# A Risk Management Approach to IT Services Contract Design

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# Dedication

I dedicate this work to Sara and Avery...

**Abstract**

Information Technology (IT) service contracts imply a transfer of risk between parties. There has been little research conducted on how firms can apply quantitative analysis of risk factors in IT service delivery and contract negotiation. This dissertation applies risk management theory and methods from financial economics to inform negotiation of contractual parameters in IT Services agreements. The research offers contributions to the development and application of risk management and investment under uncertainty models to the problem space of information technology services investment. I develop a new model for managing risk in IT services contracts. In addition, I develop new analytic models to provide both valuation and strategic direction for benchmarking IT services under opaque conditions of market opaqueness and price volatility. Essay 1 develops the optimal trade-offs of risk and return in contract negotiation and introduces a new method *IT Services Profit-at-Risk* for evaluating contractual concessions. Essay 2 provides a model of valuing price benchmark provisions in IT services contracts and gives guidance on how to value and when to execute these provisions. Essay 3 examines the role of visibility of the market prices of IT services and provides a model for valuing market price information in the context of IT services price benchmarks.

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# Chapter 1. Introduction

## *1.1 Research Questions and Context*

Contracts for IT services include provisions that specify the scope, quality, and duration of the services to be delivered. When clients and providers of IT services enter into contracts, they expose themselves to a myriad of risks. The risk exposure of an individual firm is often dependant upon the provisions surrounding contract duration, service quality, and scope. For example, a provision which limits a provider's ability to pool IT service delivery resources increases the provider's exposure to client demand uncertainty. The provider cannot shift resources in times of where client demand is unexpectedly high or low. Such provisions limit the provider's ability to *diversify* demand risk. Other risks involve poaching and misappropriation of sensitive information (Clemons and Hitt, 2004), and those risks underlying market conditions and client capabilities. While there has been a substantial body of research considering IT services contracts risk and agency issues (Clemons et al., 1993, Aubert, et al., 2005), there has been little research in quantitative-based IT services risk management.

Providers must deliver IT services to the quality specified in *service level agreements* (SLA), or they face penalties or cancelations. EDS lost over $300 million in the initial phase of its U.S. Navy/Marine Corps outsourcing contract. In a recent interview, EDS CEO, Michael H. Jordan, remarked that contractual provisions was a major cause of the losses: "we accepted terms and conditions [such that] that any mistake resulted in very high payments, way off the industry standard [in terms of onerous service levels and penalties]" (*eWeek* 2006). My research offers an approach that allows providers to assess their risk exposure to SLA performance, client demand, and technology and labor prices. I demonstrate how they can leverage quantitative assessments of the risks associated with IT services delivery across their portfolio of services contracts to negotiate contracts more effectively. I also examine the client perspective, and provide guidance on evaluating contractual provisions of price benchmarks.

Fundamentally, my dissertation seeks to answer the following question: *How can firms apply quantitative methods and risk management theory to inform decision making in IT services contract negotiation?* I look at two specific contexts of IT services risk management. First, I consider *service-delivery* risk faced by provider firms when offering customized, dedicated resources to a services contract. I then consider the *market risk* associated with the prices of IT services. Such risks are mitigated through contractual provisions such as benchmarks, abandonment and contract duration. Finally, I consider the availability of IT services price information and provide valuation of benchmarks when market price information is available. I also develop a model for evaluating under what conditions client firms should seek third-party information. All three perspectives offer theoretical advances in the financial economics of information systems and provide decision support for both providers and users of IT services.

## *1.2 Overview of the Three Essays*

### 1.2.1 Overview of Essay 1: The Profit-at-Risk Approach towards Risk Management in IT Services Contracts

In Essay 1, I explore a basic proposition: IT services vendors that understand the risk impacts of contractual provisions will be better able to manage and negotiate their portfolio of IT services contracts over time. I examine the specific context of *service delivery constraints.* These constraints limit the amount of subcontracting, offshoring or resource pooling a vendor can utilize in the delivery of services. In addition, many contracts specify an amount of dedicated resources, such as personnel or on-site technology equipment. I ask two specific research questions: How should an IT services vendor optimally set contractual parameters given an acceptable level of risk? How will a manager's risk preference inform that decision? How can we achieve a better understanding of risk exposure in IT services contracts to inform managerial decision making?

To address these questions, I apply a method of financial risk management, value-at-risk, to construct a model which assesses the risk and profit impact of contractual decisions. I show that under certain conditions firms may choose to make trade-offs of expected profits for reduced risk exposure. I extend the model to consider contract duration, timing and portfolio-level impacts. Essay 1 provides a foundation for future decision support tools for information technology services management.

### 1.2.2 Overview of Essay 2: Optimal Timing and Valuation of Price Benchmarks in IT Services Contracts

In Essay 2, I shift from the vendor perspective to the client perspective. I consider the problem of opaque prices in IT services. Once a contract for IT services has been signed, clients will have a limited view of the market price of the services. As new technologies and processes are introduced, the market price for comparable IT services are likely to drop below the price the client paid at contract inception (Overby, 2007a). To remedy the risk of paying above-market prices for IT services, client firms often insist on benchmark provisions, by which a third-party presents a study of prices of comparable IT services and price adjustments are made according to the terms of the contract. As the practice of benchmarking has evolved, clients have misused the benchmarking process by benchmarking too frequently (Harris 2007) or too late in the contract (LaVasseur, 2001). Benchmarking too early may lead to situations where the prices have not dropped far enough to be adjusted according to the terms of the benchmark provision. By contrast, if a firm benchmarks too late, they miss out on potential cost savings. The specific research questions of Essay 2 follow: What is the value of including a benchmark provision for a client? What is the optimal time and frequency of exercising benchmark provisions in an IT services contract? How will uncertainty about the IT service price drift affect these decisions?

I build a model for optimal timing of price benchmarks under conditions of a constant price drift forecast. I show that the optimal timing of the benchmark will always occur in the first half of the contract. I extend the model to consider multiple periods and show that for longer durations, or greater magnitudes of price drift, multiple benchmarks should be utilized in the contract. Finally, I extend the base model to consider uncertainty surrounding the forecast of IT services price drift. I build a model based on conditional expectations, and show the optimal timing will occur earlier in the contract, and that price benchmarks are more valuable under uncertainty, *ceteris paribus*. Based on the results of Essay 2, I offer guidance for managerial decision making under the assumptions of my model. In addition, it can also provide the foundation for decision support.

### 1.2.3 Overview of Essay 3: Visibility of IT Services Prices and the Benchmarking Decision

In Essay 3, I delve deeper into the role of visibility in IT services and the impact on the benchmarking decision. Several benchmarking firms now tout “market analysis” or “snapshot pricing” services (e.g., Pro-benchmark, TPI, Compass). A snapshot provides the client with an assessment of market prices prior to committing to a full benchmark with the vendor. Clients may choose to purchase these snapshots once in the contract or over the lifetime of the contract. The following research questions motivate Essay 3: What is the value of market price information throughout the life of the contract for the client firm? When should a client purchase these services? How does the availability of market pricing information affect the participants’ decision to benchmark or negotiate contractual terms?

I model the decision of benchmarking according to visible market prices by deriving the critical price: an observed price at which it is optimal to exercise the benchmark. I compare the value of utilizing the critical price approach across multiple discrete time periods as an upper bound of the valuation, and then compare the value of single snapshots across the contract. In addition to contract cost savings, I also model the effects of benchmark avoidance as compared to the model of Essay 2, where the benchmarks are blind. Finally, I compare the effects of information asymmetry, and show that clients may enjoy additional benefits of negotiation leverage with market price information.

## *1.3 Note on the Style of Dissertation*

This dissertation follows a three-essay format where each essay addresses a specific topic relating to the unifying theme of the dissertation: *IT services contract design under uncertainty*. In addition, I include Chapter 2, which is intended to provide the reader with background, literature review, and conceptual framework for evaluating approaches to financial risk management in information technology services and investments. Thereafter, the remainder of the dissertation is constructed as follows. Chapter 3 is Essay 1, which develops a new risk management approach to evaluating contractual parameters that constrain vendor service delivery. Chapter 4 represents Essay 2, which presents a model for the optimal timing and valuation of price benchmarks in IT services contracts. Finally, Essay 3 also considers price benchmarks, but evaluates the value of third-party price information services and considers the impact of information asymmetry among providers and clients. Since Chapters 2, 3, 4, and 5 have been published, presented at conferences or are under review, I use “we” when appropriate to acknowledge the input of my advisor and co-author on these works.

# Chapter 2. Essay 1: A Framework for Risk Management in Information Technology Services and Investments[1]

## *2.1 Introduction: The Information Technology Investment Decision*

Investment evaluation and project management for IT-enabled services [2] involve assessment and decision making under uncertainty, which has been an important stream in the overall information systems (IS) research literature (McCardle, 1985; Schwartz and Zozaya-Goristiza, 2003; Banker and Kauffman, 2004). [3] In some settings, the uncertainty is relatively straightforward for senior managers to understand, and they can gauge the expected value of a project over time as its development progresses. However, if we introduce the possibility that the value of these systems is driven by standards choices that need to be made relative to the underlying technologies (e.g., technical platform, software development environment, etc.), it is possible that there will be risk exposure relative to the value payoffs that can be obtained based on *external factors* to the firm. This especially includes changes in the technical platforms, operating systems and related software development methods, competitors' actions, and so on (Hunter et al., 2004). Risk exposure for the value of these kinds of software

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[1] Portions of this essay were published as Kaufman, R.J., Sougstad, R., Value-at-risk in service-oriented systems: a framework for managing a vendor's portfolio uncertainties. *International Journal of Service Sciences* 1, 3-4, 2008.

[2] We hereafter refer to *IT-enabled services* as those services which are either delivered (like Web services) or managed and governed (like many traditional IT outsourcing and business process outsourcing solutions) via information or communication technologies. These services will have available transaction and performance data which will enable robust risk analysis.

[3] Initial work in IT uncertainty dealt with managing software development project risk (McCardle, 1985), while latter work focused on applying real options analysis to technology risks which enable follow-on IT investments, such as ISDN and infrastructure projects (Dos Santos, 1991). Schwartz and Zozoya-Goristiza (2001) considered risks to both technology benefits and costs in an options framework. See Banker and Kauffman (2004) for a connected discussion of software economics and real options analysis.

projects may also arise due to *internal factors* in the firm. They may include, for example, managerial decisions that are taken about organizational strategy, shifting emphases on different businesses going forward, whether to source the technology project internally or externally. [4] Industry analysts have recognized the need for active risk management within the service-*oriented enterprise* (SOE) environment. Sleeper (2003), for example, has called on managers to consider diversification strategies in order to mitigate risks associated with technology standards, security and project implementation.

