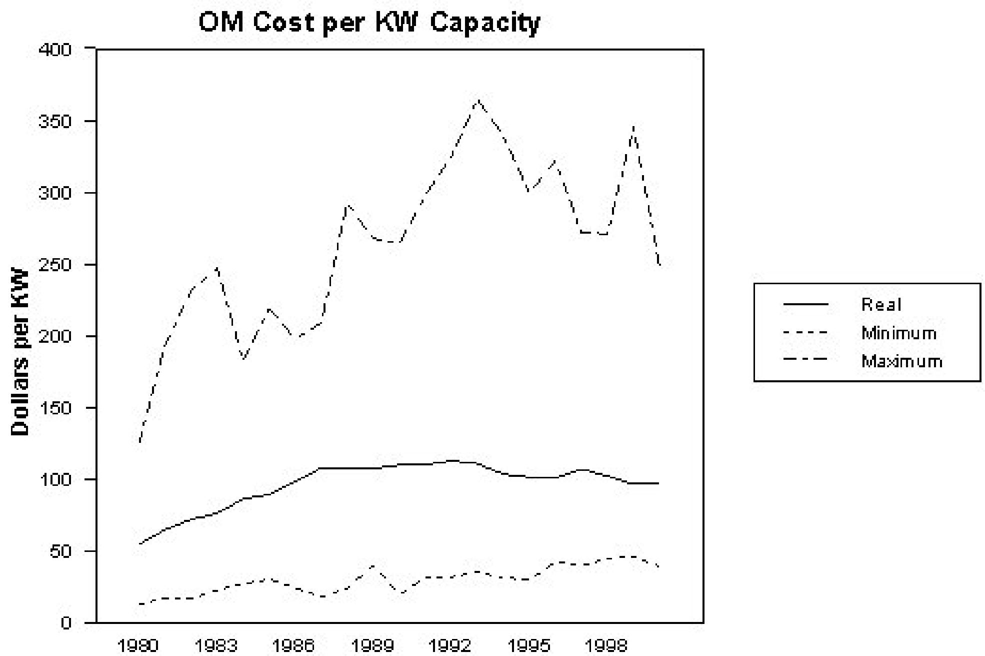
Figure 9.17: Operating and Maintenance Costs



cost growth through the early 1990s, but it appears that costs have been falling through the mid1990s.

The EIA [2] claims that reported operating and maintenance expenditures miss about 30% of actual costs. These additional costs include insurance premiums, regulatory fees, and some labor costs. This will be important when we attempt to construct profits. According to our understanding of the EIA document, however, the data do include costs of replacement power when the plant is not operating. The same document cites a report that about 67% of operations and maintenance expenditures are labor costs, and the balance is spent on materials. Nearly half of employees at a typical plant perform maintenance and support duties. Hence, much of the reported operations and maintenance costs may be attributed to labor.

Figure 9.18: OM Cost Distribution



All cost data reported here have been deflated with the GDP deflator with a base year of 2000. Cost data reported by the EIA were in 1993 prices and were deflated with a GDP deflator estimated in 1994 or 1995. While the methodology is crude, we employed the base 2000 deflator to inflate the EIA real data to nominal terms, and then to construct real figures in 2000 prices. Clearly, it would be better to use a vintage 1995 GDP deflator to construct nominal values, but use of a single deflator suffices to provide a comparison of our data to those reported earlier.

9.3.2 Fuel Costs

Average fuel costs per kilowatt of capacity are displayed in Figure 9.19. While the costs climbed rapidly in the early 1980s, they gradually have fallen since.

Figure 9.19: Fuel Costs

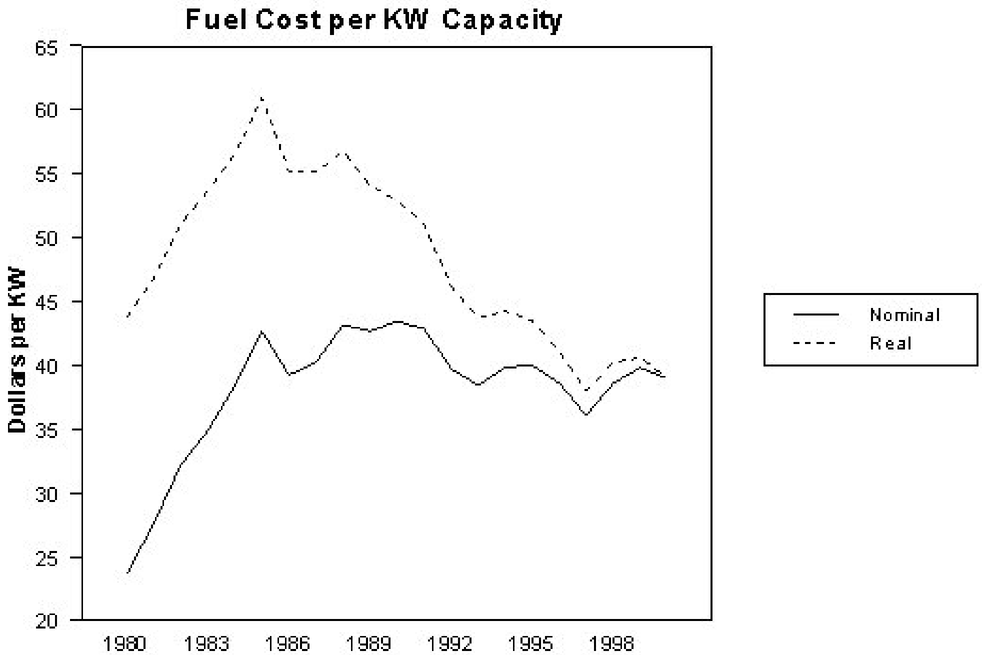
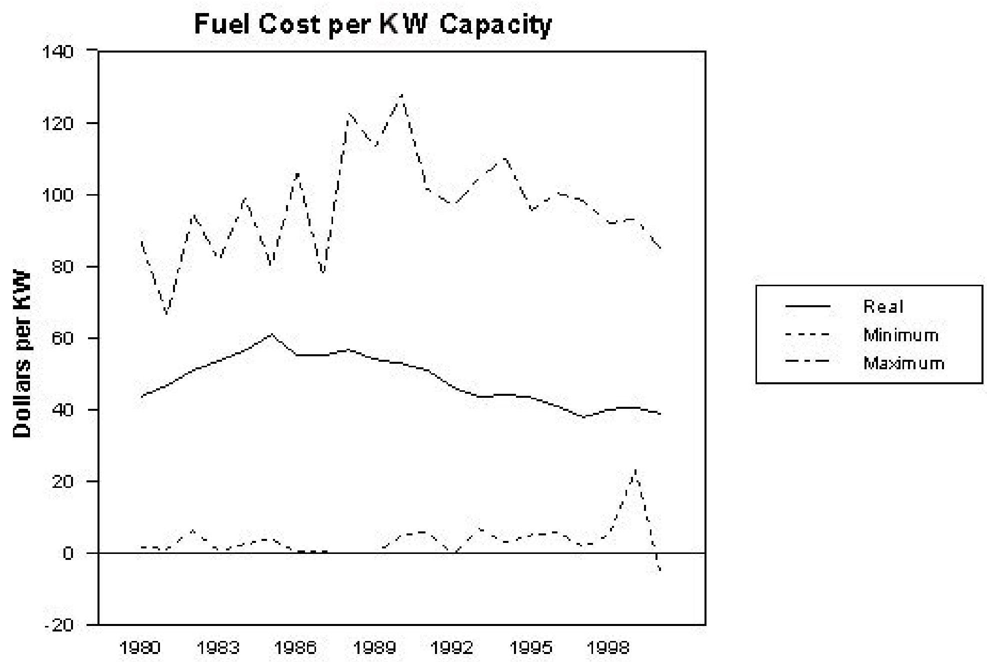


Figure 9.20 displays real average fuel costs per KW of capacity, together with the reported minimum and maximum values. Note that fuel costs peaked much earlier than operating and maintenance expenses.

Finally, note that fuel costs are capitalized. Expenditures are depreciated over a number of years, although they are displayed here in the year of purchase. Fuel rods typically remain in a plant for several refueling cycles, so that plants receive direct benefits from their investments for perhaps four to five years. For national accounting purposes, the Bureau of Economic Analysis [5] employs straight-line depreciation methods in their estimates of capital stocks, based on the standard practices of rotation and replacement of fuel rods. They assume that the average lifetime of a fuel rod is four years, although according to our data, average lifespans of three fuel cycles would correspond to about 54

Figure 9.20: Fuel Cost Distribution



months, or 4.5 years. The BEA employs Winfrey curves to calculate depreciation, assuming that the earliest retirement among a given cohort of fuel rods occurs at 45 percent of the average lifespan, and that the last rods are retired at 155 percent of the average. We duplicate an abridged version of their depreciation distribution in Table 9.2. While this depreciation schedule does not necessarily correspond to the depreciation calculations appearing on the balance sheet of the firm, it likely gives a reasonably good approximation. Note again that data series reported here makes no use of this information.

9.3.3 Capital Additions Costs

Average capital additions expenditures per kilowatt of capacity are displayed in Figure 9.21. Real costs in our data set are highly correlated with those reported

Table 9.2: Fuel Rod Depreciation

Percentage	Percent of Average Life
<45	0.0
50	1.2
75	18.7
100	53.9
125	86.3
150	98.8
155	100.0

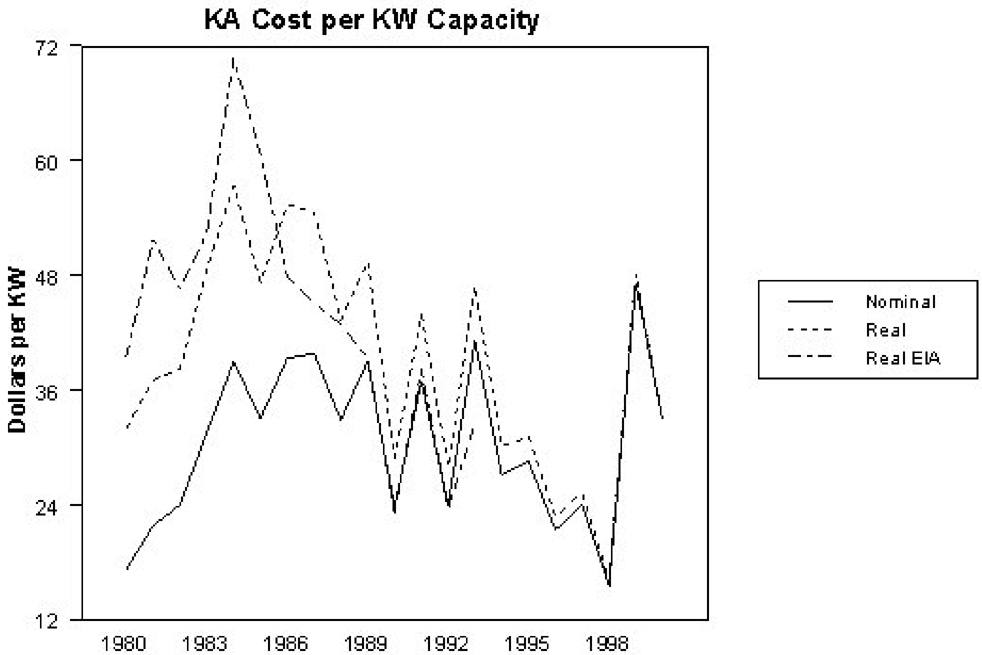
by the EIA. Such expenditures are calculated as changes in reported book value of the plants. Because of changes in the estimates and because of sales of used equipment,[8] data in some years are negative. The EIA [2] reports two reasons for negative values. First, the scrap value of replaced equipment may exceed the cost of new equipment. Second and more important are the results of changes in the plants' initial capital costs (these usually appear early in the life of the plant) and cost disallowances. These observations have been dropped from our data set. Little other manipulation of the data was done. While the EIA efforts to construct capital additions expenditures were somewhat more sophisticated, the aggregate results are quite similar.

An unfortunate characteristic of this data[9] is that all (nominal) project ex-

[8]According to the EIA [2], expenses added to this account are net of the salvage value of replaced equipment. Hence, the data reported here may understate gross expenditures on capital.

[9]See EIA [2, p. 4] for more details.

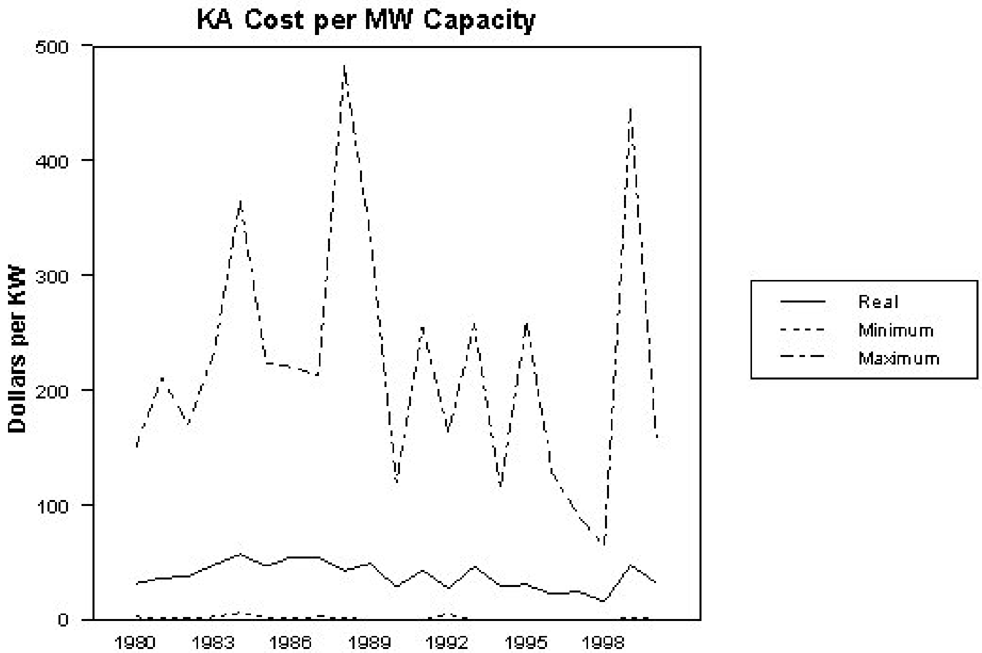
Figure 9.21: Capital Additions Costs



penditures are recorded in the year of completion. Major projects pose problems when they span multiple years, for two reasons. First, if a plant temporarily closes in order to repair or upgrade equipment, the costs might not be recorded until a following year. Second, in times of rapid factor price growth, the reporting of cumulative nominal expenses over periods with varying prices will distort our constructed real data.

Figure 9.22 displays average real capital additions costs per KW of capacity, together with minimum and maximum values. Note that maximum costs peaked in the mid to late 1980s, and generally they trended lower since then. The apparent spike near the end of the sample period needs further investigation to determine whether it is factual or indicative of a problem with the data development.

Figure 9.22: Capital Additions Cost Distribution



The EIA [2] summarizes capital additions expenses as three types. First, there are retrofits mandated by NRC regulators. Second are the repairs required to keep a plant in operation. Finally, capital additions expenses may be voluntary measures to improve performance. The EIA reports that about half of capital additions projects were forced by regulators, and about half were necessary repairs. Few were voluntary. It is likely that plants voluntarily initiated many projects since the EIA report, however, since the NRC began a program to allow capacity uprates after required investments and inspections.

The EIA [2] reports efforts by the NRC to limit the number of backfits (mandated changes in equipment and plant design) as a likely cause for the reduction in capital additions costs. The changes were initiated in 1988. While costs began falling several years earlier, the trend continued following the policy changes.

9.4 Revenue

Unfortunately, revenue data are not reported either for individual plants or sites, nor are revenue data reported frequently for the industry. Indeed, the means of assigning revenue to electricity generators is difficult to establish, for generation is but one of several stages of production. We might conclude from the literature that it is impossible to separate analysis of generation from transmission and distribution,[10] and perhaps we cannot consider generation by nuclear power in isolation from other technologies. This in turn might indicate that there is no hope of assigning revenue to nuclear power generation, since the electricity industry is integrated both vertically and horizontally.

Instead, we rely on one of few sources of revenue information. The Census Bureau [60, 61] began to publish revenue data for nuclear power generation in 1997; they again published data in 2002. Unfortunately, they published detailed data only for Pennsylvania, citing confidentiality reasons for suppressing data for other states. The revenue data for Pennsylvania and the U.S. for 1997 and again for the U.S. in 2002 are displayed in Table 9.3, where the data is in thousands of current dollars. The table also displays output data, from the EIA, in millions

[10] Lee [32] reports that generation, transmission, and distribution are not separable stages of production. He reports an efficiency loss of about 4% if generation was separated from the other processes. Nelson and Primeaux [40] cite several studies that reject vertical separability. Hayashi, et al [24] report similar findings. On a related matter, Karlson [31] reports that electricity production is not separable across purchaser types; i.e., costs for sales to residential customers are not separable from sales to commercial or industrial customers.