One can easily imagine a senior manager asking: "How exposed is the business value of each of my firm services projects to internal and external sources of risk?" and "How can an understanding of this exposure inform decisions in response to changes in my firm's technology choices, business plans and market situation?" These questions require new thinking around systems and technology investments which focus on project and portfolio risk exposure rather than project returns.

To frame the issues more effectively, we explore new methodologies associated with an area of asset valuation theory in financial economics called *value-at-risk* (VaR) (Duffie and Pan, 1997; Frain and Meegan, 1996; Linsmeier and Pearson, 1996). [5] This approach measures the worst expected loss over a given time horizon under normal

[4] Benaroch (2002) presents a table of IT risks including internal risks (financial, project, functionality and organizational risks), competitive risks and market risks (environmental, systematic and technological). He incorporates these concepts into associated real options on the IT project investment (e.g., defer, abandon, grow, lease, outsource, etc.). McGrath and MacMillan (2000) present a method for assessing technology risk factors and applying them to a real options analysis.

[5] Linsimeier and Pearson (1996) and Frain and Megan (1996) provide overviews of value-at-risk concepts and methodologies. Duffie and Pan (1997) focus on measurement of market risk in the context of value-at-risk. Jorion (2006), now in its third addition and indicating the well-accepted of this thinking, provides perhaps the most comprehensive treatment of value-at-risk techniques, methods and applications.

market conditions at a given confidence interval (Crouhy et al., 2001).[6] VaR methods permit the analyst to consider the *interdependence* of the value flows and returns of multiple projects in a portfolio that occur due to endogenous and exogenous influences.[7] We discuss the types of services project value assessment problems that VaR is able to address effectively, as well as the associated information requirements, outcomes and limitations of the methodology. We present a framework that is intended to help senior managers to bring these concepts into use in real world organizations. We also contrast the different assessment perspectives for *client firms* and *provider firms* that wish to assess the risk position of their services project portfolios.

The next section provides background on approaches used to inform the information technology investment decision. In section 2.3 we present an overview of value-at-risk, and we provide the background to orient the reader to the source of our new IT-enabled services investment evaluation thinking. Section 2.4 section proposes a new framework for the assessment of VaR methods in information systems and technology services investments. The final section summarizes the contributions of this research, and discusses a number of limitations in the VaR theory and methodology for IT-enabled services portfolios.

## *2.2 Methods for Managing IT-enabled Services investments*

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[6] See Schacter (1997), who provides three contrasting definitions.

[7] Hereafter, we will refer to *value-at-risk* and *VaR* in two different ways. We will use the full term, *value-at-risk*, to indicate the specific measurement concept, as denoted by the theory. However, when we refer to related concepts and methods, we will use the abbreviation, *VaR*, as in *VaR methods* or *VaR-based portfolio evaluation*. In the first case, we are referring specifically to a dollar value that can potentially be lost, while in the latter we are referring to a body of knowledge associated with VaR methods.

We now discuss the previous methods for managing IT-enabled services investments under uncertainty. We focus on real options applications to IT-enabled services investments. We later position VaR analysis as an alternative to real options analysis in IT services management.

### 2.2.1 Investments in IT-Enabled Services: General Characteristics

In their book *Investment under Uncertainty*, Dixit and Pindyck (1994) identify three characteristics which investments share: the investment is partially or completely *irreversible*; there is *uncertainty* over the future rewards from the investment; and there is some leeway for the *timing* of the investment. These factors are consistent with those that most analysts recognize as being appropriate for the use of real options analysis (Copeland and Tufano, 2004; Dixit and Pindyck, 1995; Luehrman, 1998, 1999). In IT-enabled services, the terms of the contract may dictate the extent to which Dixit and Pindyck's characteristics apply. For example, irreversibility may be negotiated through buyout clauses which release the provider or client from the contract. We present the argument that service-level commitments represent risks absorbed by providers in IT-enabled services contracts.

### 2.2.2 Real Options Analysis in IS Research

Real options analysis in information systems (IS) research centers on the valuation of managerial flexibility in the face of project or technology risk factors. Many of the risk factors associated with IS and IT investments map to IT-enabled services investments, from both the client and provider perspective. An option gives the bearer, the right but not the obligation to purchase (call) or sell (put) an asset at a predetermined price at a future date. Black and Scholes (1973) developed the one of the first models to price options.

Real options analysis initially focused on providing a quantification of managerial uncertainty to a project's value. Clemons and Weber (1990) and Clemons (1991) were among the first to identify the components of the IT investment decision, which laid the ground for the current IS research stream. Dos Santos (1991) presented a model to justify investments in networking technologies (ISDN) using real options. Kambil et al. (1993) utilized the binomial model to analyze the real options enabled by a hospital's technology infrastructure investment. Kumar (1996) further explores option pricing methods to derive the conditions under which risky technology projects are desirable for the firm. These early models led to more sophisticated work that balances rigor and relevance with both simulated and real data. Benaroch and Kauffman (1999 and 2000) offer a comparative analysis of the Black-Scholes and binomial option valuation approaches, as well as for analysis features involving European and American options, in the context of Yankee 24's adoption strategy for debit card network services in the New England States. Their research incorporates a rigorous sensitivity analysis using option pricing analytics that are standard in financial markets operations for option valuation in changing market conditions. Taudes et al. (2000) presented a real option model which evaluated the investment decision of an SAP R2 to R3 enterprise system software upgrade. Dai et al. (2007) explore the options enabled by firm infrastructure investments in Internet-based business-to-business supply procurement settings.

A second use of real options analysis emphasizes the strategic impacts of systems and technologies on the firm in its marketplace. Clemons and Gu (2003) suggested incorporating real options logic in the strategic planning stage by identifying and embedding options in technology projects. Benaroch (2002) also explores the notion of embedded real options while incorporating multiple risk factors. He models the flexibility-enabling solutions of systems technology and calls them *operating options*, which are intended to enable management to control IT risks. He measures the values of a set of *cascading options* that are embedded in a single project and proposes a means to optimize the mix of option-bearing IT investments. Fichman et al. (2005) presents a real option model for evaluating technology platform adoption and stresses the strategic benefits from options analysis (McGrath and MacMillan 2000). Sougstad and Bardhan (2007) build a real options model which incorporates both inter-project and intra-project risks.

Finally, real options analysis can inform the optimal timing of a technology investment. Schwartz and Zozoya-Gorista (2003) considered Benaroch and Kauffman's (1999, 2000) problem of bank ATM adoption and developed an optimal timing model based on the Margrabe (1978) asset-for-asset exchange model. Kauffman and Li (2005) looked at optimal timing of procurement systems under the uncertainties of competing standards.

Several criticisms of the approach had been noted by those inside and outside the IS research stream (Tallon et al. 2002). One such concern is the relevance of real options analysis to practitioners. Most executives, especially IT executives, are familiar only with traditional DCF or NPV models of investment analysis (de Jong and Ribbers, 1999). Real options theory often proves to be too abstract for practitioners because it requires the estimation of cost and cash flow volatilities (Gustafson and Luft, 2003).

Black and Scholes (1973) and other option pricing models rely on the assumption that the underlying asset was subject to exchange on an arbitrage-free market. Technology investments often are not easily mapped onto this liquidity assumption, which presents a significant obstacle in the estimation of volatility to the value of the underlying asset. Although researchers have employed sophisticated sensitivity analysis and made compelling arguments that the underlying technology assets are derivatively subject to market valuation through the market's assessment of the value of publicly-traded firms (Benaroch and Kauffman, 1999), most researchers and analysts recognize that the numbers generated by real option analysis cannot be validated. The best we can do is to try to come close to the truth to make the analysis process valuable. However, in the case of IT services, we do have the opportunity— especially from a provider perspective— to analyze historical project-specific performance data.

## *2.3 Overview of Value-at-Risk and VaR Methods*

*Value-at-risk* (VaR) techniques present a new theoretical frontier for financial economics-based assessments of IT value (Duffie and Pan, 1997; Frain and Meegan, 1996; Linsmeier and Pearson, 1996). Their roots were established in the aftermath of several major financial calamities in the late 1980s and early 1990s, including the fall of Barings Bank of the Netherlands (Leeson and Whitley, 1996) and other international financial problems, (Jorion, 2005), and the Orange County, California treasury disaster (*E-Risk.com*, 2005; Jorion, 2005). In both of these instances, individuals invested large amounts of capital in volatile investments, while concealing the extent of the risk exposure from upper management. In response to these failures and feeling increasing pressure from government regulators, financial services firms sought out new analytics and systems to better understand and control their risk exposure.

Initially, the methodology associated with VaR analysis focused on *passive information reporting*, which enabled firms to identify their risk positions. But this quickly evolved into *defensive information reporting*, and the use of VaR methods as a means to provide more objective measures and control risk. This allowed firms to begin to implement risk control mechanisms in their organizations that were increasingly based upon standards for risk management, thus avoiding large-scale disasters. VaR methods for controlling risk in lending and credit, money market and derivative instrument trading, and investment management operations have advanced to the point where they are almost universally accepted as a basic part of a financial firm's risk management tool kit (International Financial Risk Institute, 2000).

*Value-at-risk* represents the worst expected losses to an investment or portfolio at a given confidence level and a given time horizon. VaR analysis allows managers to quantify their risk exposure; the probability boundary of potential losses (See Figure 2.1). VaR measures are commonly used as a benchmark, where the company compares its risk position across different markets. Companies assess whether the risk position has changed relative to time or across markets. Significant deviation will signal the manager to "drill down" in the portfolio to analyze which assets account for the increased risk exposure. Such benchmarking is an example of the use of VaR methods as a *control measure*. [8]

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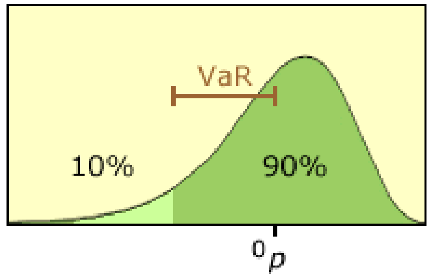
[8] Banks and financial institutions utilize VaR to send warning signals when portfolio risk exceeds management's pre-selected levels of risk tolerance. Likewise, IT firms can measure and monitor on-going risk factors within and among projects. Such an analysis may be able to complement dashboards and other portfolio management approaches. See Jeffery and Leliveld (2004) for an overview of IT portfolio-related management best practices.

**Figure 2.1. Value-at-Risk**




**Source:** Excerpted from www.riskglossary.com

Firms employ value-at-risk as a potential *loss measure*. [9] This permits them to focus on the maximum loss that can occur associated with a give portfolio. For example, banks compare daily value-at-risk to daily profit and loss measures. Some firms also use VaR metrics to set a capital cushion for the company (Jorion, 2005 and 2007). If the firm's losses exceed the value-at-risk, the company could face bankruptcy. The firm needs to be comfortable with both the level of risk, and the consequences of a loss which exceeds the value-at-risk.