Table 9.3: Revenue Shares

	Year	Revenue	Output	Implied Price	Retail	Rev.Shr.
PA	1997	$2,334,445k	67,655m	$0.0345	$0.0592	0.58277
USA	1997	$13,966,616k	628,644m	$0.0222	$0.0453	0.49044
USA	2002	$11,908,796k	780,220m	$0.0153	$0.0488	0.45527

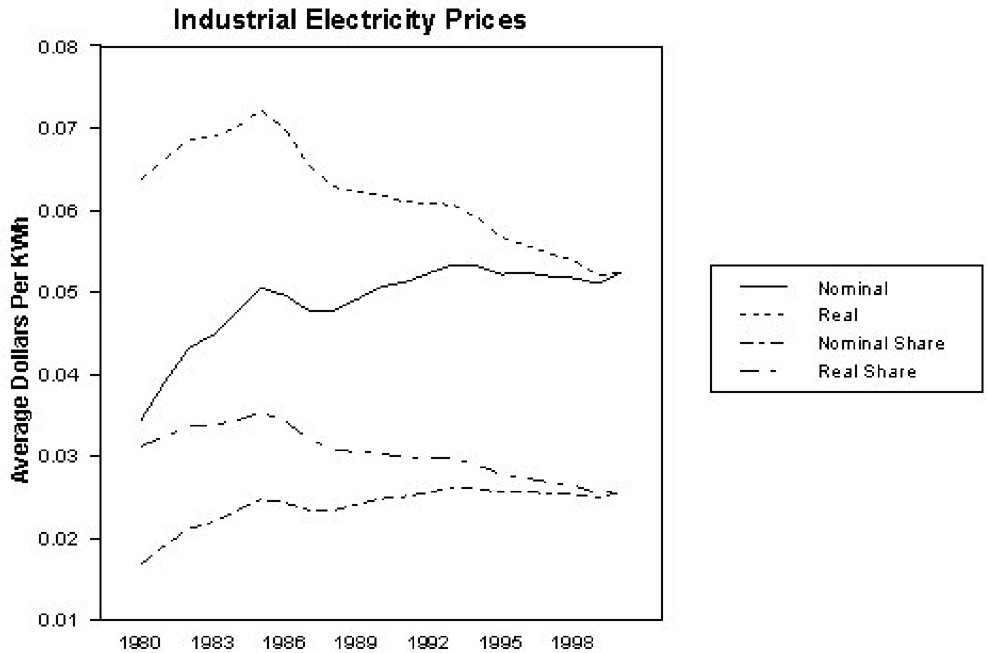
of kilowatt-hours, along with EIA industrial retail prices in current dollars per kilowatt-hour. Finally, the revenue shares assigned to generation are computed and displayed. The national data imply that nuclear power generation is assigned 45-49% of sales revenue, and data for Pennsylvania[11] put the number at 58%.

We began the process of computing revenue data for nuclear power plants by obtaining monthly producer price indexes for industrial electricity purchases for nine regions comprising the United States. We converted these indexes into dollars per kilowatt-hour by estimating regional prices in 1990 using state revenue and output data from the EIA. We constructed weighted averages of unit revenues for the power generated by nuclear power plants. We did so by multiplying monthly, plant level output data by our constructed price series, using price data for the relevant region. After dividing by total monthly output and then aggregating over time, we obtain annual price estimates. Average prices are displayed in Figure 9.23 in nominal terms and relative to the GDP deflator. While it would be more clear with a longer time series, note that relative prices peaked in the mid1980s and then began a steady decline.[12] We then constructed

[11] The electricity price figure is from the Department of Energy and is the 1995 industrial price.

[12] See, Davis, et al [14] for a discussion of this phenomenon and other history of electricity prices.

Figure 9.23: Prices

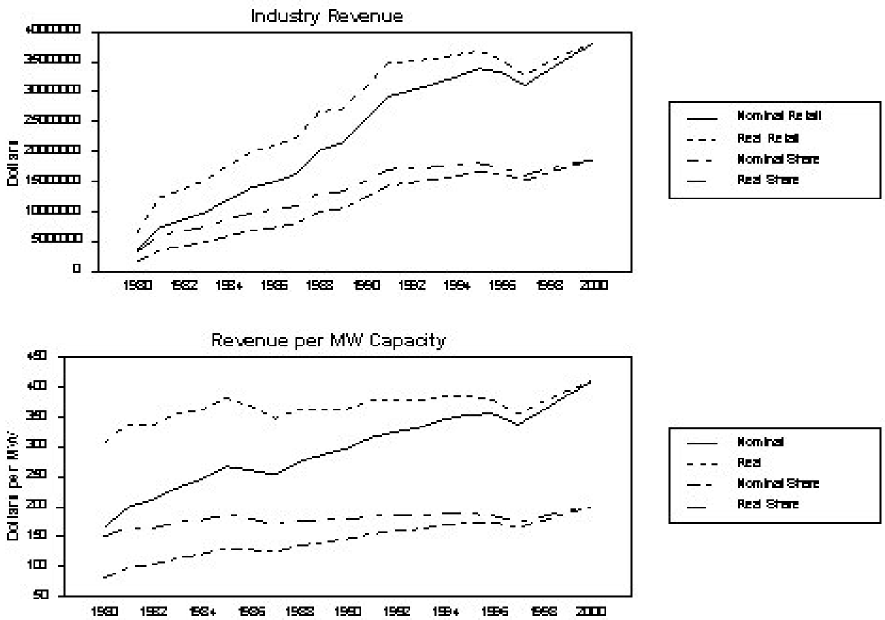


series for unit revenues received by power plant operators by multiplying the retail price by the 1997 unit revenue share reported in Table 9.3. Average revenue estimates for electricity generation by nuclear power plants are displayed in Figure 9.23.

Figure 9.24 displays aggregate revenue in nominal and real levels. Both estimated retail sales (assuming only industrial customers) and revenues assigned to nuclear generation are displayed. The second figure reports the same information in dollars per kilowatt of capacity.

Some of the revenue growth is explained by increases in output. Such growth in the 1980s primarily was due to additional units coming online. In the 1990s, such growth primarily was due to increased reliability and other improvements in capacity utilization. A second explanation for revenue growth in the early

Figure 9.24: Revenue



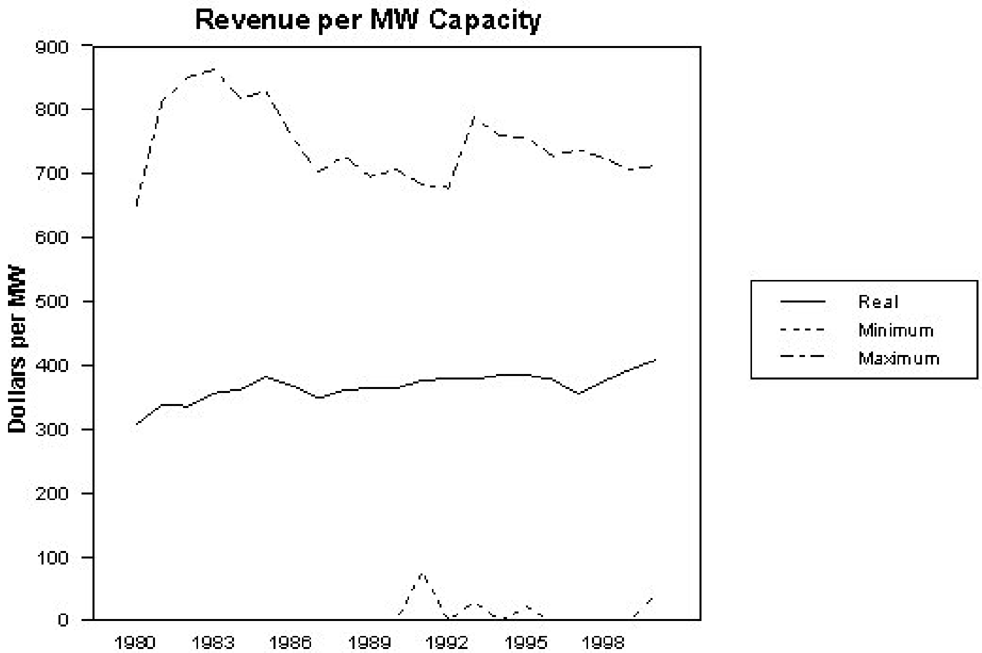
1980s is price growth. This is seen most clearly in the real revenue per kilowatt data, which grows steadily before leveling at about 1985.

Figure 9.25 displays the distribution of constructed revenue data per KW of capacity, including the average, industry minimum, and industry maximum for each year.

9.5 Profits

By combining the revenue and cost data reported above, we estimate profits for the nuclear power industry. Certainly, this exercise at best is uncertain and we face many difficulties. At most, we hope to get a reasonable idea of trends in the industry.

Figure 9.25: Revenue Distribution



Of many difficulties facing us, we mention three. First, the EIA [2] reports that operating and maintenance costs were under-reported by about 30%; we did not adjust them in the data reported here. Second, capital additions costs are depreciated over many years, but they are subtracted immediately in the following calculations. Finally, we made no attempt to account for taxes paid by the industry, nor did we adjust prices to account for taxes paid by the customers on electricity purchases. See the EIA study for a discussion of other problems with the cost data.

Estimated profits per kilowatt of plant capacity are reported in Figure 9.26. While we must be cautious in our interpretation of the data, given the concerns listed above and many others, the qualitative results seem plausible. Figure 9.27 displays the distribution of profits per KW.

Figure 9.26: Profits

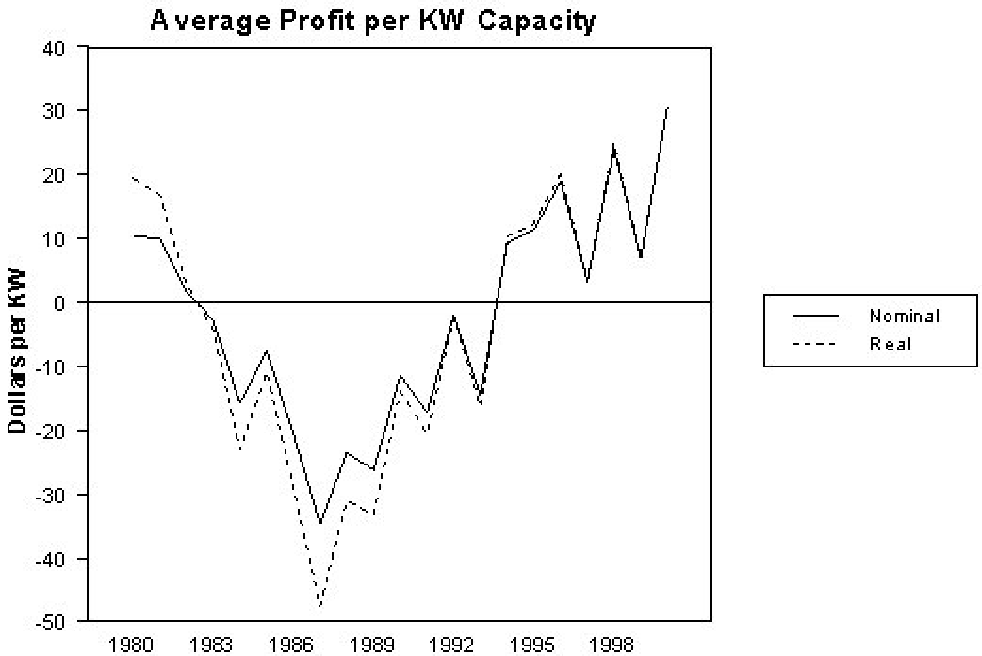
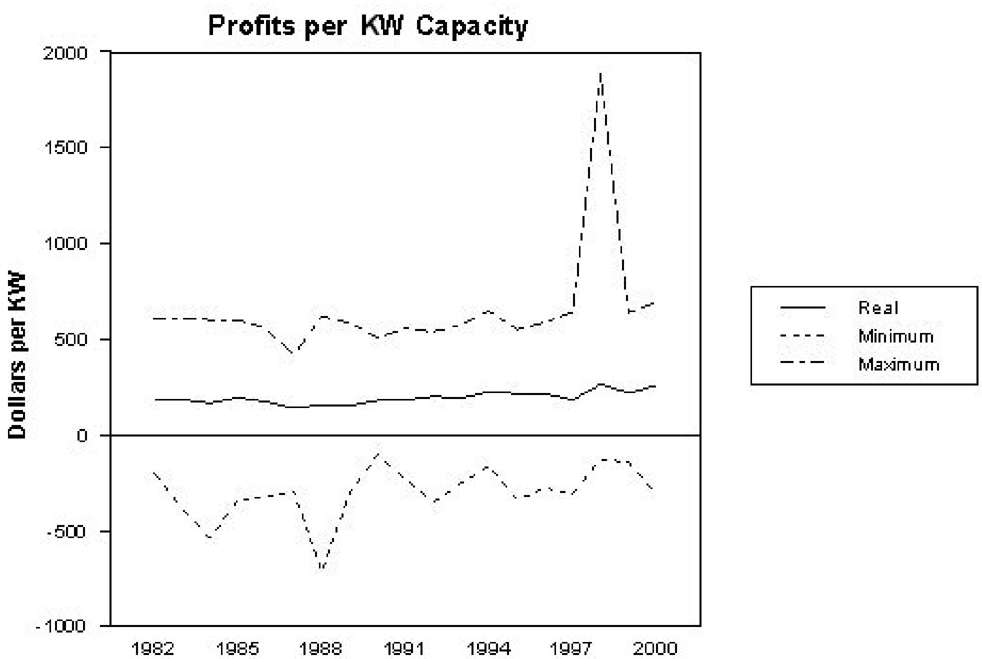


Figure 9.27: Profits Distribution



A review of the industry's history reveals that the industry was profitable in the early years. Things began to unravel in the 1970s, however. Environmental, safety, and other regulations extended construction times far beyond those expected. Extended construction times, whether due to heightened regulation or other reasons, became still more expensive with soaring interest rates. Even after the plants were constructed, operating expenses proved far higher than expected. Finally, a dramatic reduction in 1973 of the growth rate of electricity demand reduced the need for new base load generating capacity. Such woes were compounded by the reaction to the 1979 accident in Unit 2 of the Three Mile Island power plant and the 1986 accident at the Chernobyl power plant. These troubles are revealed in the declining profits shown in Figure 9.26. Rothwell and Eastman [51] report that the realized rate of return was less than the cost of capital from 1979 to 1981 for US electric utilities. Many plants closed in the unprofitable 1980s and early 1990s, a period corresponding to negative profits according to our calculations.

While trouble continued through the early 1990s, profits followed an upward trend since the mid1980s. It seems likely that some of the increase in profits per kilowatt may be explained by the voluntary removal of unprofitable, troublesome plants from the market. Other explanations include learning within the industry, especially as the industry consolidated and large companies purchased multiple plants. Regulators also learned, and they tailored their policies to achieve safety and other standards while enabling companies to reduce costs.[13]

We made little attempt to analyze the effects of capacity uprates. Such uprates promise additional future capacity in return for capital investment today.

[13] See the EIA cost analysis [2] for details and analysis.

Many plant owners are making these investments, and future studies will be needed to determine whether profits improve accordingly.

9.6 Decommissioning Costs

Little data is available for decommissioning costs, although a number of plants have been or are being decommissioned. A list of most commercial plants that are being decommissioned is presented in Appendix 9.8.1. Available cost estimates range between \$190 million and \$420 million. The GAO [3] reports that costs are expected to range between \$300m and \$400m in today's dollars. Dubin and Rothwell [17] cite costs of about \$1b for the cleanup of the damaged Three Mile Island Unit 2 reactor.

9.7 Conclusions

This concludes a brief review of monthly operating and annual cost and revenue data for the U.S. nuclear power industry. We saw that industry performance has improved dramatically. This is seen clearly as increases in the fraction of time plants operate. We also saw that costs have fallen, in real terms, per unit of plant capacity. The nuclear industry now appears far more profitable than in the 1980s.

Our data set is sufficiently broad to allow much further analysis. Unfortunately, though, some problems remain. The operating data summarized here in fact are "model" data constructed for use in a dynamic programming model.[14]

[14] See Rust and Rothwell [56] for a detailed description of the data construction process, or see the next chapter for a shorter description of the result.

Use of model data is not optimal for purposes of summarizing data as we did in this chapter. Refinement of this work likely will include replacement of model data with "raw" data.

One of the primary problems with use of model data is that it is difficult to form aggregates and averages. Construction of a matched data set, where monthly plant data is matched to annual site data, requires several aggregation processes. At this point, though, most of the data construction work is complete. Despite the difficulties noted, we are poised to begin examination of our potentially rich matched data set.

9.8 Appendix

9.8.1 Decommissioned Reactors

The following reactors were decommissioned. Reactors that were shut down before the beginning or after the end of our data set might not be listed.

Site	Unit	Month	Year	Costs
Big Rock Point		8	1997	
Dresden	1	8	1978	
Fermi	1	11	1972	
Fort St. Vrain			1989	<$189m
Haddam Neck		7	1997	
Humboldt Bay	3	7	1976	
Indian Point	1	10	1974	
LaCrosse		4	1987	
Maine Yankee		8	1997	$357m
Millstone	1	11	1997	
Peach Bottom	1	10	1974	
Rancho Seco		6	1989	
San Onofre	1	11	1992	
Three Mile Island	2	3	1979	≈$1b
Trojan		11	1992	$198m
Vallecitos			1963	
Yankee Rowe		10	1991	
Zion	1	2	1997	$417m
Zion	2	9	1996	$417m

1. Data for Fort St. Vrain are from Nuclear Energy Institute, August 1, 2006

2. Data for Trojan is in 1993 dollars, and data for Maine Yankee is in 1997 dollars. Cost estimates for the Zion plants were reported as $834m for closing both. Both are reported in a report by the GAO [3].

3. The estimate for Three Mile Island Unit 2 was provided in Dubin and Rothwell [17].

Chapter 10

A Model of Plant Operations

10.1 Introduction

How do nuclear power plant operators decide when to decommission their plants? How has their behavior been affected by the tumultuous regulatory changes in the 1980s? Can we detect effects on behavior of liability protections?

To pursue answers to such questions, we need to construct a model of nuclear power plant operators. This model will seek to reproduce operators' decisions and to determine and understand the key factors upon which those decisions are based. Nuclear plants are very expensive to build, to operate, and to repair. Consequences of poor decisions and reckless actions can be catastrophic both to equipment and ultimately to the surrounding community. For these reasons, operators carefully and consistently must determine optimal operating strategies, taking into account not only current conditions and potential short-run profits but also the effects of current decisions on the future state of the plant.

We begin our work with an existing model of plant operators, and we extend this model in several directions. Our goal is not simply to add detail, for there is no end to the list of relevant and important technological and economic details that might be included. Instead, we seek to link the existing models, which specify rather autonomous firms, to the rest of the world. In particular, we consider the effects of electricity market conditions on the behavior of operators, and we explicitly account for liability regulations imposed by industry regulators.

We do not offer a complete model here, in which other economic agents and regulators are affected by and respond to operators' behavior. In the first section of this document, we developed such a model, though operators described there were fairly primitive. Here, we offer much greater detail on operators, but little about their interaction with others. We have in mind that future work should join these efforts.

We find that our dynamic programming model is a useful tool to understand and predict the behavior of nuclear power plant operators. At least when using aggregate measures, the model is able to mimic accurately the choices made by operators, given current conditions of the plants. Historical simulations also suggest that our model accurately predicts the behavior of operators. We find that electricity prices and expected changes in prices affect significantly the level of profits and correspondingly the optimal plant activities.

We extend and apply the model in several ways. First, we consider the effects on plant values of 20-year extensions to operating licenses. We find that the values of plants increase significantly with potentially longer operating horizons. We found similar results in the application of our industry model reported in Chapter 5. Second, we extend the model to include the possibility of catastrophic accidents with destruction of the plants and liability for offsite damages. While the ability of the model to fit the data changes little, the inclusion of risk and liability concerns does affect relative values of feasible choices and thus affects predicted behavior. Finally, we employ the model in historical simulations and forecasts under various assumptions.

We do not explicitly account for regulation in this model. We discuss potential problems of this omission. We base the analysis on comparisons of two models from Chapter 2. By comparing results for a model with both liabiltiy and regulation to results for a model with only liability, we hope to learn of potential problems with our dynamic programming work. Our analysis helps us to understand and interpret the parameter estimates and predictions of the present model.

We conclude with a number of possible extensions to our work. An appendix to this document describes software developed for use in this project that can be employed in the construction, estimation, and simulation of similar dynamic programming models.

10.1.1 Background: The Rust-Rothwell Model

In a series of papers [54, 55, 56], Rust and Rothwell provide a summary of the nuclear power industry and develop a model of plant operations. Their work [55] was used to model changes in operations following the TMI accident in 1979, and their work [56] was used to predict permanent closure of nuclear power plants (NPP) under various NRC licensing plans. Their model accurately predicts lengthening of average operating spells (time between refueling shutdowns) from about 12 months to about 18 months. This may reflect changes in regulatory policy or a reevaluation of operating strategies. In the second paper, plants are modeled under two licensing regimes. First, plants are permitted to operate only until the expiration of their initial 40-year operating licenses. Next, the model is solved with 20-year extensions to each license. Their work shows that extensions typically improve the value of operations at each plant, so that plants owners are less inclined to exit the market prematurely given unfavorable economic conditions and, for this reason, many should find it optimal to seek the extensions.

NPPs are modeled as traditional profit maximizers even though they operated under regulated prices until recently. This may be justified by noting their increasing inclination to minimize costs given the increasing likelihood of cost disallowances by PUC's, falling prices of fossil fuels, and the introduction of incentive-based regulations (Rust and Rothwell [54], EIA [2], Che and Rothwell [12]).

Rust and Rothwell summarize the model as follows: "In each period the operator decides whether to run the reactor, to shut it down for preventative maintenance or refueling, or permanently close the plant for decommissioning" [56]. At the beginning of each period, each plant is in one of three conditions (or states or spells): an operating spell, a refueling spell, or a major problem spell. Given these and other conditions and the probabilities of moving from the current state to each other state given the actions of the operator, the operator chooses the option that is most likely to maximize the plant's value. Once the expected value of future operations falls below the cost of decommissioning, plant operators permanently close the plants.

10.2 Features and Contributions

Our work extends existing literature and models primarily in three areas. First, we update existing data sets to include monthly data from 1975 to 2003. We described this data in Chapter 9. Second, we consider the effects of electricity prices on operator behavior. We believe that price trends and seasonal patterns may have important effects on profitability and on the timing of plant procedures. We reported our development and analysis of price data in Chapter 8. Finally, we consider the effects of liability on profits and behavior.

Our efforts are designed and intended to support many other features and extensions of the current work. These efforts include the design of our model, collection and construction of data, and the software designed and employed in the construction and estimation of our model. We mention some of the intended extensions at the end of this chapter.

10.2.1 Data Extensions

The data set developed and employed here updates the data constructed by Rust and Rothwell [54, 56, 55].[1] Their data extended from January, 1975 to December, 1994. The data in this set extend their panel by 108 months. More important than this number itself is that these months reveal whether trends that appeared to begin in the Rust-Rothwell sample have continued. These trends include increased output and plant availability, improved reliability, and moderating cost growth.

[1] The data used to construct this set were provided by Geoffrey Rothwell of Stanford University.

The operating data comprise an unbalanced panel spanning the months from January, 1975 to December, 2003. One hundred sixteen plants are represented in the sample, with a total of 31,218 reactor-month observations in the set of data available to the model. Most, if not all, plants are represented in the data, although observations tend to be lost near the beginning and end of reactor life. In the latter years of the sample, all 104 of operational American reactors are represented in the sample. In Chapter 9, we saw that performance and profitability improved dramatically for the nuclear power industry since the 1980s. We saw great improvement in plant reliability and efficiency, so that plants operate at full capacity most of the time. Average refueling times fell sharply, and by nearly every observed measure performance has improved.

10.2.2 Stochastic Prices

Primarily because they lacked adequate accounting data, Rust and Rothwell simplified the profit function in their model to employ only operating history data. Profit-maximizing behavior was assumed, so that profits could be inferred from available operating data. However, their study did not have any direct observation of prices or revenue, nor observations of costs, so profits were "estimated" as a function of observable operating state variables, and in particular the utilization rate of the reactor (i.e. the fraction of the potential output given the rated generation capacity that actually was generated during the period). The following simplifications were necessary in their work for identification given the data limitations. First, the present value of costs of closing a plant were normalized to zero. Second, electricity prices were assumed to have zero trend, though the possibility of seasonal variation was allowed, and the profit function was divided by maximum revenues, or price times output given the choice of 100 percent plant availability in the current month. Finally, the normalized error term ϵ, which is defined below, was assumed to have a Type 1 extreme value distribution. The assumption of zero price growth was defended by price stability over the sample period and DOE projections of slow demand growth in coming decades. The normalization also requires that plant size does not affect optimal operating strategies; this assumption ignores the heterogeneity revealed elsewhere [54, page 23]. Whether these assumptions significantly limit the ability of the model to fit the data must be tested. We examine the constant price assumption by extending the model to allow for changing prices and then re-estimating the parameters. The results are compared to the Rust-Rothwell results with stationary prices.

Rust and Rothwell incorporated monthly dummy variables in their normalized profit function. These allow for a variety of seasonal effects, but perhaps most importantly they allow for seasonal price changes. Such changes especially have been important since the mid1980s, as is shown elsewhere in our work on electricity prices. These price cycles reflect changes in seasonal demand, which tends to be low in the spring and fall. These periods of excess supply allow operators to take plants off-line for refueling and repairs. As was shown in Chapter 9, plants typically refueled every twelve months in the 1970s and early 1980s before switching to 18-month refueling cycles. These refueling periods usually are scheduled for the spring or fall, but may be observed at other times to correspond to forced outages. We saw earlier that operators have become far more strict in their adherence to 12 or 18-month cycles, as we observe relatively fewer shutdowns in other months. This may be due, in part, to increased seasonal electricity price volatility beginning in the mid1980s, as we reported earlier. Plants now have greater incentive to operate in seasons with high prices and relatively less incentive to operate otherwise.

Nominal electricity rates have been rising very slowly since the mid1980s, while relative prices have been falling gradually. These facts support the zero-trend assumption for electricity prices in the optimal lifetime study [56]. Estimation was performed with data from January, 1989 to December, 1994. Both nominal prices and relative prices were stable over the estimation range, and price stability continued throughout at least the first 10 years of the forecast. Hence, the zero price growth assumption seems justified for that study.

The price data for relative and nominal prices tell a different story for electricity prices between 1973 and 1985. Electricity prices grew rapidly in this period before slowing suddenly in the mid1980s.[2] This suggests that the constant-price assumption may have been troublesome in the Optimal Response study (Rust and Rothwell [55]). The study attempted to test the behavior of power plant operators for evidence of significant changes following the 1979 accident at the Three Mile Island (TMI) power plant. To do so, Rust and Rothwell (RR) defined three periods: the preTMI period from 1975 to 1979, the transition period from 1980 to 1983, and the postTMI period from 1984 to 1993. To test for significant changes in behavior, RR estimated the model parameters first with data from the preTMI period and then again with data from the postTMI period. They found that the two parameter sets were significantly different, and they concluded that the changes in behavior were due to changes in the regulatory

[2]We investigated these matters in Chapter 8. We find evidence of a significant structural shift in electricity prices in the mid1980s.

environment. Unfortunately, they did not take into account the effects on behavior of the sudden shift in price growth in the early to mid1980s. These price changes might have lowered current-period profits significantly. If the changes in the price structure were believed to be permanent, as they proved to be, then the effect on the expected present value of future profits would have been still more dramatic. Hence, the fall in the value of plant operations, as measured by RR, cannot be explained fully by increased stringency of regulatory policies. Instead, some of the changes likely would have occurred without nuclear regulatory policy changes because of structural shifts in electricity prices.

A benefit of incorporating electricity prices in the profit function is that it allows profits to be defined in terms of dollars. Setting the units in dollars will ease later extensions to incorporate other financial data. It also eases the incorporation and calibration of other factors, such as liability under the Price-Anderson policies. A significant problem remains, however. We do not observe plant revenue, and thus we do not know the per-unit revenue level received by nuclear power plant operators. Instead, we observe retail electricity rates and attempt to construct unit revenues from these observed prices and supporting information gleaned elsewhere. This work is described in Chapter 9, though annualized, site-level figures were reported there. The construction methods for our monthly site-level data follows the same process that was described there.

The extension also allows the testing of various hypotheses regarding the effects of price changes. This especially may be important in forecasting plant closure under various price projections. Perhaps the most pressing need for relaxing the constant-price assumption is to account for changing price structures. We must return to the optimal response study to disentangle the effects of regulations from those of other economic phenomena.

10.2.3 Accounting for Physical Risk and Liability Caps

The Rust-Rothwell model does not account explicitly for the possibility of serious accidents. The risk is captured in part by the possibility of a "major problem spell" which requires shutdown for an extended period and, given such a shutdown, a positive probability of never returning to service. This ignores costs of cleanup and compensation, and it ignores the effect of an accident at one plant on the rest of the industry. Dubin and Rothwell [16] were first to calculate a probability distribution and (local) expected costs and liability of a serious accident. Heyes and Heyes [29, 27] correct the earlier calculations and extend the analysis to Canadian plants; the corrections are acknowledged in Rothwell [49]. Harding [23] provides additional detail and analysis. Other problems with the original Dubin-Rothwell work are addressed in earlier chapters, along with several extensions.

In all countries with significant commercial nuclear power production, governments have capped liability for offsite losses. In 2001, the US House of Representatives passed an extension of the Price-Anderson Act, which currently limits liability to $88 million per plant, capping industry liability at about $10 billion per accident; each plant may be liable for accidents at other plants, up to the $88 million limit for each plant (Rothwell [50], Energy Outlook [4, p. 18, 21]). Such payments are required if damages exceed the mandated private insurance coverage of $200 million per plant. In Chapter 3, we report implicit subsidy calculations between $5,000 and $5 million per reactor year, depending on the assumption, though significant questions remain. While the cap and corresponding subsidies are set at relatively low levels, the liability is nontrivial, and these amounts do not include onsite damages and loss of the damaged reactor and possibly other reactors at the site. Including the possibility of serious accidents may increase the likelihood of permanent closure, increase the likelihood of temporary closure for maintenance and repairs, and increase expenditures on maintenance (Heyes and Heyes [29]). Heyes and Heyes claim that liability caps lead to 1) inefficiently low incentives to a) prevent accidents and b) prevent escalation of damage given the occurrence of a serious accident, and 2) the encouragement of excess capacity.

Nearly all estimates related to accident probabilities and potential damage assessments are difficult to calculate, require many simplifying assumptions, and are subject to much criticism. In addition, potential offsite damages vary widely and depend on factors that vary across plants and time. These factors include property values and population density in surrounding regions and weather. Adding to the difficulty of calibrating probability and liability parameters are the profit function normalizations listed above. Still, we might select several parameter vectors and evaluate corresponding model results in an attempt to determine the effect on operators' behavior of various liability and risk levels.

10.3 The Model

There are two sets of variables in the model.[3] First, there are two vectors of state variables: a vector of observed variables x_t and a vector of state variables ϵ_t that

[3] Rust-Rothwell employed two versions of their model in [55] and [56]. We follow the extended version described in [56].

are observed by the operators but not by the economist. Observed state variables include electricity prices, indicators of conditions at the plant, and the age of the plant. These variables evolve either according to deterministic rules encoded in the model or according to stochastic processes that are estimated. Unobserved state variables are assumed to exist in order to account for deviations in the data between model predictions and reality. The second set of variables are choice variables. This vector includes permanent closure, refueling, and operating at a chosen utilization level.

After observing x_t and ϵ_t, operators choose an action from vector a_t. Actions are chosen to maximize the nuclear power plant's (NPP's) net present value V_0

$$V_0\left(x, \epsilon\right) = \max_{\left(\alpha_0, \ldots, \alpha_T\right)} \sum_{t=0}^{T} \beta^t E_{0,t} \left\{\pi\left(\alpha_t, x_t, \epsilon_t\right) \mid x_0 = x, \epsilon_t = \epsilon\right\} \qquad (10.1)$$

where β is the discount factor (profits received in the near future are preferred to profits received in the distant future). $E_{0,t}$ denotes expectations at time 0 of profits at time t. π is the current period profit function which has the representation $\pi(a, x, \epsilon) = \mu(a, x, \phi) + \epsilon(a)$, where ϕ is a parameter vector that must be estimated; details of this profit function will be given later. The state variables x_t and ϵ_t change according to Markov processes with the transition density $\lambda\left(x_{t+1}, \epsilon_{t+1} \mid x_t, \epsilon_t, \alpha_t\right)$. Lifetimes T are limited by operating licenses granted by the Nuclear Regulatory Commission (NRC), which initially were granted for 40 years; operators now may apply for 20 year extensions. The vector x is defined as $x_t = (r_t, f_t, d_t)$, where r is the type of spell, f is an observed signal of possible events not under the operator's control (the operator also observes the signal ϵ) that indicate operating conditions for the present period, and d indicates the present duration of the current spell. (A summary of these variables and their evolution, taken from [56], will be presented in following paragraphs.) Actions are chosen from vector A that includes permanent closure of the plant, shutting down to refuel, or operation at a capacity between, and including, 0 and 100 percent. The current state of a plant may limit its set of feasible actions, and regulation further may restrict the set; we address the former but not the latter concern. The laws of motion governing states r and d are deterministic, but the law of motion for f is probabilistic; its distribution ρ must be estimated.

The state variable f_t is a stochastic signal of conditions in the current period. The four possible values for f_t are interpreted as follows:

$$f_t = \begin{cases} 1 & \text{no forced outage this period} \\ 2 & \text{one or more forced outages this period} \\ 3 & \text{if r=1, enter a major problem spell} \\ & \text{if r=2, continue refueling} \\ & \text{if r=3, the major problem spell continues} \\ 4 & \text{ a major accident occurs.} \end{cases}$$

The probability distribution for f is determined by the estimation of parameters for a set of five binary logit equations $g(\cdot)$: 1) the probability of forced outages during an operating spell, 2) the probability of forced outages immediately following a refueling spell, 3) the probability of a major problem developing during an operating spell, 4) the probability of exiting a major problem spell and resuming operations, and 5) the probability of exiting a refueling spell and resuming operations. In an extended version of the model, we add to these a calibrated probability of a major accident. The estimated probabilities are parameterized as

$$\rho_i(x_t, a_t, t) = \frac{exp\{g(x_t, a_t, t, \psi_i)\}}{1 + exp\{g(x_t, a_t, t, \psi_i)\}}$$

where i indexes the five probabilities and ψ is a parameter vector.

The state variable r_t is the type of spell in the previous period. Possible values are given as

$$r_t = \begin{cases} 1 & \text{if the previous period was part of a major problem spell} \\ 2 & \text{if the previous period was part of a refueling spell} \\ 3 & \text{if the previous period was part of an operating spell.} \end{cases}$$

The variable evolves according to the equation

$$r_{t+1} = \begin{cases} 1 & \text{if } f_t = 3 \text{ and } (r_t = 3 \text{ or } r_t = 1) \\ 2 & \text{if } (a_t = 2 \text{ and } f_t < 3 \text{ and } r_t = 3) \text{ or } (r_t = 2 \text{ and } f_t = 3) \\ 3 & \text{if } a_t > 2 \text{ and } f_t < 3. \end{cases}$$

The state variable d_t is the length of the spell as of the previous period. The interpretation of this variable depends on the type of spell last period:

if r_t=1 d_t is the length of a major problem spell

if r_t=2 d_t is the length of a refueling spell

if r_t=3 d_t is the length of an operating spell.