### 2.3.1Value-at-Risk Requirements

VaR requires input variables that are similar to those used in other derivative and portfolio optimization models. The assumption of an arbitrage-free market of traded securities lies at the core of these models. However, rather than focusing on the price of the asset, VaR measures the likelihood of experiencing a given loss. This analysis requires an estimate or simulation of the distribution of returns, which is somewhat less restrictive than the assumption of arbitrage-free pricing models which the most derivative pricing models rely on (Jorion, 2007). A VaR analysis can be thought of as

[9] VaR, by definition, is a maximum loss measure at a given confidence level. VaR provides a means of quantifying risk by associating it with loss levels. Thus, a VaR loss measure can inform investment decisions by analyzing the impact of the *a priori* investment decision.

incorporating discrete steps in accordance with the figure. First, the *mark-to-market position*, or its value at the time an evaluation is undertaken, is measured. Next, the variability of risk factors is assessed, followed by the choice of time horizon for the VaR analysis. Management must then decide on the confidence interval (e.g., 95% or 99% probability) to measure value-at-risk. Finally, a *worst expected loss value* can be generated.

Table 2.1 outlines the core components required for VaR analysis.

**Table 2.1. Evaluation Components for Measuring Value-at-Risk**

| COMPONENT | DEFINITION |
|---|---|
| Mark-to-market position | Mark-to-market position is defined as the value of an asset or a portfolio based on current market value |
| Variance of asset value or returns | Measures the variability of a risk factor that underlies asset value, and is usually stated in variance or standard deviation |
| Time horizon | Time frame over which VaR is to be assessed, based on managerial discretion relative to the risk perspective |
| Confidence interval | The probability bounds on the observation of a specified value-at-risk outcome, chosen based on a firm's desire to manage outcomes up to a predetermined likelihood |
| **Note:** The material in this table is adapted from Crouhy et al. (2001) and Jorion (2007) | |

### 2.3.2 Mark-to-Market Position

VaR requires that the asset or portfolio be evaluated in terms of its current market price or *mark-to-market value*. As the name implies, mark-to-market value is analogous to a spot check of the value of a portfolio and all of its underlying assets. Mark-to-market value is essentially the same input variable as the asset price at time zero in the Black-Scholes option pricing model. However, VaR is forward-looking and the potential for losses are expectations-based, so marking portfolio value to market is incorporated as an ongoing measurement of risk. Thus, as the portfolio moves through time, its underlying assets, which are assumed to be traded in a liquid market, will change in value[10]. In the context of systems and technology investments, we will assume that costs, benefits or both will be subject to ongoing changes, thus we use initial managerial projections as proxies for mark-to-market. However, as risks change over time, the technology risk must be reassessed for each iteration of value-at-risk.

### 2.3.3 Measuring the Variability of Risk Factors

The measurement of the *standard deviation of asset returns*, $\sigma$, is a common component of financial models. [11] In the VaR framework, $\sigma$ represents the variation of asset returns over a specific time horizon. Simulation techniques, such as Monte Carlo methods, are often applied to measure the variability of asset risk factors. For traditional IT project investments, the underlying asset volatility typically will be a managerial assumption, since there will not be sufficient historical data to calibrate the variance. The literature on IS real options offers precedents for such constructs, and we further discuss this issue later in this article. However, service providers are likely to have aggregate data on projects, historical analysis may be available. For example, a provider of grid computing, or even help desk services, would have data on the number

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[10] Marking to market is an iterative process in financial risk management. As time progresses, the initial value of the portfolio is expected to change. Therefore, a VaR measurement becomes dated as time goes on; the underlying assets need to be marked to their market values. We note that this time-and-value consideration is different from the choice of the VaR time horizon. For example, consider a portfolio VaR with a six-month time horizon. A manager will likely mark the portfolio to market at much shorter time intervals than the overall time horizon. Much like time horizon, this choice of how often to mark an asset to market, or to recalibrate the VaR is an important managerial consideration. An IT manger may look at an annual VaR for a project, but reassess the value of the portfolio at quarterly or even monthly intervals.

[11] We can expect significant problems in measuring potential risk factors in IT investments. Financial exchanges such as stock markets are relatively liquid as compared to markets for systems and technologies – and some would argue there is no liquidity there whatsoever. Therefore, historical measurements of financial asset returns are likely to give a more accurate assessment market risk than would measurements or estimations associated with project level risk or even risks associated with the technology marketplace. Simulation methods may help firms estimate technology risks. Paleologo (2004) utilizes the modified Bass model of technology diffusion to estimate technology demand uncertainty, a reasonable basis.

of service levels breeched over a time frame. Such breeches could be tied directly to an increase in cost for the provider. Endogenous market-driven risks might also be modeled from wage and employment data.

### 2.3.4 Timeframe for Value-at-Risk Assessments

Value-at-risk measures the worst expected loss over a given time horizon at a chosen criterion level of probability. For example, a typical value-at-risk will suggest that losses over the next *t* days will not exceed $X at a 95% or 99% confidence interval. In the world of financial assets, value-at-risk is typically measured over a short time horizon: one or ten days (Crouhy et. al. 2001). More liquid assets tend to require a shorter time horizon for meaningful analysis (Jorion, 2007). IS investments are inherently illiquid when compared to securities. However, another consideration in choosing time horizon is time to hedge risk (Jorion, 2007). Managers should choose a time frame that allows them enough of a window to take appropriate action. If the risk considered is tied to labor, managers should consider the amount of time to hire or shift resources among projects.

### 2.3.5 Confidence Interval and Portfolio-Level VaR

The *confidence interval* is typically chosen with managerial discretion, and is determined by the nature of the analysis. For the purposes of contingency planning, a conservative confidence level or likelihood of loss will be more insightful. A firm using VaR for internal control purposes would choose a higher level, however. J. P. Morgan Chase publishes an average VaR position of its assets at a 95% confidence level in its annual report. This allows investors to assess Morgan's overall risk position and weigh it against their own risk tolerance (Jorion, 2007).

*Portfolio-level VaR* consists of a compilation of individual assets' value-at-risk. Covariances among asset risks and returns are incorporated into the model in a manner that is analogous to the *capital asset pricing model* (CAPM). If no covariance between the assets exists, then the portfolio VaR will be identical to the sum of the individual value-at-risks (Crouhy et. al. 2001). However, if there is covariance between the asset risks, then the sum of the individual asset value-at-risk will be less than the total portfolio VaR. This phenomenon is, of course, the basic effect of diversification. From a VaR point of view, diversification will lower the expected worst loss at a given confidence interval. We expect that systems and technology investments can be viewed as either (1) a portfolio of alternative projects or signed contracts (Bardhan et al., 2005), or (2) as a portfolio of existing capabilities, such as IT labor resources or existing technology infrastructures.

## *2.4 Value-at-Risk Analysis of IT-enabled services Investments*

The application of VaR techniques to systems and technology services investments requires a thorough understanding of the underlying risk factors which affect the volatility and distribution of the project returns. The identification and assessment of the distribution of returns drives the choice of the VaR method, the time horizon and the mark-to-market frequency.

### 2.4.1. When the Use of VaR Analysis Makes Sense

VaR analysis is best utilized when evaluating the risk exposure to a commitment to the project, especially related to the execution phase. Real options analysis, on the other hand, measures the managerial value of flexibility in the face of uncertainty. While real options analysis informs managers about the *a priori* value of flexibility in the face of uncertainty, value-at-risk quantifies the firm's risk exposure once a commitment to the project execution is made. To illustrate, a firm may be considering a new software implementation, and real options analysis may be used to inform managers about the timing of the investment due to competing standards in the marketplace. However, beyond the choice of platform, the firm must make decisions about the execution of the project. A clear choice in the execution decision is how to source the project. If the firm develops the project itself it will be exposed to the risks associated with the technology and labor costs associated with that product. Through outsourcing, the firm can "immunize" itself against some of these risks (Aron et al., 2005; Benaroch et al., 2007). However, outsourcing itself may imply new risks such as intellectual property theft (Clemons and Hitt, 2004) and regulatory and security exposure (Axelrod, 2004). VaR analysis allows managers to quantify the trade-offs associated with sourcing and internal development.

A related use of VaR analysis involves the assessment of impacts to the existing portfolio of signed services contracts. For example, the provider's existing skill set will determine the risk exposure to labor wage rate volatility. A VaR analysis may allow a firm to leverage existing capabilities. In the case of standards adoption risk, a firm may choose an in-house approach in order to build a new skill base within its IT department for the new competing standards. The firm, in effect, is hedging against the potential risk of having a portfolio of obsolescence risk, should the new competing standard emerge as the *de facto* standard. Another concept which VaR analysis may inform is the lag between technology investment and technology benefit realization (Au et. al. 2008).

Firms may chose value-at-risk analysis or mark-to-market frequency based on known technology investment-benefit lag.

### 2.4.2 Matching VaR Requirements to IT-Enabled Services Investments

The most important input is the risk factor which is to be considered. The specific risk from which management is attempting to shield itself drives the other input considerations in the VaR model. Researchers and practitioners have identified typical risks associated with both IT projects (Benaroch 2002) and services (Aubert 2005). Ideally, the risk factors in VaR analysis would be measurable. In systems and technology projects and services, some measurable risks might be credit risk of a trading partner, labor-wage volatility and currency risks (Kalnik, 2006). Technology cost risk may also be modeled, and standards risks may be implied from wage data as well. Wage or labor demand for specific IT platforms or solutions could be analyzed to determine the risks associated with making commitments to certain standards. For example, a provider firm may consider the cost volatility of competing standards when determining the level of commitments to implement Bluetooth vs. WiFi standards in mobile e-commerce applications.

In real options analysis, managerial estimates are often used as model inputs of volatility. Of course, the subjective nature of such assessments would necessitate the use of sensitivity analysis techniques such as first derivatives (i.e., the “Greeks”—delta, theta, gamma and rho). More rigorous assessments of volatility can be achieved using historical data. If sufficient historical data are available for the valuation of underlying asset risk factors, then the historical simulation or Monte Carlo techniques are best suited for VaR analysis (Crouhy et al., 2001). Both methods are appealing for establishing systems and technology value-at-risk because they do not require the assumption of normally-distributed returns.

Covariance of asset returns is a necessary input for portfolio-level systems and technologies VaR analysis. Managerial estimates of *cross-project returns covariance* can be utilized with appropriate sensitivity analysis. However, if data are available on the underlying asset risk factors, regression analysis is possible to calculate systems or technology asset covariance.