The variable evolves according to

$$d_{t+1} = \begin{cases} d_t + 1\{a_t \neq 2 \text{ and } r_t \neq 3\} & \text{if } r_{t+1} = r_t \\ 1 & \text{otherwise.} \end{cases}$$

Rust and Rothwell assume that electricity prices have no trend, though they might exhibit seasonal variation. The assumption is relaxed in this paper. We select a parsimonious autoregression equation for prices

$$p_{t+1} = \alpha + \alpha_{t+1} + \eta p_t + \varepsilon_{t+1}$$

where α is a constant, α_{t+1} is a parameter for monthly dummy variables, η is the parameter on the lagged dependent variable, and ε is a stochastic error term. The dependent variable p is in logarithms.

The set of feasible actions is determined by the current combination of state variables. Depending on the current state of the plant, certain operations may not be possible. Such choices are eliminated from consideration in the model. The complete choice set is:

$$a_t = \begin{cases} 1 & \text{Permanently close the plant} \\ 2 & \text{Refuel the plant} \\ 3 & \text{Temporarily shut down the plant} \\ 4 & \text{utilization between [1,25]} \\ 5 & \text{utilization between [26,50]} \\ 6 & \text{utilization between [51,75]} \\ 7 & \text{utilization between [76,99]} \\ 8 & \text{utilization} = 100 \end{cases}$$

The set of possible actions may be restricted further by regulators. We discuss the possibility later in this chapter, but this model does not account explicitly for regulatory intervention. This may prove to be problematic. Our maintained assumption is that actions are chosen to maximize profits while taking into account solely the technical and economic environment. Surely actions sometimes are chosen to comply with regulations while technical conditions and economics would seem to lead to a different choice.

The portion of the profit function μ that is composed of potentially observable variables is defined as

$$\mu(\alpha, x_t, \phi) = \begin{cases} -\phi_c & \text{if } a_t = 1 \text{ (close the plant)} \\ -c_r\left(x_t, \phi_r\right) & \text{if } a_t = 2 \text{ (refuel plant)} \\ p_t u\left(a_t\right) - c_O\left(x_t, a_t, \phi_O\right) & \text{if } a_t > 2 \text{ (operate at level } a_t\text{)} \end{cases}$$

where ϕ_c is the present value of decommissioning costs, c_r is the expected cost of refueling, c_O is the expected costs of operating at capacity a, p_t is the market price of electricity, and u is the utilization rate given the choice of availability (0–100%). With appropriate assumptions, conditional choice probabilities for each action, given the current state, can be inferred from the expected value function

$$v_t\left(x, a\right) = \mu\left(x, a, \phi\right) + \beta \int_{x'} \left[\log \sum_{a' \in A(x')} \exp\left\{v_{t+1}\left(x', a'\right)\right\}\right] p\left(dx' \mid x, a, \varphi\right) \tag{10.2}$$

where A_t is the set of feasible actions. The choice probabilities are

$$P_t\left(a|x\right) = \frac{\exp\left\{v_t\left(x, a\right)\right\}}{\sum_{a' \in A_t(x')} \exp\left\{v_t\left(x, a'\right)\right\}}. \tag{10.3}$$

The dynamic programming model is solved by backward induction using Equation 10.2. The model first is solved for the final period where the right-hand-side contains only μ (the remaining term is zero since there can be no production without an operating license). The corresponding left-hand side for the final period enters the equation for the previous period. The process continues until the current period is reached. Parameters in the profit function, the laws of motion for state variables, and the discount rate are estimated by maximum likelihood techniques that seek to reproduce actual operating histories with model simulations.

The log-likelihood function is

$$\ln\left(L_\theta\right) = \sum_{t=1}^{T}\sum_{i=1}^{M}\left\{\begin{array}{l} \ln\left[P\left(a_{t,i} \mid x_{t,m}, p_{t,i}, \phi\right)\right] \\ + \ln\left[\xi\left(x_{t,i} \mid x_{t-1,i}, a_{t-1,i}, \psi\right)\right] \\ + \ln\left[\zeta\left(p_{t,i} \mid p_{t-1,i}, \psi\right)\right] \end{array}\right\}$$

The log-likelihood is composed of three terms. The first is the predicted probability that the observed action would be chosen. The second is the probability that the observed transition of the discrete stochastic state variables would be realized. The final term is the transition density for the evolution of the continuous price series. These terms are added across time and across plants to form the log-likelihood.

The derivative of the log-likelihood function is

$$\frac{\delta \ln\left(L_\theta\right)}{\delta\theta} = \sum_{t=1}^{T}\sum_{i=1}^{M}\left\{\begin{array}{l} \left[\begin{array}{l} \frac{\delta V_t\left(a_{t,i}, x_{t,i}, p_{t,i}\right)}{\delta\theta} \\ - \sum\limits_{a' \in A\left(x_{t,i}\right)}\left\{\frac{\delta V_t\left(a'_{t,i}, x_{t,i}, p_{t,i}\right)}{\delta\theta} P\left(a'_{t,i} \mid x_{t,i}, p_{t,i}, \theta\right)\right\} \end{array}\right] \\ + \frac{\frac{\delta\left[\xi\left(x_{t,i} \mid x_{t-1,i}, a_{t-1,i}, \psi\right)\right]}{\delta\theta}}{\xi\left(x_{t,i} \mid x, a_{t-1,i}, \psi\right)} + \frac{\delta \ln\left[\zeta\left(p_{t,i} \mid p_{t-1,i}, \psi\right)\right]}{\delta\theta} \end{array}\right\}$$

10.4 Model Results

The results of Rust-Rothwell were verified with their original data set with an earlier version of this model that corresponded closely to theirs. While the parameter estimates were not identical to theirs, they were very similar. Such small differences are to be expected since the computer code developed here is different than the code for their model. Since the parameter results are similar, we do not report our estimates for their version of the model. Instead, we report results only for our extended versions.

The data set was extended to December, 2003 from the Rust-Rothwell ending date of December, 1994, so the full set is from January, 1975 to December, 2003. The model is estimated over three subperiods. The first is the period generally preceding the TMI accident: January, 1975 to December, 1979. The second allows a period of transition for the industry and regulators following the TMI accident, and is intended to capture the era of relative stability following the transition: January, 1984 to December, 2003. The third period allows the industry still more time to adjust to the regulatory changes initiated after TMI, and thus it includes data between January, 1989 to December, 2003. The preTMI and postTMI data sets correspond to Rust-Rothwell [55], where they employed data from 1975-1979 and 1984-1993. The last set corresponds to Rust-Rothwell [56], where they employed data from 1989-1994.

We employ the preTMI and postTMI samples in a test of structural stability across a turbulent episode in the industry in which many regulations were revised and introduced. Rust and Rothwell found evidence of a structural shift in operator behavior. However, they assumed that electricity prices were constant. We find evidence of a structural shift in the parameters for electricity price equations. The structural shift in prices occurred at about the same time that Rust and Rothwell claim that shifts occurred in operating policies. We want to see whether incorporating stochastic and structurally shifting prices allows stability of the remaining model parameters.

We employ the final data set, from 1989-2003, in an extended model. This model is employed to explore effects of risk to the physical plant and corresponding Price-Anderson regulation of liability. We also employ these parameters in a set of industry forecasts for optimal closure, as Rust and Rothwell [56] reported.

Rather than the retail electricity rates themselves, we are interested in the unit revenues earned by nuclear power plant operators for producing electricity. We create an approximation of unit revenues by assuming that generators receive a constant share of total revenues; the balance goes to transmission, distribution, and other activities. We multiply industrial electricity rates by this share, and then deflate the results. Note that we employ two measures of factor prices. For the sample periods 1975-1979, 1984-2003, and the combined sample, we employ average wage rates as a proxy for factor prices. We defend this selection by noting that a large fraction of operating costs are due to labor [2]. For remaining work, we employ the Producer Price Index (PPI). Given relative stability of electricity prices, the PPI, and wage rates in the 1989-2003 sample, we expect the choice of the PPI instead of wage rates to have little effect on our results.

We follow Rust and Rothwell in setting the discount rate β to 0.999. This corresponds to a real annual interest rate of 1.2%. This discount rate is small, so that operators care a great deal about potential future profits.

Estimation of such dynamic programming models is performed with the three-stage maximum-likelihood routine developed by Rust [53]. The first stage is to estimate the parameters ψ for the transition probabilities of the stochastic state variables. This vector includes price equation parameters and parameters for the binary logit functions used to predict the stochastic indicator variable f. The second stage is to estimate profit function parameters ϕ, conditional on the transition probability parameters. The third stage simultaneously estimates both ψ and ϕ.

10.4.1 First-Stage Estimation Results

In this section, we report transition probability parameters. First, we report the price parameter estimates. The discussion is brief, since a detailed look at prices is reported elsewhere. We then examine parameter estimates for evolution of the discrete stochastic state variables.

Price Parameters

The estimated equation is

$$p_t = \alpha + \alpha_{month}(t) + \eta_p p_{t-1} + \varepsilon_t \tag{10.4}$$

where p is the logarithm of relative prices in dollars per kilowatt-hour, α is a drift term, and α_{month} is a monthly dummy parameter. Estimates for four sample periods are reported in Table 10.1. Note the significance of the dummy variable parameters is samples including the 1984-2003 data, while the parameter values indicate little seasonal volatility in the 1970s. The parameters also reflect the shift from high average growth rates in the 1970s to slightly declining growth since the mid1980s.

The data series are plotted in an earlier chapter. There, we estimated several equations and considered the adequacy of Equation 10.4. We found statistical evidence of a structural break in the mid1980s, which may be seen by observing the parameter estimates reported in the table.

Reported adjusted R^2 values are very high. This may be misleading, however, given the nature of the employed data. Unit revenues for each plant were created from regional electricity prices; data on nine regions were available. At most,

Table 10.1: Price Parameters

	1/1984-12/2003	12/1979	12/2003	12/2003
	1/1975 -12/1979	1/1975	1/1984	1/1989
P_{t-1}	0.9947 (0.001)*	0.9927 (0.002)*	0.9951 (0.001)*	0.9947 (0.001)*
α	-0.0166 (0.002)*	-0.0298 (0.006)*	-0.0147 (0.002)*	-0.0143 (0.003)*
α_{Dec}	-0.0031 (0.001)*	0.0049 (0.002)*	-0.0049 (0.001)*	-0.0007 (0.001)
α_{Jan}	-0.0042 (0.001)*	0.0091 (0.002)*	-0.0055 (0.001)*	-0.0113 (0.001)*
α_{Feb}	-0.0060 (0.001)*	0.0098 (0.002)*	-0.0074 (0.001)*	-0.0048 (0.001)*
α_{Mar}	-0.0067 (0.001)*	0.0111 (0.002)*	-0.0084 (0.001)*	-0.0110 (0.001)*
α_{Apr}	0.0077 (0.001)*	0.0065 (0.002)*	0.0077 (0.001)*	0.0097 (0.0010)*
α_{May}	0.0324 (0.001)*	-0.0009 (0.002)	0.0353 (0.001)*	0.0349 (0.001)*
α_{Jun}	0.0052 (0.001)*	0.0123 (0.002)*	0.0045 (0.001)*	0.0011 (0.001)
α_{Jul}	-0.0037 (0.001)*	0.0094 (0.002)*	-0.0050 (0.001)*	-0.0035 (0.001)*
α_{Aug}	-0.0037 (0.001*	0.0123 (0.002)*	-0.0054 (0.001)*	-0.0054 (0.001)*
α_{Sep}	-0.0311 (0.001)*	0.0066 (0.002)*	-0.0349 (0.001)*	-0.0413 (0.001)*
α_{Oct}	-0.0246 (0.001)*	-0.0029 (0.002	-0.0268 (0.001)*	-0.0296 (0.001)*
$\overline{R}^2$	0.989	0.993	0.989	0.987
$NOBS$	25900	2309	23713	18878

we thus have nine unique price series for use with 116 plants. Statistics are computed as if we have 116 unique price series.

Transition Probability Parameters

We next review the transition probability parameters. Five binary logit functions are employed in the model to forecast the values of f. The parameter vector is denoted ψ. Subscripts indicate the corresponding binary logit function, with 1) of the probability of forced outages during an operating spell, 2) rf the probability of forced outages immediately following a refueling spell, 3) om the probability of a major problem developing during an operating spell, 4) mo the probability of exiting a major problem spell and resuming operations, and 5) ro the probability of exiting a refueling spell and resuming operations. Parameter values are reported in Table 10.3.

First, we examine the ψ_{rf} parameters. Note that the parameter for the constant, $\psi_{rf}(1)$, is positive for periods including the preTMI sample, and the parameter is negative otherwise. This indicates that for all else equal, forced outages following a refueling became less common. The parameter on reactor ages, $\psi_{rf}(t)$, is negative in all samples. This indicates that reactors become more reliable as they age, at least according to this measure of reliability. Note that we lack sufficient data for old plants, and we have not allowed a quadratic term, to capture possibly increasing risk at old plants.

We next examine the parameters ψ_{ro}. Given our assumption that the duration of refueling spells is not under the control of the operator, these parameters indicate the likelihood of refueling completion after given lengths of time. We include parameters for refueling lengths 1-4, and another dummy parameter for spells longer than four months. In addition, we include a linear trend for all spells longer than four months. Note that we do not have sufficient data in our small preTMI sample to estimate each parameter. While one-month refueling spells are slightly more common in the 1989-2003 sample, they were uncommon in all periods. Two-month refueling spells became much more common after TMI. Note that the trend parameter ψ_{ro} on long refueling spells is negative for all samples, but that the likelihood of exiting a refueling spell falls more quickly with duration in the 1989-2003 data set.

The parameter vector for forced outages in the midst of an operating spell, ψ_{of}, includes terms for a constant, plant age, linear and quadratic operating spell duration, and whether forced outages were observed in the prior period. Note that for all else equal, forced outages were much more common in the preTMI sample, and much less common in the 1989-2003 sample than even the 1984-2003 sample. The parameters on plant age have become smaller with later sample periods. Perhaps we have an omitted variables problem and should add a quadratic term, or perhaps operators are learning better operating procedures so that age is less important. For all sample periods, the parameter on duration is negative and the parameter on duration squared is positive. This means that reliability initially increases during the operating spell, but then peaks and begins to fall. However, both the increases and the subsequent declines are far less significant in the 1989-2003 period. Finally, in all samples we observe persistence; forced outages in one month indicate a significantly greater probability of outages in the next.

We next review the parameter vector ψ_{om} that predicts the likelihood of a major problem arising during an operating spell. Recall that we do not have in mind catastrophic events like the Chernobyl disaster. All else equal, major problems were least likely to arise in the preTMI and 1989-2003 samples. Data including the troublesome mid1980s yield higher estimates. The parameter on plant age is not significant for any sample, but it seems that (young) plants in the preTMI sample grew unreliable more quickly than (older) plants in later samples. Reliability fell relatively quickly over the operating spell in the preTMI sample. If forced outages occurred in the preceding month, then major problems are more likely to arise in the current month; note that we lack sufficient data to estimate a parameter in the preTMI sample.

Finally, we review the parameter vector ψ_{mo} which gives the probability of moving from a major problem spell to an operating spell. All else equal, the probability is quite small in the (small) preTMI sample, and it is relatively large and stable in other samples. The probability increases with duration in all samples. Apparently, the probability was much smaller in the mid1980s than in the preTMI period and in 1989-2003.

10.4.2 Second-Stage Estimation Results

We now examine the second set of parameters. These profit function parameters are conditional on the first-stage estimates of the price parameters and transition probability parameters.

In the estimates reported here, we assume that plants operate under forty-year licenses. This is counterfactual for some plants, since the NRC specified a process for obtaining 20-year license extensions. In recent years, some operators have applied and received these extensions. We will compare 40-year and 60-year estimates later.

Table 10.3: Transition Probability Parameters

	1/1975-12/1979 1/1984-12/2003	1/1975 12/1979	1/1984 12/2003	1/1989 12/2003
$\psi_{rf}(1)$	0.1496 (0.107)	0.4693 (0.332)	-0.0709 (0.138)	-0.5597 (0.189)*
$\psi_{rf}(t)$	-0.0047 (0.001)*	-0.0050 (0.006)	-0.0037 (0.001)*	-0.0023 (0.001)*
$\psi_{ro}(d_t = 1)$	-3.2027 (0.155)*	-186.908 (∞)	-3.2098 (0.160)*	-3.0582 (0.160)*
$\psi_{ro}(d_t = 2)$	-0.4795 (0.060)*	-0.9752 (0.220)*	-0.4046 (0.062)*	-0.1130 (0.075)
$\psi_{ro}(d_t = 3)$	0.0899 (0.063)	0.3557 (0.203)	0.0474 (0.069)	0.2841 (0.097)*
$\psi_{ro}(d_t = 4)$	0.3114 (0.106)*	1.0083 (0.409)*	0.2322 (0.119)*	0.3824 (0.165)*
$\psi_{ro}(d_t \geq 5)$	0.4374 (0.186)*	0.2806 (1.343)	0.4463 (0.182)*	0.7046 (0.267)*
$\psi_{ro}((d_t - 4)$ $\times(d_t \geq 5))$	-0.1801 (0.051)*	-0.0048 (0.812)	-0.1818 (0.051)*	-0.2714 (0.085)*
$\psi_{of}(1)$	-0.5374 (0.048)*	0.1487 (0.222)	-0.8475 (0.047)*	-1.2881 (0.065)*
$\psi_{of}(t)$	-0.004 (0.0001)*	-0.0047 (0.002)*	-0.003 (0.0002)*	-0.002 (0.0002)*
$\psi_{of}(d_t)$	-0.0388 (0.010)*	-0.0484 (0.050)	-0.0251 (0.010)*	-0.0176 (0.012)
$\psi_{of}(d_t^2)$	0.0006 (0.0006)	0.0008 (0.003)	0.00002 (0.001)	0.00002 (0.001)
$\psi_{of}(f_t = 2)$	0.5714 (0.036)*	0.4362 (0.092)*	0.5332 (0.041)*	0.4021 (0.056)*
$\psi_{om}(1)$	-7.7606 (0.466)*	-8.9300 (2.83)*	-7.6875 (0.525)*	-8.4049 (0.781)*
$\psi_{om}(t)$	0.0001 (0.002)	0.0135 (0.015)	-0.0003 (0.002)	0.0020 (0.002)
$\psi_{om}(d_t)$	0.1474 (0.027)*	0.2556 (0.201)	0.1356 (0.028)*	0.1304 (0.045)*
$\psi_{om}(f_t = 2)$	1.5749 (0.292)*	-112.070 (∞)	1.8344 (0.328)*	2.0270 (0.379)*
$\psi_{mo}(1)$	-3.6812 (0.477)*	-8.2008 (27.236)	-3.7099 (0.475)*	-3.6719 (0.567)*
$\psi_{mo}(d_t)$	0.05106 (0.02)*	0.4821 (2.374)	0.0517 (0.021)*	0.0528 (0.025)*
$NOBS$	25900	2309	23713	18878
LL	-13540	-1569	-11899	-8745

Rust and Rothwell incorporated monthly dummy variables and other non-parametric terms in their specification of the profit function. We impose additional structure in our model, and we also incorporate stochastic prices. The additional structure comes by defining separate revenue and cost functions, and by allowing seasonal fluctuations only in prices. That is, profits exhibit seasonal variation only because prices tend to be higher in the summer and winter, and so revenue tends to be higher in those periods. We assume that costs do not exhibit seasonal variation.

Profit parameters

Estimation periods are identical to the transition parameter estimates above: 1) a preTMI period from January, 1975 to December, 1979, 2) a postTMI period from January, 1984 to December, 2003, 3) a combined period, and 4) a period from January, 1989 to December, 2003.

Despite the differences in the treatment of seasonal profit variation, and given the addition of stochastic prices, and although code for this model is very different than that used in Rust-Rothwell, estimates of profit function parameters are similar to the corresponding estimates reported in Rust-Rothwell [56]. This may indicate that their seasonal dummies primarily were capturing price fluctuations. However, we did not test the significance of cost function dummies in the extended model. Instead, they were eliminated for sake of simplicity. Note that the parameters reported in Table 10.4 are normalized cost levels, and so the values naturally are positive.

Parameter $\phi_{a=2}$ gives the monthly cost of refueling. Note that refueling costs per month seem to have grown significantly. If plants that are refueling get a signal that they are free to operate, but instead they continue to refuel, then their monthly costs increase by $\phi_{a=2,f=1}$. This parameter also is larger for later samples. Given our assumption that the lengths of refueling spells are exogenous, these indicate that plant operators have become less inclined to begin refuelling of their plants.

There are three parameters for costs of temporary shutdowns. First, the parameters $\phi_{a=3,f=3}$ gives the monthly cost of a major problem spell. Major problem spells seem to be about as costly in the 1989-2003 sample as in the preTMI sample, but both are more costly than in samples that include the mid1980s. This is a reasonable result for our revealed preference approach, since extended closures were common following the TMI accident. This indicates, however, a limitation of our model. We do not take account adequately of regulatory intervention. Many temporary closures were due to mandated inspections and equipment modifications. In such cases, the observed actions were due to regulatory mandates rather than ordinary profit motives. The parameter $\phi_{a=3,f<3}$ gives the cost of failing to operate when operations are feasible, and $\phi_{a=3,f=2}$ gives the cost of failing to operate when at least one temporary shutdown would have been required during the month. In the first case, it seems that it has become increasingly costly for plants to forgo the opportunity to produce power. However, the costs of passing on the opportunity to produce power for only part of a month have changed little. Note that the latter parameter could not be estimated precisely with the preTMI sample.

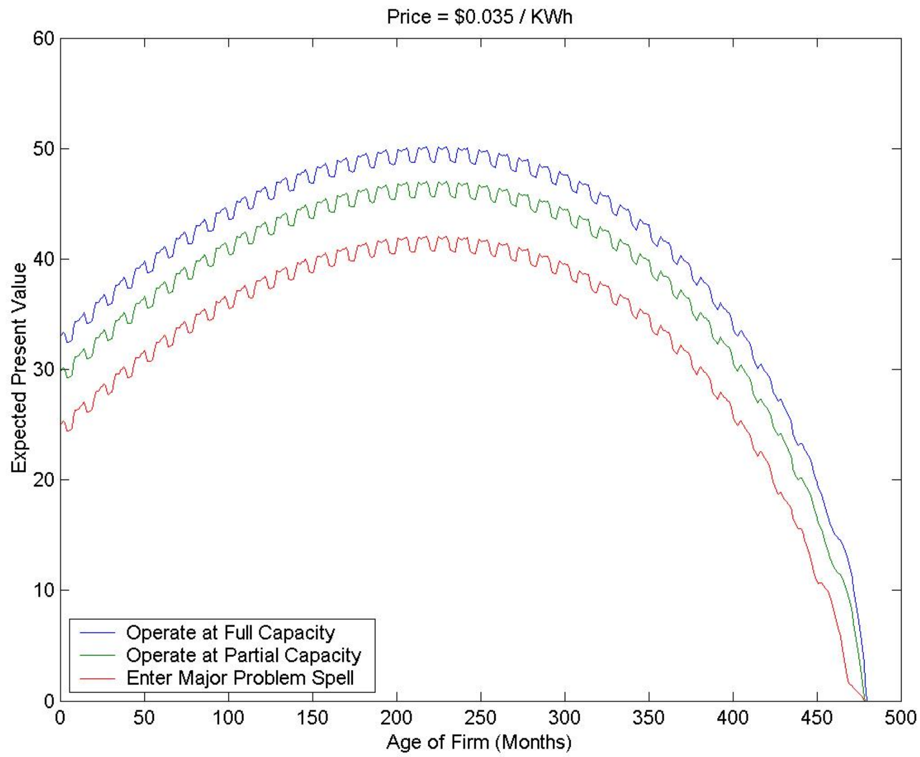
Remaining parameters estimate the costs of producing power. $\phi_{d,u>0}$ is a trend term on the length of the operating spell. Costs may grow slightly more quickly in later samples than in the preTMI sample so that operating spells tend to be shorter. Costs of operating for fractions of available time have grown substantially and monotonically as the sample periods shift to later dates. Note that parameter estimates are negative for the costs of producing at full capacity. This may indicate that operators have a stronger preference for producing at full power than is explained by our model. A possible reason is that starting and stopping production is risky and is hard on equipment. Hence, operators prefer production over refueling or temporary shutdowns, but they strongly prefer to operate for full months rather than to stop and restart during the month. This may indicate problems with our assumptions about regulation; that is, that operators' decisions are limited only by technical constraints and not by regulatory mandates. The final parameter, $\phi_{u=1,f=2}$, gives the cost of operating despite a forced outage signal. The large parameter values indicate that such possibly irresponsible behavior is very expensive and is avoided; such behavior has grown more costly.

We display the value functions at given price levels in Figures 10.1 and 10.2. The figures plot the present value of operations, first for electricity prices of \$0.03 per kilowatt-hour and then for \$0.10 per kilowatt-hour. The results are based on estimates using the 1989-2003 sample, so that expected price growth is modest or slightly falling. Three curves are displayed in each, and plant age is on the horizontal axis. First, we display values for a plant that in in its fifth month of an operating spell that received a signal that it is free to operate for another month without problems. Second, we graph the value of a plant in its fifth month of an operating spell that receives a signal that it is free to operate, but that it will need to shut down at least once in the following month. Finally, we plot the value of a plant in its fifth month of operations that receives a signal that a

Table 10.4: Profit Function Parameters

	1/1975-12/1979	1/1975	1/1984	1/1989
	1/1984-12/2003	12/1979	12/2003	12/2003
$\phi_{a=2}$	3.1574 (0.027)*	2.1446 (0.182)*	3.3052 (0.029)*	4.1266 (0.034)*
$\phi_{a=2,f=1}$	3.1085 (0.242)*	2.3494 (0.953)*	3.2912 (0.268)*	3.4141 (0.350)*
$\phi_{a=3,f=3}$	0.3220 (0.213)	0.4403 (1.575)	0.3335 (0.225)	0.4517 (0.228)*
$\phi_{a=3,f<3}$	2.9108 (0.199)*	2.3672 (1.050)*	2.9454 (0.225)*	3.0607 (0.268)*
$\phi_{a=3,f=2}$	3.5515 (0.407)*	3.7944 (46.26)	3.5885 (0.411)*	3.5357 (0.497)*
$\phi_{d,u>0}$	0.0862 (0.002)*	0.0888 (0.013)*	0.0857 (0.002)*	0.0901 (0.002)*
$\phi_{u\in(0,.25]}$	3.9344 (1.720)*	3.5409 (8.187)	3.9988 (1.918)*	4.1224 (2.633)
$\phi_{u\in(.25,.50]}$	3.3226 (0.751)*	2.7475 (2.789)	3.4055 (0.851)*	3.4900 (0.983)*
$\phi_{u\in(.50,.75]}$	2.4085 (0.223)*	1.9268 (0.768)*	2.4845 (0.238)*	2.5151 (0.276)*
$\phi_{u\in(.75,1)}$	1.0996 (0.044)*	0.2553 (0.108)*	1.2289 (0.054)*	1.2946 (0.071)*
$\phi_{u=1}$	-1.437 (0.007)*	-1.005 (0.089)*	-1.487 (0.008)*	-1.612 (0.009)*
$\phi_{u=1,f=2}$	5.4531 (1.20)*	3.2571 (1.060)*	6.1085 (2.682)*	6.1708 (3.257)
$NOBS$	25900	2309	23713	18878
LL	-23753	-2147	-21551	-16747

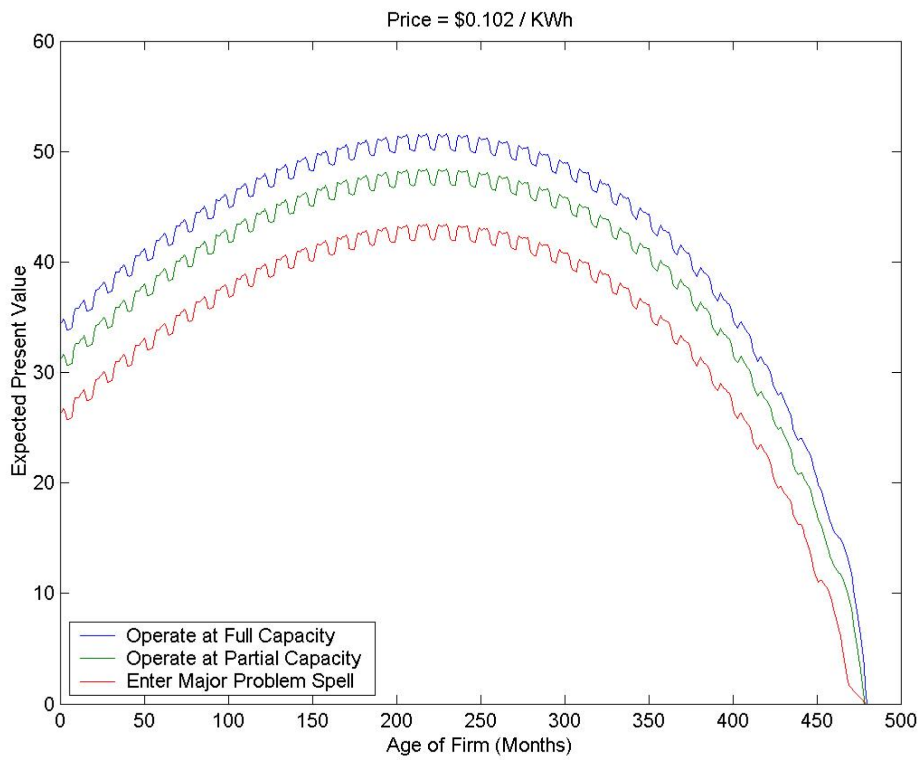
Figure 10.1: Firm Values at Low Prices



major problem has arisen. We see that there are significant differences in values between plants that run at 100% capacity in a given month and an otherwise identical plant that runs at limited capacity. There also is a significant loss of value when major problems arise, so that operators are more likely to close their plants permanently.

Note that the seasonal volatility of electricity prices causes a great deal of volatility in firm values. While the apparent effects on value of price average growth rates seem small, we do observe greater plant values at higher electricity prices.

Figure 10.2: Firm Values at High Prices



10.4.3 Goodness of Fit

We can get a sense of the performance of our model, and its capacity for replicating the behavior of plant operators, by comparing the frequency of each action observed in the data to the aggregate probabilities predicted by the model. Following the notation of Rust and Rothwell [56], we compute the nonparametric choice probabilities as

$$\hat{P}\left(a|X\right) = \int_{x \in X} \hat{P}\left(a|x\right) \hat{F}\left(dx|X\right) \equiv \frac{1}{N}\sum_{i=1}^{N} I\left\{a_i = a, x_i \in X\right\}$$

where a is the action chosen by the operator, x is a state vector from the set of states X in a given partition of the data set. Here, X is the entire data set. In short, we calculate the nonparametric choice probabilities as the number of times a particular action is chosen divided by the total number of observations.

We summarize the model's predictive accuracy as

$$P\left(a|X,\hat{\theta}\right) = \int_{x \in X} \hat{P}\left(a|x,\hat{\theta}\right) \hat{F}\left(dx|X\right) \equiv \frac{1}{N}\sum_{i=1}^{N} P\left(a|x,\hat{\theta}\right) I\left\{x_i \in X\right\}$$

Employing the estimated parameters, we sum the model's choice probabilities for each feasible action, given the observed combination of state variables. We divide the sum by the total number of observations to get an estimate of the probability that a given action will be chosen, conditional on the state variables. In this case, we do not partition the set of state variables, so that all observations are included. The nonparametric and parametric choice probabilities are reported in Table 10.5 for the 1989-2003 sample period. We find, as did Rust and Rothwell, that the model seems to replicate very well the choice probabilities at the aggregate level.

Table 10.5: Aggregation of Choice Probabilities

	Nonparametric	Parametric
Shut Down	0.0006	0.0009
Refuel	0.1368	0.1362
$u = 0$	0.0634	0.0639
$u \in [1, 25)$	0.0069	0.0070
$u \in [25, 50)$	0.0132	0.0133
$u \in [50, 75)$	0.0348	0.0354
$u \in [75, 100)$	0.1190	0.1206
$u = 100$	0.6253	0.6228

10.4.4 Structural Stability Test Results

We turn now to the question of whether the behavior of nuclear power plant operators changed significantly within our sample period from 1975 to 2003. In their more limited model, Rust and Rothwell [55] discovered that parameter estimates shifted significantly when they split the sample. They attributed most differences to optimal responses to regulatory changes following the Three Mile Island accident in 1979.

Rust and Rothwell discovered several differences in their results, depending on the sample periods. First, operators shifted from 12-month operating cycles in the 1970s to 18-month cycles in later periods, on average. Second, they estimate that over 90% of expected discounted profits disappeared for reasons including stricter safety regulations, increases in expected decommissioning costs, and stricter standards for price setting that forced owners to bear cost increases. Finally, they noted a decrease in the frequency of "imprudent" or reckless behavior.

In our earlier work in Chapters 5 and 8, we discovered reasons to question whether the conclusions reached by Rust and Rothwell are valid. More precisely, we question not their observations but rather their conclusions. We found evidence of a significant structural break in electricity prices that occurred in the mid1980s. We assume that unit revenues earned by power plant operators experienced a corresponding structural shift, so that rapidly-growing price patterns in the 1970s shifted to a gradually falling relative price trend. The simple fact that relative prices grew rapidly in the early part of the sample period leads us to question the assumption that prices were stable and that zero price growth was a reasonable assumption to simplify the model. Of particular concern is the fact that the pattern of price growth shifted at roughly the same time Rust and Rothwell observed changes in the behavior of power plant operators. In addition, the introduction of significant seasonal volatility likely affects the timing of operators' decisions. We thus believe that Rust and Rothwell assumed too quickly that changes in operator behavior should be explained as optimal responses to changes in regulation. We have no reason to doubt their reasoning, for certainly there were many regulatory changes that did affect behavior. We must remember, however, that operators also respond to economic changes, including shifts in demand and prices. We studied this problem using the industry model of Chapter 5.

We thus attempt to reconstruct the Rust-Rothwell structural stability test [55, p. 35] to determine whether the behavior of the firms remained consistent over time. This time, however, the model is extended in two important ways.[4] Less

[4]Another difference is that we use the extended version of their model developed in [56].

important, perhaps, is that we extend the data set from 1993 to 2003. Our sample periods thus are 1975 to 1979 and 1984 to 2003. The more important change, and the one of particular interest, is the inclusion of stochastic and potentially trended prices. The allowance of different price structures will allow us to consider whether remaining parameters, and in particular the profit function parameters, change in response to regulatory reforms.