## *2.5 A Framework for IT-Enabled Services Investment Analysis*

We next introduce a framework (Table 2.2) for the application of VaR and compare it with real options analysis for IT-enabled services investments. The framework examines a set of eight logical and sequentially-relevant issue areas with respect to the underlying constructs of the financial models and the requirements of the managerial analysis. The first two issues are the analysis level of the application of the valuation method, and the evaluative orientation used. Real option analysis and VaR methods are different in terms of their treatment of single projects and portfolios of projects. Also, some projects require current evaluation while others need a more forward-looking approach (e.g., technology projects involving standards), while some initiatives are better informed by an assessment of current risk exposure (e.g., outsourcing).

From a decision making perspective, benchmarking, risk control assessments, and strategic timing of investments can be treated with real options and VaR methods. Perhaps the difference lies in the information each communicates to senior managers about value, specifically, the expected net value of a project or a portfolio versus the expected loss of a project or a portfolio.

**Table 2.2. A Framework for IT-Enabled Services Investment Analysis**

| Issue Area | Real Options Analysis | VaR Methods |
|---|---|---|
| Analysis level | Project | Portfolio or project |
| Evaluative orientation | Current value assessment<br>Predictive forward valuation | Current assessment of risk exposure<br>Forward-looking assessment of risk |
| Decision perspective | Normative guidance for project go/no go, timing, staging. | *Ex post* evaluation of committed risk exposure<br>New project impact on portfolio of existing capabilities<br>Benchmarking tool |
| Asset interdependence | Within and between-project dependencies for value flows<br>Staged project implementation | Correlated endogenous and exogenous asset risk factors |
| Input requirements | Risk-free rate of return<br>Time to maturity<br>Variance of asset returns<br>Underlying asset value<br>Strike price<br>Cost-benefit correlation | Variance of asset returns<br>Covariance of asset returns<br>Time horizon for analysis<br>Mark-to-market<br>Confidence interval |
| Computational methods | Binomial model<br>Log-normal binomial model<br>Black-Scholes model<br>Asset-for-asset exchange model<br>Embedded option models | Delta-normal method<br>Historical simulation<br>Monte Carlo simulation |
| Volatility assessment | Managerial assessment for non-market-<br>traded systems and technology assets<br>Use of historical and market data for traded assets<br>Proxy measures to gauge volatility | Managerial assessment in delta-normal method based on historical data<br>Volatility measure is implicit in the last 100 days of data when simulation used<br>Asset returns, volatility must be assessed in Monte Carlo simulation |
| Values computed | Option and project value<br>"Greeks," derivative sensitivity | Project and portfolio value-at-risk<br>Contemporaneous valuation |
| Managerial insights | Valuation of future option-enabled investment opportunities<br>Identification of strategic embedded options<br>Framework for timing and staging project investments | Signaling for exogenous risk exposure<br>Managerial control for endogenous risk<br>Understand aggregate risk exposure<br>Willingness-to-pay<br>Managerial "right-sizing" of investments |

We also expect, for example, that the use of real option methods and VaR methods will involve somewhat different challenges with respect to establishing a meaningful reading of asset return variance and covariance. The notion of implied variance (Manaster and Kohler, 1982) may offer a method to derive asset return variance from observed system and technology prices. Both VaR and real options analysis yield different analysis output, and they may also be used somewhat differently by managers. Option models yield option value, as well as readings on the sensitivity of option value subject to changes in the key drivers of value. One key benefit of option models in IT services contracts may be the pricing of buyout clauses or "options to abandon." VaR methods yield information on current value, and value-at-risk, so they have a dual perspective of discounted benefits and the extent of potential losses.

Finally, the reader should recognize that the managerial insights gained from the real options and VaR methods have commonalities as well as divergent features. Both, for example, provide useful information on willingness-to-pay for the underlying project, based on the associated cash flow, variance, covariance, and cost of capital rates. The VaR methods tends to emphasis the costs of risks "blowing up," while the real option methods represent the value of managerial flexibility so as to avoid future problems. VaR methods also seem to provide a basis, through willingness-to-pay to avoid exogenous risks, for "right-sizing" protective investments, as well as providing a means to control endogenous risks in the firm, through measurement-based managerial control mechanism.

Fundamentally, VaR analysis provides a real-time view of the potential risk exposures faced by a firm. The information that is provided can be on an *ex ante* or *ex post* basis. From an *ex ante* decision perspective, VaR methods are often employed as a benchmarking tool, for example, in the financial services sector where rates and market changes affect financial asset values. Such analysis also can inform firms about the *ex post* effects of changes in underlying asset risk factors associated with their projects.

Thus, VaR appears to be worthwhile—and definitely different from real option pricing methods—in terms of its capabilities for aiding effective management and control of systems and technology project investments.

Overall, in our view, VaR methods offer significant promise to yield managerial insights on such issues as risk factor diagnosis and signaling, risk factor control, and overall systems and technology portfolio risk exposure.

### *2.6. Applications and Limitations of Value-at-Risk Techniques to IT Investments and Services*

Systems and technology investments have long been subject to risks. Because technology changes at such a rapid pace, the time frame for analysis is relatively short. In addition, the development of technology has typically been a proprietary affair, and standards generally do not prevail until the market has chosen a winner. Finally, IT investments are notoriously hard to quantify. However, with the emergence of service-oriented enterprises, and modular service components, new sources of data and analysis are available to researchers and practitioners. VaR analysis represents a new way of thinking about systems and technology investments. Rather than focusing on one-time expected profit, VaR allows managers to actively manage the trade-offs associated with risk reduction. As we show in our example, VaR can provide justification for stabilizing technology infrastructure investments which do not directly contribute to increased benefits or reduced costs. Combined with proper benchmarking and risk analysis, VaR techniques can aid in managerial decision making and reduce firm exposure to the risks associated with IT-enabled services procurement and management. We next discuss the contribution, limitations and future applications of VaR techniques to systems and technology investments.

As with option theory, IS researchers face significant obstacles in the practical application of VaR methods. Managerial application requires advanced and in-depth knowledge of asset valuation theory and mathematics. We note several specific limitations that will need to be overcome: the typical lack of historical data that managers who wish to assess systems and technology projects and portfolios must face; the problem (as we know from past research on technology options) of the lack of a liquid traded technology project asset; and the difficulty for managers to estimate project value variances and application-to-application value correlations (Gustafson and Luft, 2003). There are promising avenues to explore, however. Firms such as SAS, SAP, and Digital Fuel offer services-related analytic software which will allow both provider and user firms to gather historical data on services performance (O'Neil and Hubert, 2007). Thus, firm-specific (endogenous) risk may be modeled by mining such data. In addition, the ubiquity of IT services may allow for the modeling of exogenous risks from labor availability, wage and pricing data. Cutting-edge analytic software along with greater transparency in the services marketplace should provide practitioners with new sources of data for the assessment of operational risks in IT-enabled services.

User firms, in our view, will have greater difficulties with this than vendor firms, where it is possible to gauge what specific elements tend to drive value and ROI across similar kinds of projects (e.g., outsourcing vendor projects). Thus, we believe that it is important to begin to build a "grass roots" understanding of the perceptions of senior managers relative to the co-variation in value of different kinds of projects that involve similar embedded technologies (Au and Kauffman, 2003 and 2005). We don't expect either of these issues to be easily overcome without further research efforts with real senior managers in real world project valuation contexts. Nevertheless, initiating study of these issues appears to be an appropriate goal of future research in this area. On the technical side, we believe that new modeling techniques and numerical simulation methods will pave the way for advances, and so we foresee somewhat fewer problems there.

# Chapter 3. The Profit-at-Risk Approach towards Risk Management in IT Services Contracts[12]

## *3.1 Introduction*

Advances in open-standards architecture, information and communications technologies, and the realization of large offshore talent pools have led to an increase in service-driven information technology (IT) solutions (Karamouzis 2005). Recent developments in grid computing, web services, application service providers (ASPs) and business process outsourcing (BPO) allow firms to adopt flexible, service-driven solutions. Some pundits predict the end of the traditional model of IT acquisition in favor of a purely service-driven technology marketplace (Carr 2005). In addition, many technology vendors now tout flexible, service-driven approaches to IT delivery, such as IBM's On-Demand, and HP's Adaptive Enterprise.[13] Service-driven IT strategies reduce the requirements for up-front investments for user firms and permit shared exposure of many technology risks with the vendors through contracts (Dietrich et al. 2007).

Structuring IT services contracts poses unique challenges for service providers.

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[12] Portions of this essay were previously published in Kauffman, R.J., Sougstad, R.S., Risk Management of Contract Portfolios in IT Services: The Profit-at-Risk Approach, *Journal of Management Information Systems*, 25, 1, 2008. 17-48. Additional portions of this essay were presented at the *2007 Workshop on Information Systems Economics.*

[13] *Service science, management, and engineering* (SSME) is an emerging field of research in both industry (e.g., for IBM) and academia (e.g., Arizona State University, and the University of California at Berkeley, among others). Some concepts fundamental to services research include spontaneous consumption and production, knowledge interactions across organizations, as well as the application of inter-organizational communication technologies (Chesbrough and Spohrer 2006, Horn 2005). Researchers face challenges such as formalizing systems of services and codifying tacit knowledge which exists among providers and users of services, as well as modeling service systems (Maglio et al. 2006). Readers are referred to the July 2006 issue of *Communications of the ACM*, which is dedicated to services science, management and engineering.

With the increased flexibility offered by service-driven IT solutions comes increased complexity and exposure to risk. IT services contracts typically cover a vast array of terms, such as service level, quality, timeliness, and penalties and incentives around these contractual parameters. Such contractual obligations, in fact, are contingent liabilities to which the vendors are obligated.[14] Underscoring many of these liabilities are risks involving technology costs, standards, and skills. Established IT service vendors with multiple contracts across a diverse client base can be thought of as managers of financial portfolios, the value of which will be determined by the interaction of underlying risk factors among client contracts. Decisions regarding an individual contract may impact the overall risk exposure of a provider's portfolio. For example, a manager may obligate the firm to provide a specialized programming skill as part of a contract to which the firm already faces availability constraints. While the manager may have made a profit or revenue-maximizing decision regarding the structure of the contract, the added contingent liability may subject the firm to unacceptable risk to the profitability of its overall IT services contract portfolio. In addition, risk exposures may differ according to technology or even across labor markets for IT outsourcing (Clemons and Aron 2004). We propose an analytic model and a decision support approach to quantify the fundamental trade-offs related to IS contract service levels, profitability and risk.