We might expect that the increase in seasonal volatility, as was noted earlier, might explain the increased adherence to strict 12 or 18-month operating cycles, though it does not explain the transition from 12 to 18 months. We might suppose that the change in relative price trends, from increasing to decreasing, might explain some of the disappearance of estimated profits noted by Rust and Rothwell and also reported here. Of course, no change in electricity prices will explain the trends in operating costs observed in Chapter 9, so this explanation too is incomplete. Still, it seems that prices should matter a lot, especially given the sharp change in price growth. We test the parameter estimates for our model in an attempt to discover whether our extended model captures adequately the causes of operator behavior or whether there remain unexplained changes that we too might attribute to regulatory effects.

We concluded already that there is a structural break in prices. We now consider changes in the evolution of other state variables. We employ a likelihood-ratio test on the hypothesis of stable profit function parameters. Again, this test excludes the price equation, although results of a separate test were reported earlier. Using results reported in Table 10.3, we find that

$$\chi_{19} \sim -2\ln\lambda = -2\ln\frac{-1569.6 - 11899.6}{-13540.2} = 0.01$$

The null hypothesis of structural stability for the discrete stochastic state variables cannot be rejected.

We now turn attention on profit function parameters. These estimates are conditional on the first-stage estimates of transition function parameters. The test utilizes results reported in Table 10.4. Given the test result

$$\chi_{12} \sim -2\ln\lambda = -2\ln\frac{-2147 - 21551}{-23753} = 0.0046$$

we cannot reject the null hypothesis of structural stability.

What should we conclude about the stability of our model? First, caution is in order. Before making bold claims about the superiority of this extended model, the results should be subjected to further analysis. On the other hand, the test results lend support to our arguments that the Rust-Rothwell conclusions were misleading, and that demand-side changes explain some of the observed patterns in operator behavior. Regulatory changes certainly did affect behavior within the nuclear industry, and we should examine further the effects of regulation by extending this work according to our industry modeling efforts.

10.5 Extensions and Applications

In this section, we extend and apply the dynamic programming model. We begin by estimating parameters for the model assuming that firms operate with 60-year licenses. Next, we estimate a model in which firms face the possibility of a serious accident with corresponding costs and liability. Finally, we apply our earlier estimates to perform historical simulations and construct forecasts.

In addition to the basic 40-year model described above, we constructed and estimated two alternative models. First, we estimated a 60-year version to account for available 20-year extensions to operating licenses that first became available in the 1990s. Second, we extended the basic model to include risks of serious accidents with corresponding operator liability. Both alternatives were estimated over the 1989-2003 sample period. Parameters are displayed in Table 10.6. The first column of the table replicates the profit function parameter estimates reported above for the 1989-2003 sample. The center column reports estimates for a model with 60-year operating licenses. The final column reports estimates for a 40-year model with risk and liability. Details are provided below. Transition probability estimates essentially remain unchanged from those reported earlier for the same sample, and so we do not report them again.

10.5.1 60 Year Operating Licenses

We consider possible twenty-year extensions to the original 40-year operating licenses. The legislation to allow plants to apply for license extensions was not passed until well after the start of the data sample in January, 1989. Further, not all plants operating at the end of the sample in 2003 received extensions, applied for extensions, or even stated intentions to apply. However, we might suppose that forward-looking operators anticipated by 1989 or so that license extensions would be offered in the future, and we might further assume that they formed their operating policies accordingly. Hence, we estimate parameters for a 60-year model using an otherwise unmodified version of the model described above. We compare the parameters to those estimated allowing only a 40-year operating horizon. Parameters for the 40-year model are shown in the first column of Table 10.6 and parameters for the 60-year model are shown in the second column.

Table 10.6: Alternative Models

	Base Model	60 Year Model	Risk&Liability
	1/1989	1/1989	1/1989
	12/2003	12/2003	12/2003
$\phi_{a=2}$	4.1266 (0.034)*	4.5610 (0.033)*	3.7415 (0.035)*
$\phi_{a=2,f=1}$	3.4141 (0.350)*	3.3063 (0.328)*	3.3780 (0.343)*
$\phi_{a=3,f=3}$	0.4517 (0.228)*	0.5455 (0.225)*	0.0534 (0.228)
$\phi_{a=3,f<3}$	3.0607 (0.268)*	3.1162 (0.275)*	2.6619 (0.267)*
$\phi_{a=3,f=2}$	3.5357 (0.497)*	3.4706 (0.502)*	3.5399 (0.497)*
$\phi_{d,u>0}$	0.0901 (0.002)*	0.0987 (0.002)*	0.0903 (0.002)*
$\phi_{u\in(0,.25]}$	4.1224 (2.633)	4.0007 (2.655)	3.7377 (2.676)
$\phi_{u\in(.25,.50]}$	3.4900 (0.983)*	3.3547 (0.985)*	3.0962 (0.991)*
$\phi_{u\in(.50,.75]}$	2.5151 (0.276)*	2.3839 (0.276)*	2.1136 (0.276)*
$\phi_{u\in(.75,1)}$	1.2946 (0.071)*	1.1582 (0.071)*	0.8923 (0.071)*
$\phi_{u=1}$	-1.612 (0.009)*	-1.6918 (0.009)*	-2.019 (0.009)*
$\phi_{u=1,f=2}$	6.1708 (3.257)	6.0832 (3.081)*	6.1991 (3.334)
$NOBS$	18878	18878	18878
LL	-16747	-16893	-16747

This is different than the approach taken by Rust and Rothwell [56]. Their data set ended before any plants obtained license extensions. They estimated parameters using a 40-year model, and then they solved a 60-year model using the previous parameter estimates. Because we have a longer sample period, and because this extended sample includes observations for plants that have obtained extensions, we proceed differently.

Consider the estimates reported in Table 10.6. First, note that the parameter estimates for the 40-year and 60-year models are very similar. However, the log-likelihood values suggest that the 40-year assumption fits the data slightly better than the 60-year model. We did not test for significance of the differences, and we cannot make claims about the importance of these small differences.

The cost of refueling is slightly higher in the 60-year model, but the cost of entering a refueling spell despite freedom to operate is lower. The monthly cost of a major problem spell is higher, as is the cost of an unforced shut down. If an operator chooses to close for the entire month, with the alternative being to operate for only part of the month, then this choice is less costly than under the 40-year horizon. The increase in costs with duration of operating spells is virtually unchanged, as are monthly costs for operating at rates greater than zero and less than 100 percent. The benefit of running at 100 percent is slightly higher, but the cost of ignoring problem signals is lower. A number of the differences noted here may be explained by operators taking greater care to maintain their plants in order that the plants may remain operable for greater lengths of time.

We thus observe few differences in the estimated parameters. A possible reason is that regulators force operators to behave conservatively, so that firms operating under 40-year horizons appear to have longer-run objectives. We return to these topics later.

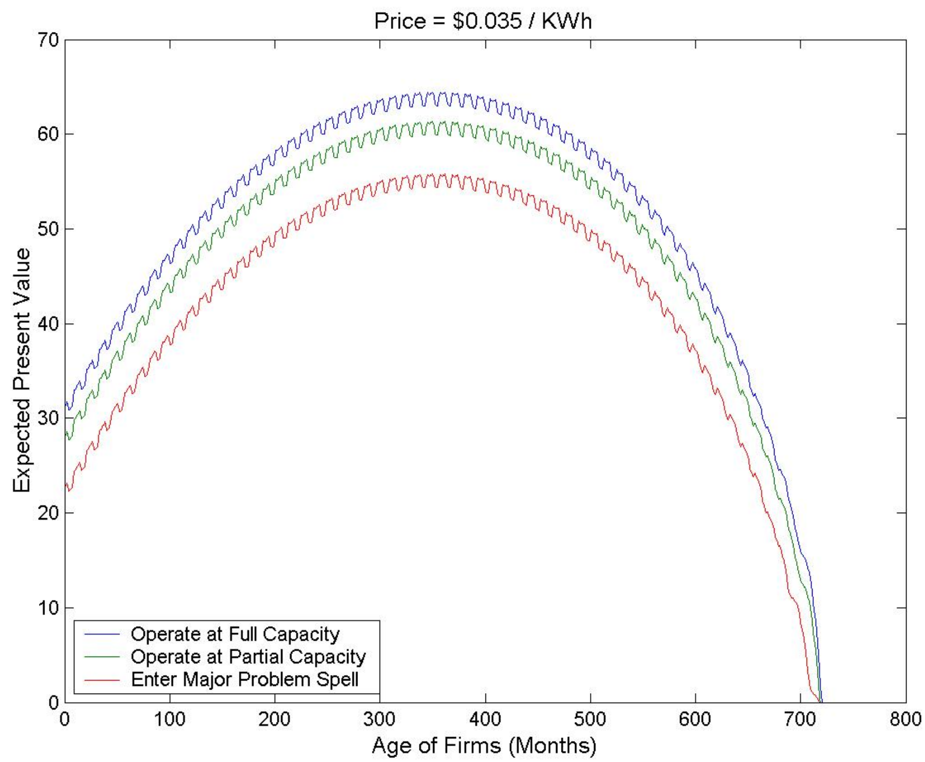
We display firm values in Figure 10.3, assuming at each age plants are in the fifth month of an operating spell and receive either a signal to operate without problems, a signal that operations are feasible but problems will occur, or a signal that a major problem has occurred and an extended shutdown will begin. Note that maximum values are realized at about 350 months, in contrast to maximum values at 225 months when 40-year licenses are enforced. Also, maximum values are over 60 units versus the 50 units seen earlier in Figure 10.1. These differences are the amounts operators with plants of a given age facing the given vector of state variables would be willing to pay for 20-year extensions to operating licenses.

10.5.2 Risk and Liability

Our base models do not incorporate the possibility of serious accidents like the one at Chernobyl or even at Three Mile Island. Incorporation of such details requires that we go beyond standard econometrics, for such events are very rare. We wish to determine whether we can detect in the data responses by operators to such risks and the corresponding liability faced by plant owners.

We begin the analysis of risk and liability by introducing simple features of risk and liability to our model. We allow plants to receive a stochastic signal indicating whether or not a significant accident occurs. We calibrate the risk of an accident to 0.008% per month, and we arbitrarily set the cost to the plant operator of an accident at 5,000 units. This roughly is 100 times higher than the maximum plant values of about 50 units displayed earlier in graphs. We have in

Figure 10.3: Firm Values with 60-Year Licenses



mind that this liability covers both onsite damages to the plant and workers and liability for offsite damages under the Price-Anderson Act. The implementation is rather naive, in that we distinguish only between the accident risk (zero) when the choice is made to decommission the plant and the given risk otherwise. In reality, risks are relatively high when the plant is in the process of being powered down or restarted. However, we did not account for these details, although such extensions would be simple given the necessary risk assessments. Parameters were estimated on the 1989-2003 data set with 40-year licenses assumed; they are reported in column three of Table 10.6.

The log-likelihood values virtually are identical for this and the base model. It appears that the two versions fit the data equally well. Still, parameter estimates seem significantly different. The cost of a refueling shutdown is lower, but the cost of refueling when operating is possible is about the same. The cost of a major problem spell is higher, although the parameter estimate is less precise. The cost of remaining idle during an operating spell is somewhat lower. Costs increase at about the same rate during an operating spell, but otherwise the cost of operating at partial capacity generally is lower. Profits at full capacity are greater, and the cost of "imprudent" behavior is the same.

We see that such simple introductions of risk and liability are of limited value. Far more useful would be to consider the effects of risk and liability on regulation, and then to consider the effects of all three on the firm. We return to these matters below. Also useful would be to consider the variations in risk of various activities. These likely would create greater difference in our parameter estimates.

10.5.3 Simulations and Forecasts

We employ our parameter estimates using the 1989-2003 sample, assuming 40-year operating licenses, to simulate the history of the Three Mile Island Unit 1 nuclear power plant. We then forecast the remaining years of operation for the plant, still assuming a 40-year license.

The historical simulation is intended to indicate the ability of the model to predict behavior, given the condition of the plant. We thus construct our simulation by observing actual state variables and then determining the corresponding activity offering the greatest value. We perform the simulation from February, 1989 to November, 2003.

Historical activity data is displayed in Figure 10.4, and simulations are displayed in Figure 10.5. In general, it appears that the model does a good job at predicting the optimal activity given current plant conditions.

We employ the price parameters and transition probability parameters for other state variables, together with the profit function parameter estimates, to construct a forecast for Three Mile Island from November, 2003 to January, 2014. We ran 100 forecasts, with each starting with the actual November, 2003 vector of state variables. We calculate average predicted utilization rates in each forecast period. These predicted rates are graphed in Figure 10.6. Note that the plant was 359 months old at the end of our data series. We assume that the original 40-year operating license remains in place, so that the plant must close by 480 months of age. Our model predicts that, if possible, operators will run the plant to the end of its legal lifespan.

Suppose that in 2004, electricity prices suddenly reverted to their 1975-1979 pattern of high growth rates. Given this assumption, and maintaining the cost

Figure 10.4: Three Mile Island Activities

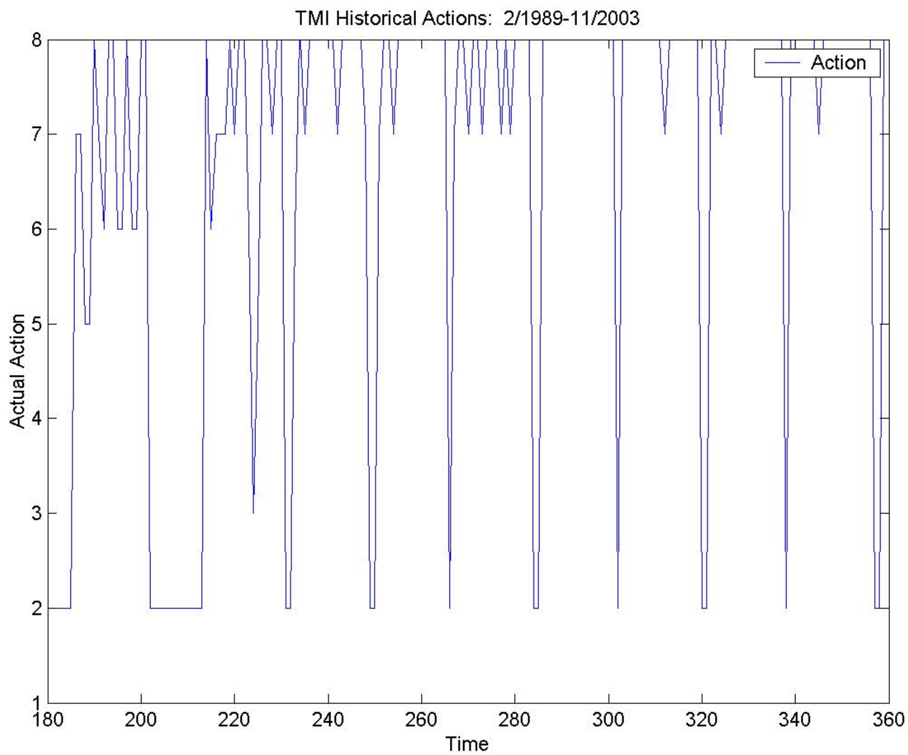


Figure 10.5: Three Mile Island Simulations

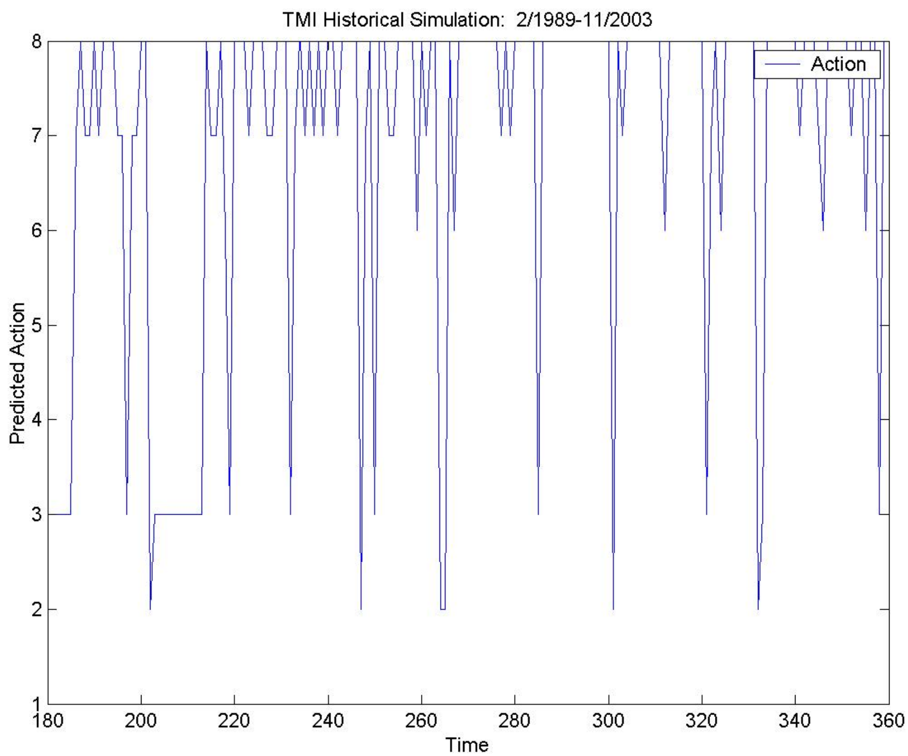


Figure 10.6: Three Mile Island Forecast

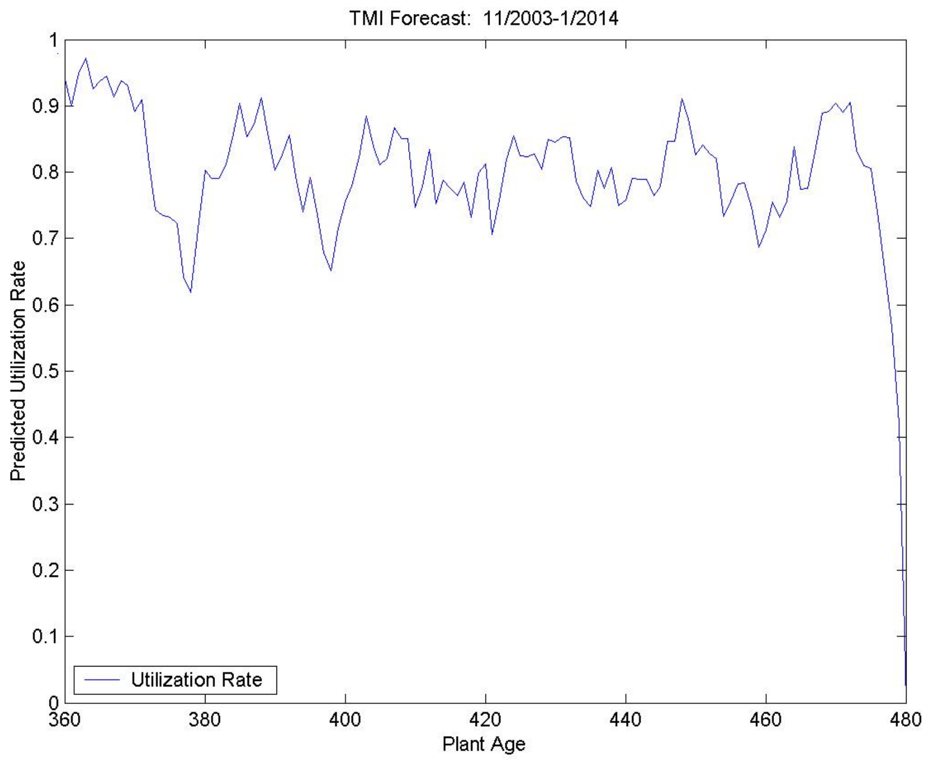
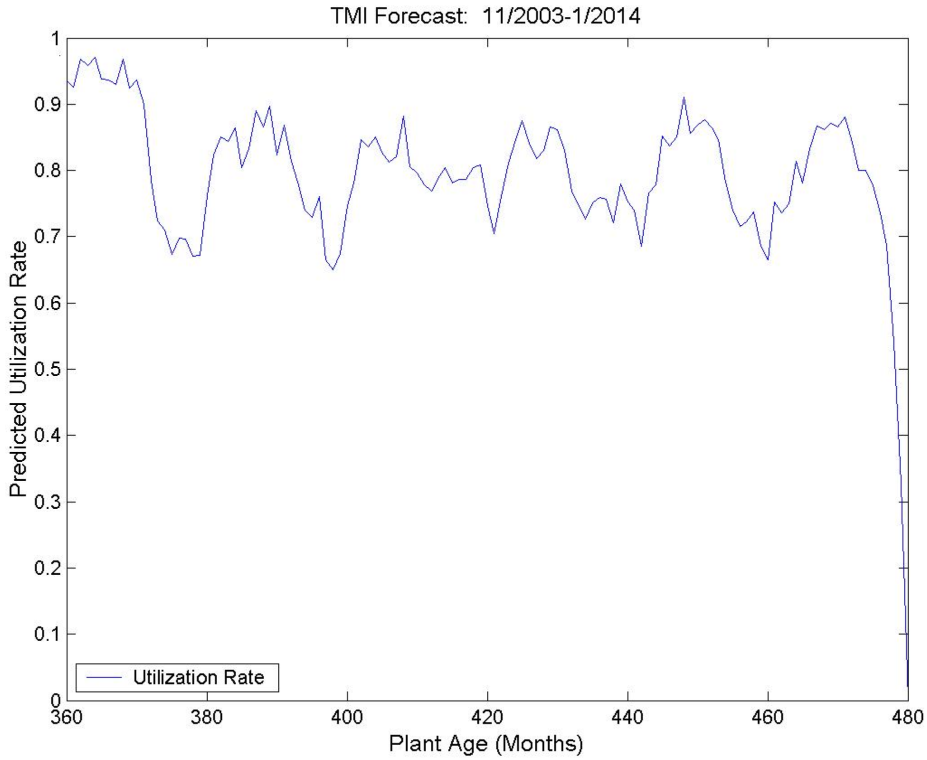


Figure 10.7: TMI Forecast: High Price Growth

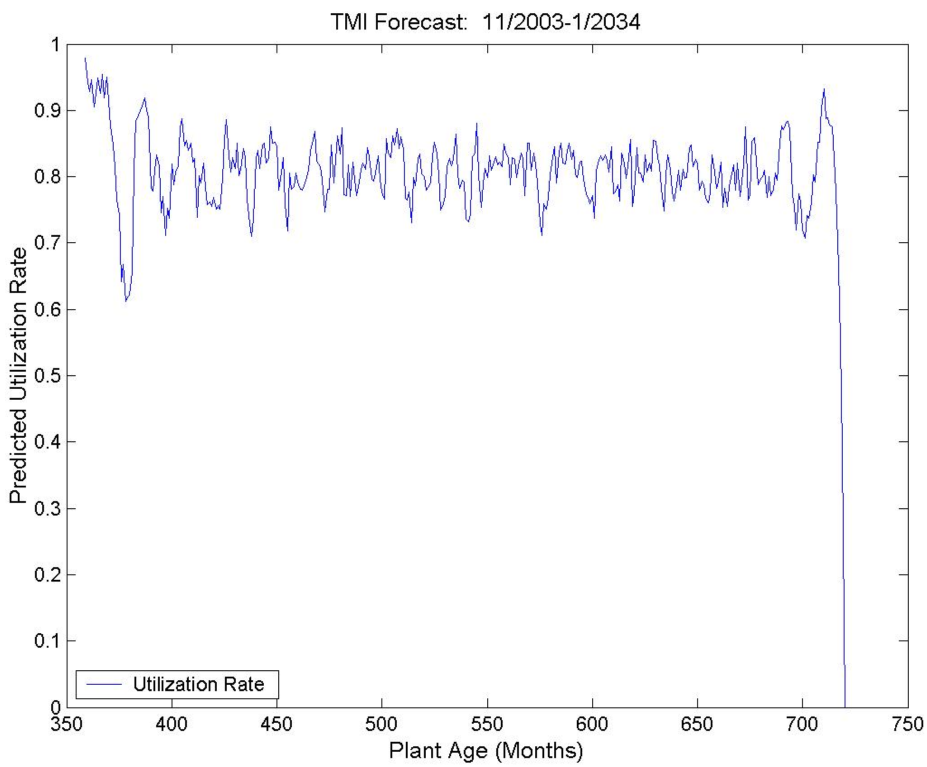


and transition function parameters for the 1989-2003 sample, we constructed an alternative forecast for TMI. We maintain the assumption of a 40-year operating license. The forecast is shown in Figure 10.7.

Finally, we forecast utilization rates for TMI assuming the 1989-2003 price pattern but with a 60-year operating license. The result is shown in Figure 10.8.

In all cases, we see that utilization rates average about 80%, and perhaps the average declines slightly with plant age. In all cases, TMI is predicted to run until forced to close. We observe few noticeable differences between forecasts with low and high-growth price assumptions, although differences may be more apparent using other measures. In the same way, few obvious differences exit in the forecast assuming 60-year licenses.

Figure 10.8: TMI Forecast: 60-Year License



10.6 Regulatory Factors

In Chapters 2 and 4, we considered industry models in which firms operated under the supervision of regulators. We saw that in some cases in which regulators had the authority to restrict firms' behavior, they would choose not to do so. In other cases, they would set policies that at least some firms would find binding.

In the model of the firm developed in this chapter, we do not account for regulation. We do not claim that firms operate without oversight, and neither do we assume that firms' decisions are unencumbered by regulatory policies. Instead, we ignore explicit accounting for regulation solely for sake of simplicity.

We might consider the effects of these omissions on our model through use of our earlier work. That is, suppose the real world was like the model with both regulation and liability, but suppose we modeled the world with a liability-only model. What differences should we expect between our results and reality? By comparing the results of our two models from Chapter 2, we can learn of potential problems with the results of the present chapter. Of course, the present model omits explicit investment decisions, while regulation in the earlier model took the form of restrictions on investment decisions. Also, we will perform the comparison using results for the static model because we have more complete analysis and descriptions for that version. Despite such discrepancies, the comparison may provide useful guidance for our dynamic programming work.

Key results in the Chapter 2 liability-only case are that only firms facing full liability invest at the socially optimal level. Firms that receive liability protections invest at suboptimal levels. Firms may exit the market sub-optimally if profits are too low. Liability protection may be preferable to none if consumers value the benefits of higher consumption to the safety of zero production and if liability protections leave unprofitable operations viable. Firms' investment decisions are not affected by regulators.

In Chapter 2, we considered three cases in which both regulation and liability are applied. First, there is the possibility that regulation will be set so that it fails to bind for any firm. In that case, there are no observational differences between the liability-only and the liability-and-regulation cases. If this reflects reality, then there may be no problems with the current dynamic programming model.

In the second and third cases, regulation was set to high levels so that all firms found regulation binding. The primary differences between the cases are whether firms remain profitable and whether all firms receive liability protections. If the second case is true, then some firms receive protections, all firms find regulation binding, and at least some firms are profitable. If the third case were true, then all firms receive protections, all firms find regulation binding, and no firm is profitable. It seems that neither case is quite right, for we believe that some firms are profitable but that all receive benefit of liability protections. We believe that both are correct in suggesting that regulation binds for all. We noted in the applications and extensions section of Chapter 2 ways that the extreme implications of the model might be lessened. Some of the suggested ways extend the results for the third case, so that all firms receive protection, all firms find regulation binding, and some firms are profitable. Because generally it seems the most in line with reality of all our models, we will pursue comparisons between this third case and the liability-only case.

In our industry models in Chapters 2 and 4, there were explicit investment costs but no indirect output costs to investment. We considered direct and output costs to investing in Chapter 5. In this chapter, we do not consider explicit investment decisions, nor do we include restrictions of investment on output. Investment is lurking just below the surface, however, since most investment typically is done when plants are refueling or operating at zero capacity. We might assume that plants are investing when we observe either activity. In principle, direct investment costs then would be included in estimated parameters for those activities, and indirect costs would be given as the opportunity cost of forgoing production at full capacity.

10.6.1 Investment

Because the activities of nuclear power plant operators are regulated heavily, including their investment activities, then we expect to observe "suboptimal behavior" recorded in our data, in contrast to the "optimal" behavior otherwise recommended by our dynamic programming model. In the sense provided by models in Chapter 2, regulators put lower bounds on investment levels, so that firms invest more than they would prefer. In the dynamic programming model, this would be observed as behavior that seems overly conservative. Specifically, we would see plants spending too much time refueling and operating at zero or partial capacity.

Would our estimation technique actually measure direct investment costs? Because firms choose to refuel more often than predicted, the revealed preference technique suggests relatively lower costs for those activities compared to the alternatives. Hence, regulation restrictions are at odds with our profit maximization assumptions, and the relative costs of refueling and limited production may be underestimated.

10.6.2 Short-Run vs. Long-Run Profits

Because of "excessive" observed investment levels, profits would appear too low given the predictions of the dynamic programming model. It might be argued that regulators care more about the long run than do operators who prefer short-run profits. However, in our model operators do care about the long run, for following the findings of Rust and Rothwell we calibrate a small discount factor. Still, firms may have too little incentive to consider the effects of their behavior on consumers, thus giving regulators reason to step in. The restrictions they impose, which presumably are intended to enhance safety, could improve expected long-run profits while diminishing profits in the short run. This would be the case if greater investment countered depreciation of the plant and enhanced safety. Investment thus could extend the useful life of the plant and increase it reliability as it ages. Hence, regulation could make it appear that firms care more about the future than in fact they do. Then short-run profits would appear lower than the model would predict, and the expected value of future profits would be higher. This might explain the Rust-Rothwell findings that the discount factor is very small.

10.6.3 Exit Decisions

It is difficult to determine the effect of "excessive" investment on firms' decisions to decommission their plants. If higher investment leaves the plants more reliable and safer, then serious problems should occur less frequently and expected liability should be lower. On the other hand, lower short-run profits would slow recovery of repair costs. This would make operators more inclined to exit when major problems arise. We thus might expect to see too many firms exit compared to the predictions of our model.

In conclusion, we need to be careful as we interpret the parameter estimates and results of our model. More work is needed to address these problems. One possibility is to follow the lead of our industry model by incorporating the regulatory decisions. The regulations could take the form of restrictions on the set of feasible activities. Another possibility is to incorporate the cost data into our estimation process. This may help to reconcile the unlikely profit function implications of our revealed preference approach given unobserved regulations by forcing the estimates to match available financial data.

10.7 Possibilities for Future Work

10.7.1 Electricity Supply

Following Rust [52], we can employ our model to construct an aggregate supply function. That is, we can determine the relationship between aggregate output generated by nuclear power plants and electricity prices. Our estimation of optimal responses to electricity prices provides sufficient information to compute an industry supply curve by computing average optimal output at various electricity price levels. As in Rust's work, we could compute supply curves over a much greater price range than has been observed in the price sample. Our structural, "bottom-up" approach allows results superior to those of reduced form estimation.

10.7.2 Optimal Closures

Rust and Rothwell [56] constructed industry output forecasts based on optimal closure projections. In their model, prices were constant, or at least prices had a constant mean. Prices in our model are not stationary. We estimated price equations both in high-growth and low-growth eras. If we assume that future price growth corresponds to growth in one of the past eras, then we could solve the model accordingly. We then could project optimal operator responses based on the price forecasts.

Determination of aggregate optimal output and closures would be useful directly, and the results could be used in extended studies to provide still more value. Direct results include aggregate output and industry capacity. Of course, we need to incorporate information on plant sizes, together with our model's optimal output and closure decisions.

Optimal closure is of particular importance. First, when plants close in sufficient numbers to significantly affect electricity supplies, we expect a corresponding affect on electricity prices. This endogeneity is not built into the present model, but it could be captured in an extended model. Second, we expect very significant investment in electricity generation equipment, both to meet new demand and to replace lost capacity as existing nuclear plants are decommissioned. Results from our model thus could be used to forecast needed replacement investment. Finally, closure of nuclear plants would have environmental consequences as well. If we suppose that nuclear capacity will be replaced with coal and natural gas plants, then closure of nuclear facilities means an increase in carbon dioxide and other emissions. Together with a set of assumptions about replacement technologies and emissions specifications for those technologies, our model could be used to predict changes in air pollution.

10.7.3 Incorporation of Financial Data

In Chapter 9, we developed sets of monthly, plant-level operating data and annual, site-level financial data. Our unreported work includes establishment of matches between the data sets. We intend to initiate panel data analysis of the matched data set, and we believe that even simple regression techniques may reveal interesting patterns and relationships in the data. While earlier versions of both data sets were analyzed elsewhere, we know of no other attempts to investigate the matched sets.

A potentially interesting use of the matched data is the incorporation of financial data into our dynamic programming model. Currently, our model employs no financial data. We attempt to uncover features of the firms' profit function by examining their behavior. Theoretically, these revealed preference techniques will lead us to the truth about the nature of profits, but so far we have no verification, and we have not exploited all available data. So far, we know of no attempts to employ both operating and financial data in a dynamic programming model. However, we believe such techniques can be developed, and our model would provide a suitable demonstration of these extensions to the dynamic programming literature.

Cost Models

Before we begin employment of the cost data, it is useful to review other attempts in the literature. The 1995 EIA study [2] likely provides the most comprehensive and recent analysis of nuclear power plant costs. Available cost data, including the cost data used in that study, are available only in annual frequencies. Our dynamic programming model, on the other hand, operates on monthly frequencies. Assuming that the frequency problems can be resolved, work published by the EIA may provide guidance in modeling cost minimization.

In their model [2, p. 28], four factors determine nuclear power plant operating costs:

1. NRC regulatory activity and industry experience

2. Plant aging and utility/operator experience

3. Economic and State regulatory incentives to improve performance

4. The prices of inputs used to generate electricity from a nuclear power plant.

The present value of costs are given by a constrained minimization problem where the objective function integrates discounted expected future costs of investment goods, maintenance, replacement power, and other inputs. The integral equation is minimized, though minimization is subject to two constraints: 1) capital stock changes with new investment and the depreciation of existing capital, where depreciation depends on maintenance expenditures and utilization rates, and 2) electricity sales must be provided by replacement power or produced by the plant, where production depends on capital, utilization, and other inputs. If safety and output are modeled as joint goods, then a third constraint can be added, where safety is a function of capital and other inputs. A DOE/EIA publication [1] and Hewlett and McCabe [25] provide similar models in discrete time. As discussed in the EIA 1995 update, those works show the continuous time model to be equivalent to a dynamic discrete time model with myopic expectations; Hewlett and McCabe provide evidence to support the assumptions of myopia. Clearly, this warrants further research given other evidence suggesting sophistication of plant operators; our dynamic programming models rely on the importance of such forward-looking behavior. Authors of the 1995 EIA study partially solve the model described above and estimate parameters of the resulting equations with annual data.

Writers of the 1995 EIA report noted patterns in the cost data that we reported earlier. Real total nonfuel and operating costs per kilowatt grew rapidly from the mid1970s to the mid1980s, but total costs were stable through the mid 1990's. Operating and maintenance costs per kilowatt continued to increase, but the growth rate fell sharply in the late 1980s. Capital addition costs per kilowatt of capacity peaked in the mid1980s and then gradually fell through the early 1990s. At the time, they determined that declines in costs per kilowatt-hour partly were due to modest factor price reductions but primarily were due to increases in productivity. These trends were not homogeneous across reactor types (pressurized or boiling water), vintages, or single versus multiple reactor plants (Rothwell [48]). We might suppose that the bulk of recent profitability improvements also are attributable to productivity gains. Perhaps in future work we should continue to give primary attention to productivity and related technological development and output decisions, along with regulation that constrains the range of operators' choices and thus may limit output in the short run. Still, an ideal model would include at least an index of factor prices.