Sourcing IT solutions in the form of services implies a new breed of risks for user

[14] As contingent liabilities, obligations to provide services do not appear on the balance sheet, income statement or changes in funds statement of service providers. Sarbanes Oxley 401(a) requires disclosure of off-balance sheet contractual obligations in the "Management Discussion and Analysis (MD&A)" in the companies' financial filings with the Securities Exchange Commission (2003). Firm's often face legal action from clients if these obligations are not met, and future revenues and profits may be contingent upon the firm's ability to meet their contractual obligations.

firms, such as misappropriation of sensitive information and incentive alignments (Clemons and Weber 1990, Han et al. 2004 , Kauffman and Mohtadi 2004). Indeed, such risks and approaches to risk mitigation have long been the subject of IS research (Aron et al. 2005, Benaroch et al. 2007, Clemons and Hitt 2004). Bhargrava and Sunderasan (2003) model a pricing scheme for utility computing services and show that the service vendor is an aggregator of user *demand risk*. User firms can increase capacity in their contract without the upfront investment required in a traditional IT solution strategy. Thus, the vendor takes on the risk of the individual user firm's demand uncertainty.

Service-driven IT solutions allow for a great deal of managerial flexibility and risk sharing between IS users and their service vendors. However, this flexibility implies an increased number of decision criteria for both clients and vendors. In a service-driven solution, the contract contains many parameters which parties must negotiate. These parameters will affect not only the value of the solution or contract at hand, but also the value of the overall portfolio of contracts a firm holds. Contractual parameters such as service and security level, service sourcing, timing, incentives, and penalties transfer demand and performance risk from the clients to the providers, which can lead to cost overruns. Contractual risk factors will either amplify the overall risk exposure of a firm, or lessen it due to negative correlations which allow for *strategic hedging* of IT services contracts. [15] Managers are faced with a fundamental tradeoff: how to maximize the

[15] *Hedging* refers to the reduction or elimination of risk from a position whose value is subject to change from exogenous shocks. In financial portfolio management, hedging often involves placing assets which are negatively correlated in a position together. A common example is the mixture of equity (stock) and debt (bonds) securities within a portfolio. Stocks and bonds tend to exhibit negative correlation. An increase in the value of the bond typically, though not always coincides with weaker returns in the stock

profitability of services contracts while maintaining an acceptable level of risk exposure to the overall contract portfolio.

New methods and quantitative tools are required to actively manage both individual contractual profitability and overall portfolio value and risk tolerance. Thus, we ask the following fundamental research questions: (1) How should an IT services vendor optimally set contractual parameters given an acceptable level risk? (2) How can we achieve a better understanding of risk exposure in IT services contracts to inform managerial decision making? We develop our evaluative approach using *value-at-risk* (VaR) concepts from financial economics, a theory base that offers unique potential for the study of IS economics and management issues (Bakos and Kemerer 1992, Clemons and Weber 1990, Kauffman and Walden 2001). Value-at-risk represents the worst expected losses at a given confidence level based on an estimated distribution of returns. We build upon the value-at-risk approach to develop the measure of *profit-at-risk* in IT services contracts, a measure which allows managers to quantify risk exposure with rigor, but at the same time offers a meaningful, approachable means of decision analysis. [16]

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market. Investors often utilize derivatives such as short selling to minimize risk positions. A protective put is another common example. Investors holding a position in a stock often purchase *protective puts*, which gives them the right to sell their stock at a pre-specified price, minimizing potential downside losses. In the context of services management, provider firms may diversify their contract portfolios by seeking clients in multiple industry verticals in order to reduce their risk exposure of economic downturn in any one industry. These observations suggest the need for valuing risky assets and ensuring appropriate selection of risky investments in stock portfolios and capital budgets (Lintner 1965, Markowitz 1952, Sharpe 1964).

[16] Hereafter, we will refer to *value-at-risk* and *VaR* in two different ways. We will use the full term, *value-at-risk*, to indicate the specific measurement concept, as denoted by the theory. However, when we refer to related concepts and methods, we will use the abbreviation, *VaR*, as in *VaR methods* or *VaR-based portfolio evaluation*. In the first case, we are referring specifically to a dollar value that can potentially be lost, while in the latter we are referring to a body of knowledge associated with VaR methods. In contrast, we will use *profit-at-risk* and *PaR* in our model interchangeably, as the lowest expected contract profits at a certain confidence level over a contract horizon.

To provide answers to these research questions, this article is organized in six sections. Section 3.2 discusses relevant background theory from the real options, VaR and risk management, and IT services pricing literatures. Section 3.3 introduces our baseline model of *profit-at-risk* (*PaR*), which embeds VaR concepts, and provides information on the set-up of a simulation of IT services portfolio valuation dynamics for the addition of new services contracts, as a means to explore the power of this new perspective. Section 3.4 analyzes a base case model, introduces constraints on contract profitability, and explores the impacts of adding contracts on portfolio value. In Section 3.5, we turn to further analysis of the role of correlation between portfolio contract liabilities, the implications of contract duration on IT services portfolio value. In section 3.6 we explore the concepts of efficiency and optimality in the context of IT services profit-at-risk. Section 3.7 concludes with a discussion of our contributions to theory and practice, and an evaluation of the limitations of this research that should be addressed in future research.

## *3.2 Background Literature*

This research draws on three primary theoretical perspectives. The VaR literature from financial economics structures managerial decision-making with regards to risk tolerance. The IS real option analysis literature informs the modeling of information technology risk factors and the value of managerial flexibility in the context of sequential IT investments. Finally, the pricing of IT services and information economics provides insights that support the formulation of our new modeling approach for IT services portfolio management.

### 3.2.1 Value-at-Risk (VaR)

VaR portfolio analysis techniques were pioneered by a team at J.P. Morgan in New York City. Jorion (2007) defines *value-at-risk* as *a measurement of the worst expected loss over a given time horizon under normal market conditions at a given confidence interval*. [17] For example, a value-at-risk of $10 million at 95% confidence and over time horizon of thirty days implies that the manager can be confident, with 95% certainty, that the loss will not exceed $10 million over the next thirty days. One of the strengths of the VaR approach is this rather simple and intuitive framework for understanding a risk position. The clarity of this approach is especially appealing to managers of IT services, who would likely have less exposure to the theories and methods of risk management as compared to their financial services counterparts.

The need for new risk management techniques was motivated in part by several major financial calamities in the late 1980s and early 1990s, including the fall of Barings Bank (Crouhy et al. 2001, Jorion 2007) and other international financial problems, and the Orange County, California treasury disaster (Jorion 2005, 2007).VaR provided management with a new means to better understand and control firm-wide risk exposure. Initially, financial institutions used VaR analysis for passive information reporting to understand their risk exposures. However, VaR techniques quickly grew towards *defensive information reporting*, where firms began to implement standards and controls to avoid large-scale disasters. As a result, VaR is now used as an active risk management tool. Today, VaR methods are widely accepted as a basic part of a

[17] The interested reader should examine literature on portfolio risk and hedging methods by Agarwal and Naik (2004) and Campbell et al. (2001), and additional VaR-specific methods conducted by Basak and Shapiro (2001), Berkowitz and O'Brien (2002), Glasserman et al. (2000), and Lucas and Klassen (1998). See Stybo Beder (1995) for a more critical evaluation of the application of VaR methods.

financial firm's risk management tool kit, which is essential for the effective management of overall portfolio risks.

Several researchers have examined optimal portfolio construction under VaR constraints. Liebowitz and Kogelman (1991) and Lucas and Klaasen (1998) were among the first to construct optimal portfolios subject to shortfall constraints in the form of minimum returns. Campbell et al. (2001) developed a model to optimize portfolio selection between stock and bond investments in a VaR framework. Anderson et al. (2001) produced a model of credit risk optimization under *conditional value-at-risk*, which addresses the issue of *kurtosis* by taking a mean value of expected losses.[18]

### 3.2.2 Real Options Analysis of IT Investments

Real options analysis in information systems (IS) provides both strategic and quantitative approaches to analyzing the role of flexibility in the face of IT project uncertainties. In traditional financial economics (Black and Scholes 1973, Cox et al. 1979) an option gives the bearer the right, but not obligation to buy or sell an asset at a given price at a given point in time. Real options apply this concept to *real assets*, such as IT asset investments, to help managers to value the flexibility of options such as the ability to expand, abandon or defer investments (Benaroch 2002, Dixit and Pindyck 1994). Real options analysis has been used in three primary ways. First, real options can

[18] *Kurtosis* is a means of measuring the extent to which a distribution is different from the normal distribution so that more observations occur in its tails. Although the means and variances of two expected profit distributions may be the same, their kurtosis may be different, which could expose a firm to different risks with profitability. If the data exhibit a high degree of kurtosis, VaR techniques may underestimate the firm's risk exposure. A related, broader issue is the problem of *coherence* (Acerbi and Tasche 2002) in VaR techniques which assume normal parametric distributions. Artzner et al. (1997, 1999) have written that appropriate measures of risk need to be characterized by a number of key axioms. *Sub-additivity* is one of them. Portfolios under the usual VaR assumptions are not sub-additive: they may not accurately represent an aggregate view of portfolio risk. See Jorion (2007) for a thorough discussion of cohesion and VaR techniques. We will discuss the implications of our distributional assumptions later.

be viewed as a strategy which places emphasis on active managerial choices of flexibility-enabling capabilities in the face of risk and uncertainty (Clemons and Gu 2003). A second approach is to employ quantitative methods to evaluate option-enhanced net present value (NPV) for projects (Benaroch and Kauffman 1999, 2000, Dos Santos 1991), prioritize among investment choices (Bardhan et al. 2004), or evaluate combinations of real options in order to set and maintain IT project strategies (Benaroch et al. 2006, 2007). Finally, real options can be used to inform the investment timing decision (Kauffman and Li 2005, Kauffman and Mohtadi 2004). These approaches compare the value of waiting vs. the project NPV; where the two are equal is the optimal time to start investing.

Real options analysis informs our VaR approach in several ways. First, the literature has made contributions toward the identification and estimation of risk factors associated with IT investments. We consider some of the same managerial issues such as timing and exit options (in terms of a contract's start time, its duration and its exit clauses), but from the perspective of the provider of IT services. Whereas most real options analysis considers the IT project as a capital investment, we conceptualize the IT services provider as a manager of a portfolio of contingent liabilities. Our primary concern is with the initial configuration of the contracts, since the contract configurations dictate the degree of flexibility allowed going forward. In many respects, the contract constrains the options available to the provider.

In this article, we use VaR methods rather than real options analysis because IT service contracts are usually characterized by complex negotiations between providers and clients regarding service level commitments and prices (Dietrich et al. 2007).

Kleindorfer and Wu (2003) and Wu and Kleindorfer (2005) have modeled contract options for both capacity and duration considerations in the context of B2B exchanges. Compared with options analysis, VaR is better equipped to evaluate the dynamic give-and-take between revenue and the risk exposure to cost overruns in the market context though. In addition, one of the key "value tenets" of a large services provider is the ability to leverage resources across projects. VaR portfolio analysis provides the ability to evaluate risk and profits across a portfolio of contracts in a way that real options analysis does not. The latter is better suited to the analysis of sequential IT investments.

### 3.2.3 IT Services Pricing

Research in IT services pricing has its roots in auction economics. Westland (1992) modeled IT services prices based on congestion and network externalities, and Kauffman and Kumar (2008) have extended this perspective when demand and congestion externalities are countervailing in their impacts. Gupta et al. (1998) developed a model for dynamic pricing of network access based on usage. Bhargava and Sundaresan (2003) presented an optimization model for quality-contingent IT services and later develop a model to price grid computing solutions with demand uncertainty using an auction mechanism (2004). Cheng and Koehler (2003) further specified optimal pricing policies for Web-delivered applications using queuing theory. Huang and Sundararajan (2005) modeled the adoption patterns of firms utilizing on-demand computing. They considered the infrastructure choices which providers must make in order to fulfill their clients' demand for computing. These works inform IT services research by explicitly modeling the trade-offs between the costs of providing adequate service, while managing the risks and uncertainties associated with customer demand. One of the main value propositions of the IT service provider for its clients is the absorption of risk. Bhargava and Sundaresan (2003) modeled one type of absorption, demand: users of grid computing services are shielded from fluctuations in demand and providers are able to absorb this risk through economies of scale. The key insight is that the risk faced by the individual client differs from the risk faced by the provider, once the provider takes over the service. We expand upon this case to include other types of services risks.

Economics of information goods and software pricing research also have contributed to our research. Sundararajan (2004) examined fixed fee vs. usage-based pricing of information goods in situations of incomplete information. He modeled the transaction costs associated with monitoring usage-based as non-linear pricing schemes and found that firms should offer combinations of fixed and usage-based pricing models in the face of these transaction costs. Kenyon (2005) modeled IT outsourcing pricing implications in the face of variable capacity constraints on the part of providers. Choudhary (2007) examined quality and versioning investments from the perspective of *software as a service* (SaaS) versus traditional fixed-fee licensing. He found that in most cases, software vendors will invest more in quality under SaaS strategy than under the traditional fixed-fee strategy. Dai et al. (2005) model the effects of electronic sourcing systems on supplier/buyer relationships and the effects upon centralized vs. decentralized governance. These works are important in that they consider variable and often uncertain costs associated with delivering IT services. Our model extends these concepts to consider risks associated with the cost of service delivery. These risks may be associated with cost increases in labor, contract monitoring or infrastructure investments required to deliver the service.

One of the few works that incorporates VaR theory in an IT setting is by Paleologo (2004). He introduces a method for pricing utility computing services called *price-at-risk*. He argues that traditional cost-based pricing is not value-maximizing given the dynamics of utility computing services due to the reduced contract duration (vs. traditional outsourcing), low customer switching cost, high levels of demand uncertainty, high sunk costs, and the short product life cycle of a utility computing infrastructure. He models these uncertainties with a confidence interval approach which has similarities to a VaR model. He also uses a stochastic process for market adoption using a form of the Bass (1969) model for technology adoption.

## *3.3 Model Development*

IT services encompass a broad range of application domains. Software development and business process outsourcing, IS security services, utility computing and Web-delivered application services are all areas in which pricing, service levels, and other parameters act as decision variables which will affect the overall profitability of the services contract. Examples of optimization parameters to consider are security and performance levels, contract timing (e.g., when to start, ability to abandon contract), the amount a firm can sub-contract within the overall contract, and incentives and penalties.

### 3.3.1 Model Specification

One of the key requirements for parameter selection is that the decision affects the customer demand, or *willingness-to-pay* (WTP) for the service. [19] Thus, a *contract* can be thought of as a complex product with differing dimensions of quality, with the different service levels acting as a quality parameter. For the model in this work, we consider a *base case* in which a firm enters into an outsourcing contract for business process outsourcing (BPO). The firm chooses to offer a certain service level mix. In this example, we consider dedicated or pooled BPO resources, such as an IT help desk. We define *pooled resources* as either subcontracted, offshore or near-shore services, for example, a help desk call center owned by the vendor. The customer will prefer *dedicated resources* though; they will value the continuity and stability that dedicated resources provide. Thus the client's willingness-to-pay is modeled as a function of the *service level*, which we define as the proportion of dedicated resources and pooled resources in the contract. The firm then selects a service level to maximize contract profits, subject to some level of risk, which we measure via profit-at-risk.

The *profit-at-risk constraint* in our proposed model is an application of value-at-risk theory and methods to the IT services contract parameters. *Profit-at-risk* (*PaR*) is defined as the lowest expected profit at a given confidence for a given time horizon. Profit-at-risk is a more complex measure than value-at-risk and what we see in traditional risk-based portfolio analysis. When we apply the profit-at-risk construct, the service level choice affects the revenue according to the client's willingness-to-pay, and

[19] There is a considerable body of research involving the economics of insurance, which models willingness-to-pay for risk avoidance (List and Gallet 2001, McClelland et al. 1993). These works draw on knowledge about convex preferences and experimental economics for modeling the amount consumers will be willing to pay for insurance against risky outcomes. We assume a functional form for willingness-to-pay for this simulation, but as we discuss later, additional empirical work must be conducted to model a manager's true willingness-to-pay, which will be affected by individual risk aversion, as well as technology, firm and market influences.

also affects expected costs according to the cost function faced by the provider firm. Thus, the portfolio return is not a linear combination individual asset returns as it is in traditional portfolio analysis. We model the costs of providing IT services as a stochastic variable. Costs will have an expected future value also, as well as a random volatility component. The overall profit-at-risk constraint is calculated by subtracting the expected cost overruns at the confidence level from the expected profits. The service level mix affects both the contract risk and cost structure, and revenues; these measures can be used to construct the profit-at-risk estimate. To specify the profit-at-risk constraint, we consider four factors that are analogous *value-at-risk inputs*: mark-to-market position, risk factor variability, time horizon, and confidence interval. See Table 3.1 and 3.2 for the value-at-risk and profit-at-risk equivalents and a full set of definitions for the key language that we use in this research.

**Table 3.1. Value-at-Risk Inputs and Profit-at-Risk Equivalents**

| SYMBOL | VALUE-AT-RISK INPUT | PROFIT-AT-RISK EQUIVALENT |
|---|---|---|
| $M$ | Mark-to-market position | $C$, estimated parameter cost at $t = 0$ |
| $\sigma$ | Risk factor variability | Future cost volatility |
| $t$ | Time horizon | Time horizon |
| $\alpha$ | Confidence interval | Confidence interval |
| *VaR* estimate | $M\sigma\alpha t$, from delta-normal method | Profit-at-risk: $PaR = R(S)-C(S)-C(S)[1+\sigma\alpha\sqrt{t}]$ |
| $\omega$ | Portfolio weight | The weight is placed on $S$, the proportion of high-level services or dedicated resources in the IT services contract input mix |

**Note**: *Mark-to-market* position represents an initial valuation of the asset or project. $\sigma$ is the standard deviation of asset returns or other project factors. $\alpha$ is the confidence interval set by management that a threshold, called the *value-at-risk*, will not increase beyond over the time horizon, $t$. We also note that *profit-at-risk* (*PaR*) must scale to incorporate the extremes of cost increases, rather than asset losses. Thus, the value $1+\sigma\alpha\sqrt{t}$ also must scale to the upper distribution. The reader should note that $\omega_i$ traditionally refers to the proportion of wealth that is invested in asset $i$ in a portfolio. In the IT service provider context, this is not wealth, but instead the availability of the highest quality service input available, especially highly capability IT labor.

**Table 3.2. Value-at-Risk (VaR) Terminology**

| TERMS | DEFINITIONS |
|---|---|
| *Value-at-risk* | The worst expected loss which an investment will incur over a discrete time period at a specified confidence interval. |
| *Mark-to-market position* | The value of an asset or a portfolio based on current market value. In the case of systems and technology investments, this will be the current project value or the current expected cost of a project input. |
| *Variance of asset value or returns* | Measures the variability of a risk factor that underlies asset value, usually stated as a variance or a standard deviation. |
| *Time horizon* | Time frame over which value-at-risk is to be assessed, based on managerial discretion relative to the risk perspective. The time horizon is typically chosen based on the asset's liquidity. For example, inter-bank loan analysis is typically done with daily increments, whereas a mutual fund may use a 30 or 90-day time horizon. |
| *Confidence interval* | The probability bounds on the observation of a specified value-at-risk outcome, chosen based on a firm's desire to manage payoff and return outcomes up to a predetermined likelihood. |
| *Correlation of asset value or returns* | Measures the extent to which asset returns co-vary with one another. The values could range from -1 (perfect negative correlation), to 0 (no correlation), to +1 (perfect correlations). This input is used when looking at portfolio-level value-at-risk. |
| **Note:** The material here is adapted from Crouhy et al. (2001) and Jorion (2007) | |

The choice of *S* affects the firm's risk exposure to the cost parameters that occur in the process of offering the services. We will examine not only the profit-at-risk of an individual contract, but also the effect of a *PaR* position on the *aggregate liability* that the firm has as a result of its portfolio of contracts.

### 3.3.2. Profit-at-Risk Analysis Approach

We consider a monopoly IT services vendor that offers two distinct levels of service: high (*H*) and low (*L*). [20] The service levels represent *dedicated on-site resources* vs. *pooled offshore resources*, and we think of service level in aggregate in terms of the mix of these two. We assume that the service vendor negotiates with a firm

[20] Our decision to model the IT services provider as a monopolist obviates the need for a game-theoretic treatment of the issues we will discuss in this article. Since IT contracts are usually unique to the client-provider relationship and involve intricate negotiations (Dietrich et al. 2007), the assumption of the monopolistic provider allows us to isolate this one-on one interaction. Although this is an interesting potential future research direction for this work, moving to the analysis of a duopoly or a competitive marketplace for IT services would add unnecessary complexity to the analytical framework that we have built, without providing any basis for increasing the clarity of theory development and managerial illustrations that we will provide for the reader.

that requires *D* fixed demand hours of service. The high service level costs more for the vendor to provide and is more volatile because the vendor has less flexibility in shifting and sharing resources. The high service level is preferred by customers because they value the stability and familiarity of the dedicated resources, and this is reflected in the *willingness-to-pay function*. *Service level S* is the percentage of the hours demanded which will be fulfilled with high service level input costs, $C_H$. See Table 3.3 for our mathematical notation.