Incorporation of License Extension Costs

In their original licenses, power plant operators typically received permission to generate at 95 percent of designed capacity to provide a safety margin. Many plants have applied for increases of allowed rates, which could lower costs per kilowatt and increase industry capacity by 5730 MWe by the mid2000s (Quinn, et al [44]). Hagen, et al [22] document estimates of 10,000 MWe, but claim that these estimates are unattainable. Capital cost expenditures are required for these uprates, although the costs are lower than for equivalent expansion of capacity with competing technologies, and operating costs per kilowatt of capacity also should be lower. Still, there is much uncertainty in cost estimates, and some reactor designs have much greater potential for expanded capacity. These investment decisions, and certainly the resulting changes to the cost structure and to output, should not be ignored.

Our model assumes that plants' cost structures do not depend on plant size. Of course, it would be interesting to extend the model to allow differing capacity levels. Even without capacity detail, it would be interesting to investigate our model's implications for whether capacity uprate costs would be worthwhile investments. After incorporating available financial data so that our model's unit profit function is defined in terms of dollars, we could compute total plant profits before and after capacity expansion. If the difference is greater that expected expansion costs, then we might conclude that such plants ultimately will choose to expand.

10.7.4 Investment and Learning

Significant learning effects are realized at individual reactors, within groups of reactors owned by single firms, and across the industry (Rothwell [45], David and Rothwell [35], Lester and McCabe [33], Lewis and Yildirim [34], Zimmerman [63], and EIA [2]). An unexplored topic is the benefit obtained from pooling knowledge within international firms; the matter is relevant given the recent purchase of three American reactors by British Energy, which operates 15 reactors in the UK (although the technology employed in the UK plants is somewhat different than technology employed here). Rothwell summarizes the consolidation among domestic NPP's, which may yield benefits of shared knowledge and other efficiency gains (Probability Distributions [50]; Risk of Early Retirement [48]). Information may be shared among operators via industry organizations (e.g. INPO "facilitates communication among nuclear utilities on issues related to plant safety and reliability," Lester and McCabe [33]) and by regulators. The benefits of pooled experience are limited by the lack of standardization of domestic NPP's (Lester and McCabe [33], and David and Rothwell [13, 35]; Rothwell [46] discusses the related matter of the effect of organizational structure on efficiency). Rothwell suggests that "it is likely that the owners of noncompetitive units will either (1) try to sell their units to or merge with more efficient managers rather than retire them early or (2) organize themselves into coordinating management groups…" [48]. If our modeling efforts of the nuclear power industry are expanded to incorporate these possibilities, predicted closures may fall as projected profitability increases. While the task of disentangling learning from other effects like age, regulation, and technological change is formidable, the papers above include a variety of methods to measure learning within and among NPPs.

Issues in Investment in Nuclear Capacity

Investment decisions are critical to the successful operation of NPP's. Investment is not addressed directly by our dynamic programming model, although it is addressed in the EIA's cost model [2]. Our work on liability and regulation includes detail on certain types of investment, including investment in maintenance and safety enhancements. Our summary of cost data includes three spending categories: operations and maintenance, fuel, and capital additions expenditures.

Given the increasing probability of new construction of NPPs, we could use our model to compute the value of a new plant. Of course, this would mean that we implicitly assume that new plants would be built with the same technologies as existing plants, so that the structure of their operating costs and the evolution of their state variables would be identical to those of plants in our sample. If the present value of a new plant exceeds the expected construction and financing costs, then we might conclude that new construction will take place. New NPP's currently cost about $2000 per kilowatt, an amount substantially greater than the $500/kW for existing plants (Rothwell [50]) and the relatively low capital costs for coal and gas plants (Hagen, et al [22]). Other authors [6] make the same point. Still, energy companies recently have announced plans to build new plants, and regulators are granting permits and negotiating tax incentives. Plants that are most likely to begin operations are new reactors at existing sites, partially constructed plants that currently have been abandoned, and plants that currently are shut down because of damage or unfavorable economic conditions (Hagen, et al [22]).

There are significant learning effects in the construction of new plants; construction experience in other countries could lead to lower costs here. Zimmerman [63] documents learning-by-doing effects and improving accuracy of cost expectations. In past decades, costs initially were underestimated significantly; economies of scale were overestimated in the jump from small government-sponsored demonstration projects to large commercial plants. The experience of the French nuclear industry suggests costs can be lowered substantially with standardization of technology, the operation of multiple reactors by single firms, and consolidation of regulatory authority (David and Rothwell [13]). Domestic adoption of technologies proven elsewhere may grant benefits of standardization. Chances of streamlining the regulatory process are uncertain in the current era of market restructuring. Some benefits of consolidation of existing plants likely are realized already (Rothwell [50]); whether the efficiencies of operating multiple existing plants will extend to efficiencies in building new plants is not clear.

Ellis and Zimmerman [18] note that the Clean Air Act improved the ability of NPPs to compete with fossil fuel alternatives; the effects of carbon taxation may similarly make NPPs more competitive in the future. Rothwell and Eastman [51] document periods in the late 1970s and early 1980s when the realized rate of return and the allowed rate of return were less than the cost of capital. A number of authors have addressed similar matters regarding NPPs in restructured markets.

Even without construction in new plants, output likely will continue to increase at existing plants. Capacity factors and reliability have been increasing for over a decade; even higher utilization rates are projected (for example, see the Energy Outlook [4]). Understanding of the causes of the U-shaped capacity factors displayed in Chapter 9, where performance initially improves and then declines with plant age, is important to predicting future performance. Significant effects on utilization include regulatory effects, learning-by-doing, technological improvements, expenditures on maintenance and other improvements, and the effects of economic and regulatory incentives (DOE [2]). Examination of the record of new construction and utilization of competing technologies, especially coal plants, may shed light on the operation of NPPs. There is some evidence that such phenomena that first seem peculiar to nuclear plants in fact extend to competing generators (see, for example, Ellis and Zimmerman [18]). For example, low utilization in the 1980s may be the result of excess capacity caused by a decrease in the growth of demand. The statistics also may be misleading, since even among NPPs, "only Babcock & Wilcox (the manufacturers of TMI) reactors experienced a significant decrease in productivity after 1979," but their struggles pulled down the industry average productivity (Rothwell [45]).

These investment decisions, and certainly the resulting changes to the cost structure and to output, should not be ignored.

10.8 Conclusions

We constructed and solved a forward-looking model of nuclear power plant operations. Important extensions of our work relative to earlier efforts include the addition of price equations and incorporation of the risk of serious accidents. More work is needed to expand our results and to confirm them. However, initial results indicate that the mid1980s change in price structure may account for structural instability observed in earlier models.

Our model of power plant operators summarized key features of the fuel cycle and other technological factors in a vector of state variables. Given the current realization of plant conditions, and given current and expected electricity prices, operators choose a feasible activity to carry out in the current month. We found our model capable of reproducing observed behavior with a great deal of accuracy.

Our work shows the importance of considering demand-side factors when modeling nuclear power plant operations. Extensions of earlier work to incorporate electricity prices indicates that prices significantly affect operator behavior. Earlier work seemed to indicate that changes in regulation were responsible for changes in plant values and in operator behavior. Our work shows that at least some of the observed changes in fact were due to changes in the price structure.

We employ the model in the study of effects of license extensions offered to operators in the 1990s. As we found in Chapter 5, and as earlier writers found, the values of plants increased significantly when extensions became available. We also find evidence that operators take greater care of their plants in order that they might survive to greater ages.

We incorporate details of accident risks and liability. In general, more work is needed to incorporate estimates of risk that depend on plant activities. Still, our simple implementation of risk and liability information shows that optimal policies do respond to these factors.

We noted a number of possible extensions to our work. Perhaps the extension with the greatest potential is to incorporate financial data to refine our estimates of plant profits. We already have accumulated most of the necessary data to support this work, as we reported in Chapter 9. We intend to focus considerable effort on this extension.

Chapter 11

Conclusions

11.1 Conclusions

We set out to build a unifying model of the nuclear power industry to make sense of key factors in a complicated market. The work began our efforts to form a framework upon which future studies may be built. We established an admittedly abstract model of the nuclear power industry in order to guide construction of more realistic economic models. We then built models of the industry with greater realism, guided by the lessons learned in building the industry models and analysing their properties. Along the way, we gained a better understanding of this industry which remains much studied but little understood.

11.1.1 What We Did

We constructed and analyzed nuclear power industry data that reveal dramatic changes in the industry over the past thirty years. In the 1980s, with soaring costs, public opposition, and burdensome regulations, the future of the industry was in doubt. Our matched data set reveals, both in the cost data and in the activities of individual plants, that in following decades productivity improved dramatically while cost growth stabilized and profits per unit of output increased. While we were able to construct only crude measures of revenue and profits, our data seem to confirm impressions given by media reports that the industry has returned to profitability. Construction of profit estimates for the nuclear power industry is a rare, if not unique, contribution. Still more rare is the construction of revenue and profit data for each site of nuclear power operations.

We set upon the ambitious task of developing an extensible model that initially incorporates the key features and economic agents of the nuclear power industry and ultimately can can support both additional micro and macro level details. In this way, we hoped to support efforts to make sense of existing literature. It is our impression that while many useful studies have been completed, they often focused narrowly on specific topics. Relatively little modeling work has been done to tie together these fragments of understanding of this complicated industry.

Our models include as a key feature an element of the nuclear power industry that typically receives little attention in the formal literature. This feature is the limited liability protections offered under the Price-Anderson Act. It is our belief that little is understood about the effects on the industry of this policy. Operators clearly prize it, and legislators have extended it repeatedly since it first passed in 1957. Environmentalists and consumer activists revile it, and they suppose that the industry would collapse without such protections. Strangely, perhaps, few studies have been published that attempt to calculate the policy's value to the industry, or even to enhance our understanding of the specific nature of the benefits. We began with a fairly extensive model of the industry, derive optimal regulation and operator behavior, and then derive equations for implicit subsidies to the industry. The result indicates that earlier attempts to quantify the level of subsidies failed to account for certain costs to the industry arising directly or indirectly from liability protections. We show the importance of considering the full set of regulations faced by the industry, and we advise against attempting to determine costs or benefits to the industry of a particular policy without considering possible indirect effects.

There is a large literature on the economics of nuclear power, including many studies on the struggles of the nuclear power industry in the late 1970s and 1980s. The struggles were observed both in the construction of power plants and in their operation. Many explanations for the observed difficulties have been proposed, and many of them have been tested. Summary studies also have been published in an attempt to make sense of the many ideas. Unfortunately, few models have been presented that are suitable to incorporate dissimilar causes of the industry's troubles. Our models seek to support three primary explanations: costs and other firm-level causes, effects of regulation, and demand-side effects.

While we spent much of our time thinking about the interaction among several economic agents, we also spent considerable time focusing on the agent of primary concern to us. Of the countless models of nuclear power plant operators, we chose to extend existing dynamic programming models. We extended the previous work in three ways. First, we extended the data set to determine recent industry trends. Second, we incorporated demand-side effects on operator behavior by including price equations in the model. Finally, we examined the effects of the risk of catastrophic accidents on operator behavior.

11.1.2 What We Concluded

Costs have stabilized, productivity has climbed, prices may be increasing, and so the industry now seems more profitable than at any time since the mid1970s. These impressions given by the data are supported by the high interest in expanding capacity of existing plants and the recent interest in building new plants, despite remaining uncertainties of community tolerance and support of regulators. The recent apparent willingness of regulators and perhaps the public to consider expansion of the industry signifies a great shift in attitudes toward nuclear power. These relatively positive inclinations, together with apparent economic profitability, suggest that life for nuclear power plant operators is far better than in the 1980s.

Part of the reason that plants are able to operate profitably is that liability protections remain in place. Whether critics claim correctly that these benefits contribute significantly is a question still unanswered. Our work revealed problems in earlier estimates of the magnitudes of implicit subsidies. We offered alternative calculations that suggest that the amounts are lower than previously reported, but doubt remains. Our derivations of implicit subsidy calculations reveal that existing views of implicit subsidies are too narrow, and that more effects of liability protections on plant operations must be taken into account in order to identify and quantify benefits.

We conclude that earlier efforts to build dynamic programming models of nuclear power plant operators insufficiently accounted for primary determinants of operators' decisions. In particular, earlier efforts omitted demand-side factors that affect profitability. In addition, we saw that at least in theoretical models, the effects of regulation on operators' behavior and on profits can be highly significant.

11.1.3 What Is Next?

As we began, we announced our objective. Our sights were sufficiently high so that we could not possibly arrive at our ultimate destination by the end of the present study. Rather, our goal was to begin well, so that at this point much work would remain to be done, supported and prompted by our beginnings.

Did we succeed? We might address the question by considering possibilities for future work that are inspired and supported by the work we now conclude.

We established three frameworks and employed them in our work. They were 1) compilation and unification of operating and accounting data sets for individual plants and sites, 2) an abstract model of the nuclear power industry, including nuclear power plant operators, industry regulators, and consumers, and 3) a detailed model of nuclear power plant operators.

The data set developed remains largely unexploited. In particular, we made little effort to investigate the relationships between the operating data and the cost data. While earlier samples of both sets were studied elsewhere, we are aware of no other efforts to combine and study the full set. Many questions might be answered by such studies, including “What is the average cost per month of refueling?” “What is the cost of a typical extended problem spell?” “Can we link the moderation of cost growth to changes in operators’ behavior?” A very interesting possibility is to incorporate the cost data with our dynamic programming model. This offers the possibility to go beyond the revealed preference approach to profit function estimation. We at least would like to know how well the profits implied by our model correspond to actual accounting data.

Our model of the nuclear power industry remains rather primitive. A number of difficulties with the present model were presented in the text. In particular, work to make the nature of uncertainty regarding potential damages correspond more closely to reality would yield a model more satisfying. In particular, we would prefer a model in which each plant faces a distribution of potential damages, so that each plant operator receives benefits from liability limits.

An extension of particular interest is to make investment unobservable to regulators, perhaps following Shavell [58]. In such a model regulators monitor investment and detect imperfectly violation of standards. Monitoring is costly, and the level of regulation, the degree of monitoring, and the severity of punishment for violations would be endogenous. This would represent much better the real world with violation of regulatory standards, occasional detection of such violations, and subsequent penalties.

The model can be extended indefinitely by adding other details, such as competing generating technologies. We then could use the model to analyze tradeoffs between, for example, nuclear power with its inherent risk and coal power with its carbon dioxide and other emissions.

We also would like to consider political interests related to nuclear power. In particular, the effects of political interests on the regulation of nuclear power could be studied with our model.

Our extended dynamic programming model of nuclear power plant operators remains rather primitive, as it is devoid of many details important to the industry. While the model could benefit from incorporation of additional detail at the microeconomic level, we believe the greatest promise may be realized by further integrating the various modeling efforts and data work in this paper. We noted in the paper that the model is constructed under the assumption that operators are rather simple profit maximizers. In reality, they operate under high levels of regulation. We thus remain skeptical of some of our profit function estimates, for they seem to indicate high profitability for frequently-chosen actions that more likely were required by regulators. By extending our work on regulators and combining it with our work on power plant operators, we might improve our model and gain additional insights regarding the operation of nuclear power plants.

Chapter 12

Appendix

12.1 Software

In this appendix, we summarize very briefly the software constructed to support the econometric dynamic programming work reported in Chapter 10. The software was designed to be useful for construction of a variety of dynamic programming models, and it is intended to make such work less difficult and thus much quicker, so that more attention may be paid to economics and less to programming.

The approach to numerical dynamic programming follows the work of Miranda and Fackler [38]. They offer a textbook and an accompanying set of numerical and dynamic programming tools for Matlab. Our tools instead are written in C++. While the approach to writing code necessarily differs because of the nature of the programming languages, we loosely follow their techniques to separate the model-specific portions of code from remaining code. We similarly follow their example in our approach to solving finite-horizon and infinite-horizon models with possibly both discrete and continuous state variables and discrete choice variables.

The primary difference between our software and the tools of Miranda and Fackler is that we offer econometric analysis in addition to simply solving numerical models. Our software currently allows models to be solved either with quasi-Newton optimization methods or with derivative-free methods.

We also follow the lead of Inforum programmers at the University of Maryland who built and maintain the set of modeling tools for C++ known as Interdyme [36]. It was their intention to facilitate the construction of large-scale interindustry models by offering tools to handle data construction and management, regression estimation, and other standard procedures. By relying on these tools, the job of setting up and debugging large economic models can be done far more quickly and reliably. The modeling tools for C++ are supported by G7, the Inforum program for econometrics and database construction. Typically, G7 is used to prepare data and estimate regression parameters for a model. The model then is built using Interdyme tools and employing the databanks and regression equations. Once the model is solved, G7 again is used to analyze and report the results.

We too used G7 to collect and organize data on nuclear power plant operations. Once the databank was constructed, we used Interdyme tools linked to our dynamic programming model to read the data. After loading the data into objects defined by our own data storage classes, further data processing was performed as described in the Rust-Rothwell papers. With this data in hand, the process of solving the model and estimating its parameters could begin. While thus far we depended on Interdyme rather little, we intend to integrate our efforts far more completely in the future. The greatest contribution received thus far from the Inforum efforts is the specification of useful objectives and techniques in the design and implementation of modeling tools.

Future documentation will offer a detailed guide to the design and use of our software.

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