**Table 3.3. Definitions of Mathematical Notation in the Model**

| VARIABLE | DEFINITION |
|---|---|
| $\pi$ | Firm profits |
| $S$ | Service level mix (0% to 100%) |
| $R(S)$ | Willingness-to-pay for service level $S$ |
| $C\ (S, C_H, C_L)$ | Total cost |
| $PaR$ | Contract profit-at-risk |
| $C_H, C_L$ | High (low) service level, $H$ ($L$) cost |
| $\sigma_H, \sigma_L$ | Std. dev. of high (low) service level $H$ ($L$) cost |
| $\rho_{HL}$ | Correlation of $H$ and $L$ service level costs |
| $\sigma_c\ (S, \sigma_H, \sigma_L)$ | Standard deviation of total contract costs |
| $\alpha; t$ | Confidence interval; time horizon |
| $k$ | *PaR* constraint (a constant chosen by manager) |

The costs can be modeled as $dC = \mu dt + \sigma dz$, a stochastic Gauss-Wiener process. [21] So the future costs will have a mean value, $\mu dt$, along with a random component, $\sigma dz$, which may increase or diminish depending on market conditions or other risk factors that represent volatility. In constructing profit-at-risk, we utilize the *delta-normal*

[21] A *Gauss-Weiner process* is a continuous time stochastic process with independent increments and, thus, independent random variables. A *Brownian motion stochastic process* is the most well-known instance, involving a "random walk" with random step sizes (mathworld.wolfram.com/WienerProcess.html). Both are extensively used in financial economics to model the diffusion of costs, asset prices, and other indicators.

*method* of *local valuation* (Jorion 2007) rather than a *full valuation method*. This is a critical point for the reader to understand, since it bears on our ability to successfully apply the methods we have proposed in the IT services context. [22] Full valuation approaches rely on historical data to estimate distributions of asset returns. In this research, we apply VaR theory to develop a new technique, *profit-at-risk*, in order to assess the potential value, impact and usability of risk-based assessments on IT contracts. Our simulations are limited to those that are consistent with a local valuation approach, however. This approach assumes that the risk factors affecting an asset can be modeled using an estimate the standard deviation of assumed normally-distributed asset returns. In Section 3.7, we will discuss the implication and limits of local valuation methods, as well as applications where historical data can be used in order to model IT services risk factors with less restrictive assumptions. [23]

In the general form, the objective function is:

$$\text{Max}_{(S)}\ \pi = R(S) - C\,(S, C_{H,}\ C_L) \tag{1}$$

$$\text{Subject to:}\qquad PaR = R(S)\ - C(S, C_{H,}\ C_L)\ [1 + \sigma_c(S, \sigma_H, \sigma_L, \rho_{HL})\alpha\sqrt{t}] \geq k \tag{2}$$

$$0 < S \leq 1 \tag{3}$$

### 3.3.3. Simulation

To simulate the model at work, we next present an example with assumed functional forms for the willingness-to-pay function and the cost function. We first model the

[22] We would like to acknowledge the suggestion of an anonymous reviewer, who encouraged us to make clear how historical information or the lack of historical information on input costs affect the analysis. It turns out, as we learned from going through the process of evaluating what we can contribution in both instances, that there will be many opportunities in follow-up research to begin to build historical data sets for a range of IT services contexts.

[23] See Dos Santos (1991) for an explanation and treatment of standard deviation of returns for IT investments.

client's willingness-to-pay. For the purposes of this analysis, we consider the client who enters into negotiation with a range of preferences relative to service levels, *S*, which we model as $R(S) = V S^{.5}$. This function states that as the mix of high-level services nears 1, the firm's willingness-to-pay for the services bundle approaches the stand-alone value of the on-site services. This function is reasonable; the customer firm will be willing to pay close to the full value, *V*, when *S* nears 100% (or 1), indicating that all high quality inputs are being used in the provision of the IT service. The client will be willing to pay much less for the services as *S* approaches 0% (or 0). The purpose of this functional form assumption is to simulate the client's preferences. It does not have any substantive impact on our research contribution, which is the development and evaluation of a new risk management technique for IT services.

Our intuition is that the customer wishes to ask for dedicated on-site services and the provider wishes to negotiate some flexibility to augment on-site services with pooled shared services. The provider prefers a lower mix of the dedicated resource. We assume again that the dedicated resource is more costly and has a higher risk of cost increases. This may perhaps be due to local wage conditions and the provider's constrained ability of the firm to shift the dedicated resources among projects. We model the total cost of the contract as a linear combination of the high or *dedicated service level resources* and low or *pooled service level resources*. By using this form we assume that the dedicated and low service level resources are perfect substitutes from a productivity standpoint; that is to say, they can both perform the project requirements in the amount of hours demanded by the client (*D*). In addition, we assume that the firm can model the expected costs for the fixed hours demanded (*D*) so we do not make considerations for economies of scale in this model. [24]

We assume a normalized standard deviation for estimating the cost increases under the delta-normal method, rather than measures derived from actual return variances. We utilize the standard formula from financial economics for estimating a two-asset portfolio (Markowitz 1957). We also consider the impact of one contract to an existing portfolio of contracts. For example, a firm might have a portfolio of contractual liabilities of 60 hrs of $C_H$ and 30 hours of $C_L$. An additional contract for 10 hours will affect the overall value of the portfolio of contracts depending on service level $S$. Thus, if $S = 50\%$, the mix of the contract portfolio would be 65 hours of $C_H$ (5 hours are added) and 35 hours of $C_L$ (5 hours also are added), resulting in a portfolio service level $S = 65\%$.

Our objective function now follows:

$$\text{Max}_{(S)}\ \pi = V\,S^{.5} - (S\,C_H + (1\text{-}S)\,C_L) \tag{4}$$

$$\text{Subject to } PaR = \quad V\,S^{.5} - (S\,C_H + (1\text{-}S)\,C_L)$$

$$[1+\sqrt{\sigma_H^2 S^2 + \sigma_L^2 (1-S)^2 + 2S(1-S)\sigma_H \sigma_L \rho_{HL}}\ \alpha\sqrt{t}] \geq k \tag{5}$$

$$0 < S \leq 1 \tag{6}$$

In the unconstrained case, we can see that the first and second order necessary and sufficient conditions for maximization are as follows with respect to $S$:

$$S^* = (\ V/2(C_H - C_L)\ )^2 \tag{7}$$

$$d^2\pi/d_2S = \text{-}.25V\,D\,S^{\text{-}1.5} < 0, \text{ where } V, D, \text{ and } S \geq 0. \tag{8}$$

[24] We would advise practitioners to consider these cost and productivity factors, but they are not germane to our analysis of risk exposure in IT services. Such productivity models have been well treated by operations researchers. Interested readers should examine Sherman and Zhu (2006), who present managerial approaches to evaluate service performance and productivity using data envelopment analysis (DEA).

The related input parameter assumptions are in Table 3.4.

**Table 3.4. Initial Numerical Inputs for the Model**

| VARIABLE | DEFINITION | VALUE |
|---|---|---|
| $D$ | Services contract hours, fixed demand | 100 |
| $C_H$ | Cost of high (*H*) service level | 17 |
| $C_L$ | Cost of low (*L*) service level | 3 |
| $\sigma_H$ | Standard deviation of high (*H*) service level costs | 60% |
| $\sigma_L$ | Standard deviation of low (*L*) service level costs | 20% |
| $\rho_{HL}$ | Correlation, H and L service level costs | 0 |
| $S$ | % of portfolio in high (*H*) service level | 51 |
| $1\text{-}S$ | % of portfolio in low (*L*) service level | 49 |
| $\alpha$ | Confidence interval | 95% |
| $t$ | Time horizon | 1 |
| $V$ | Firm willingness-to-pay for high services ($S = 1$) | 20 |

The choice of input parameters allows us to highlight the full managerial impacts of this approach, and we feel that they are reasonable in the context of the model and decision choice (dedicated on-site services, vs. pooled off-site, or offshored services).

## *3.4 Modeling Analysis and Results*

We first examine the base case for a single contract. We extend the simulation to incorporate portfolio effects. We then consider the sensitivity of the results to timing elements and correlations. We further evaluate the managerial impact of contract investment and the option value of contract length.

### 3.4.1 Base Case Analysis: A Single Contract

**Unconstrained Profit.** Table 3.5 illustrates our simulation of optimal profits unconstrained by any *profit-at-risk* (*PaR*) lower limits. The second column in Table 3.5 ("None") illustrates our base case. In this scenario, the firm has *expected unconstrained optimal contract profits*, E($\pi$), of \$414, with an *expected minimum expected contract profit-at-risk* (*PaR*) of -\$130. The optimal *service level balance* is $S$ = 51% in high service level costs (and thus 49% in the low service level costs).

**Table 3.5. Expected Profits and Profit-at-Risk (*PaR*) for Given Constraints**

| MAX *PAR* | NONE | $0 | $50 | $100 | $120 | NONE |
|---|---|---|---|---|---|---|
| Willingness-to-pay (WTP) | 14.29 | 12.92 | 12.16 | 11.00 | 9.98 | 15.49 |
| Percent high service level (*S*) | **51%** | 42% | 37% | 30% | 24% | **60%** |
| Contract standard deviation | 32% | 28% | 26% | 20% | 21% | 37% |
| Revenue | 1,429 | 1,292 | 1,216 | 1,100 | 997 | 1,549 |
| Expected cost | 1,014 | 884 | 818 | 723 | 648 | 1,140 |
| Maximum cost ↑ (95%) | 1,559 | 1,292 | 1,166 | 1,000 | 877 | 1,842 |
| Expected contract profits | 414 | 408 | 399 | 376 | 349 | 409 |
| Contract profit-at-risk (*PaR*) | -130 | 0 | 50 | 100 | 120 | -293 |

**Note**: Confidence interval for analysis: 95%. All values are stated in 000s of dollars, except for service level *S* and contract standard deviation. Service level balance is stated in terms of high service-level costs as % of total costs. *PaR* = profit-at-risk, an instantiation of the value-at-risk construct for the present analysis. $0, $50, $100 and $120 all denote different *PaR* levels, based on constraints set up in the analysis. The values for willingness-to-pay, contract standard deviation and *S* are rounded here to two decimals for appropriate precision.

**Profit Constrained at 95% Confidence Interval.** If the firm wishes to be certain at the 95% confidence interval that its IT services contract will not lose money (3rd column from left, 0), then the firm's optimal service level to rebalance to 42% high service level costs and 58% low service level costs. Note that in this case the expected profits are reduced by only $6, from $414 to $408. Thus, for a relatively small reduction in profits, a firm can reduce its risk exposure by $130.

### 3.4.2 Trade-Off Analysis: Profit vs. Risk Reduction

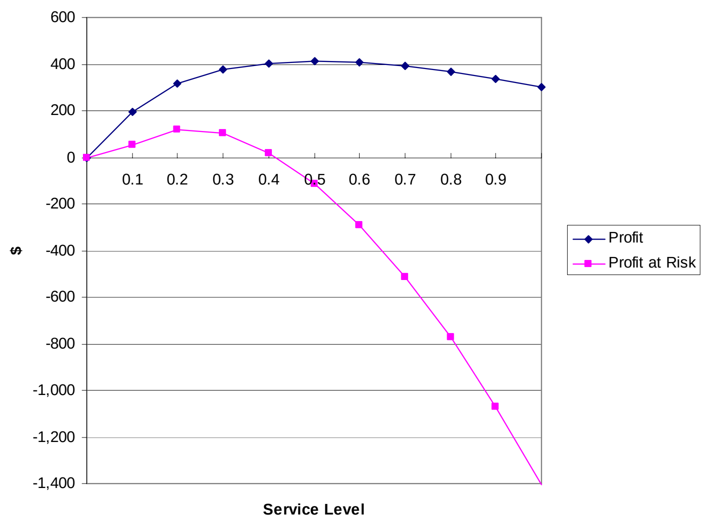
**Profit-at-Risk Constrained at $100.** Moving right in Table 3.5 shows the trade-off between profitability and risk reduction. For example, a manager concerned with meeting a specific earnings target might require that the firm's minimum profitability should be $100. Then, the column marked $100 is relevant. Here we see that the loss in expected profits, $\pi$, of $38 (= $414 - $376) is substantial in financial terms.

A new issue arises regarding agency, governance and managerial incentives. Note the far right hand column in Table 4 now (also marked with "None", meaning there is no binding *PaR* constraint). In this scenario, a manager has set a service level of 60% (i.e., 60% high service level costs and 40% low service level costs). This is not an optimal profit structure, even though the impact to profits is marginal at \$6 (= \$414 - \$409). However, risk exposure more than doubles from -\$130 to -\$292. What's more troubling is that the overall revenue of the contract is higher than the optimal contract at a 51% service level (again, \$414 vs. \$409). We should point out that many firms reward lower-level management on revenue targets, and do not consider the potential losses that may accrue <u>at any confidence level</u> whatsoever. So, depending on how a firm's incentives are aligned, a manager might want to "sell" this sub-optimal contract to the upper management. This is an instance where the principal's (provider firm) and agent's (provider sales manager) incentives for mechanism design are not in unison. This simulation of value-at-risk indicates that the impacts to contractual decisions in IT services can highlight risks in incentive packages.

**Constraint: Profit-at-Risk > 0.** Figure 3.1 shows the relationship between contract profitability and profit-at-risk, and supports Table 3.5.

Profit maximization occurs at the service level balance of $S$ = 51% (x-axis). The profit-at-risk curve acts as a constraint which is imposed by management. For example, if management requires the firm to have a positive expected profit with 95% confidence (*PaR* > 0), then the optimal service level balance would violate the constraint. We note that the dual formulation of our problem, unconstrained profit maximization, is useful in providing a lower-bound to risk exposure, which occurs at the point where S = 22%. This permits us to say that the contract that would yield the highest worst-case profits at the given confidence level. Further, all contracts between the maximum profit and maximum profit-at-risk define the efficient frontier. As illustrated in Table 3.5, if we constrain profit-at-risk below $120, we shift the profit maximization point to the left. Under these parameters, profit maximization will then occur at the local maximum where the profit-at-risk constraint holds with equality.

**Figure 3.1. Contract Profit vs. Profit-at-Risk (*PaR*)**




**Note:** Figure 1 shows the simulated results of changes in the service level balance and the impact on both expected profit and *PaR* using the inputs of Table 3. Profit-at-risk (*PaR*) is the constraint, and it is set by management. For example, if management requires the minimum profits to be positive with 95% certainty, than the optimal profit point ($S$ = 51%) will fall outside the constraint boundary.

### 3.4.3 Portfolio Impacts

We now consider the impacts of adding the contract examined above to an existing portfolio of services contracts. Here the firm has aggregated its obligations for providing the skills in question to its existing contract portfolio of 1,000 total hours. We examine the impact on the portfolio of adding another contract. See Table 3.6.

**Table 3.6. Portfolio Impacts When a New Contract Is Added**

| VARIABLE | VALUE FOR DIFFERENT HIGH-LOW SERVICE BALANCE | | |
|---|---|---|---|
| Percent high service level hours (*S*) | 51% | 42% | 39% |
| New contract expected profits | 414 | 408 | 403 |
| New contract profit-at-risk | -130 | 0 | 32 |
| *Initial Portfolio* | | | |
| Portfolio expected profit | 4,081 | 4,081 | 4,081 |
| Portfolio profit-at-risk | -32 | -32 | -32 |
| *Portfolio with New Contract* | | | |
| Portfolio expected profit | 4,496 | 4,489 | 4,484 |
| Portfolio profit-at-risk | -151 | -32 | 0 |

**Note**: This table shows the impacts of adding a contract to a portfolio of services contracts. All values are stated in 000s of dollars, except the service balance *S.* We utilize the same initial inputs in Table 3, and vary *S* in three different scenarios. Optimal profits occur when the service balance is *S* = 51%. However, by lowering the service value to *S* = 42% and sacrificing profits of $7 (= $4,496 - $4,489), the firm can actually reduce the risk of its overall contract portfolio, as we see with contract *PaR* of $0, instead of $130 or $32, or the service mixes of 51% and 39%.

The column where the balance between high and low service input costs is 51% and 49% (*S* = 51%), the unconstrained optimal, shows the additional contract adds -$119 (= -$151 - (-$32)) to the risk exposure of the firm's new profit-at-risk of -$151. We can see that if the firm has previously established a profit-at-risk constraint of $100, then it might prefer the high-low service input costs balance of *S* = 42%, where the new contract adds no additional risk exposure. However, the initial portfolio implies that the risk exposure may be out-of-balance and that the firm may wish to set expected profits to a non-negative dollar value. Thus, the manager should choose the right-hand column, where *S* = 39%, to obtain useful guidance with risk management. Here again, the firm sacrifices profits of $9 from the optimal structure (= $414 - $403), but has a 95% confidence interval of certainty that the firm will not incur losses over the next year.

Table 3.7 illustrates a different scenario. Here the portfolio is initialized under conditions in which the profit-at-risk is relatively high. Thus, the manager may wish to consider the *risk cushion* within the contract portfolio which might enable strategic decisions to be made. For example, consider a customer who refuses to negotiate for IT services terms with less than 51% of services at the dedicated on-site high service level.

**Table 3.7. Portfolio Risk Absorption**

| SCENARIOS | VARIABLE | VALUE |
|---|---|---|
| *New Contract* | $S$ , percentage of high service level hours | 51% |
| | New contract expected profits | 414 |
| | New contract profit-at-risk | -130 |
| *Initial Portfolio* | Portfolio expected profit | 4,081 |
| | Portfolio profit-at-risk | 195 |
| *Portfolio with New Contract* | Portfolio expected profit | 4,463 |
| | Portfolio profit-at-risk | 83 |

**Note:** This table shows the ability of the firm to select a profit-maximizing contract which violates the $PaR > 0$ constraint. Since the provider's portfolio of existing contracts implies a positive *PaR*, the firm can add the profit-maximizing, but risky contract with $S = 51\%$, while still maintaining a positive \$83 *PaR* for the overall contract portfolio. All values are in 000s of dollars with the exception of service balance *S*, which is a percentage. Initial inputs for this simulation are taken from Table 3.

As shown earlier, this structure, while profitable for the firm, implies significant risk exposure, with a contract profit-at-risk of \$195. However, the portfolio is able to absorb some slack. Profit-at-risk for the portfolio as a whole falls from \$195 to \$83, which is still strictly greater than zero. Thus, if the customer firm is of strategic value, the IT services vendor may be willing to sign this contract since the overall portfolio profit-at-risk is still positive.

## *3.5 Extended Analysis Correlation and Duration*

The model that we have presented can aid several other dimensions of managerial decision-making in the IT services context. Correlated risk factors and strategic portfolio hedging—two especially interesting potential applications of VaR methods for IT service providers—can be encompassed in this analysis. Most technology risk factors will exhibit correlations by which an increase in one risk factor will likely be accompanied by an increase or decrease in another separate risk factor. We consider three instances of related risk factors: negative correlation, positive correlation, and weak or very low correlation. We next extend the simulation and discussion to the issue of correlated risk factors within a services contract, as well as to contract duration.

### 3.5.1 The Impacts of Correlation of Risk Factors

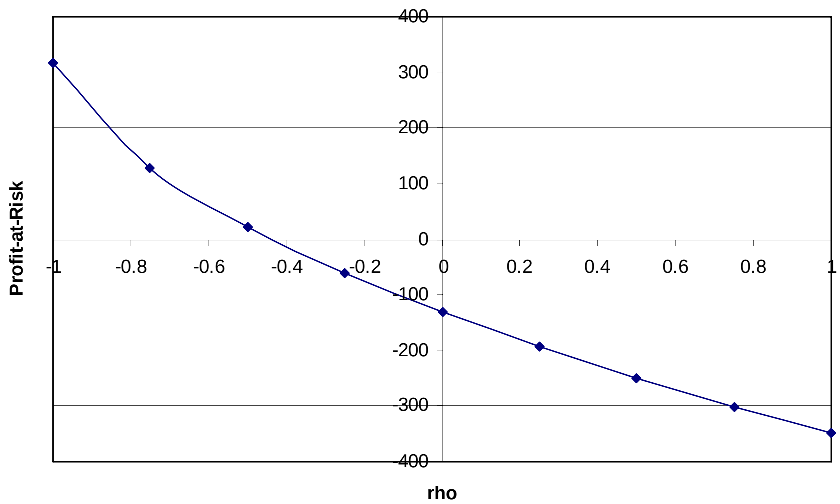
The role of correlation in assessing the value outcomes of IT services portfolios is important for managerial decision-makers to understand as a means to evaluate whether they are taking on appropriate risks with their mix of services business. We first will explore negative correlation and cancellation of effects between risk factors as an extension to our prior analysis, and then we will further consider positive risk-amplifying correlations. We close out our discussion in this sub-section by discussing the impacts of low or negligible correlations, and the role of nearly-independent contract risk factors.

A *negative correlation* of risk factors often occurs when two technologies are competing for standards adoption Kauffman and Li (2005). For example, the recent competition between Bluetooth and Wi-Fi has led to negatively-correlated risk factors. Due to the need for standards in wireless technologies, success in one platform is likely to lead to the failure of the other technology, from a market perspective. For IT services vendors, this negative correlation likely will affect the overall risk profile of their portfolio of contractual liabilities to support their customers. The cost of supporting a non-standard technology likely would be greater than the cost of supporting the "standards winner." Thus the vendor may observe from the marketplace the relative likelihood of success of the two technologies. Rather than making an "all-or-nothing" choice of which standard to support, the vendor may wish to attempt to hedge its position by taking on contracts supporting each standard. As the technologies evolve and the uncertainty around a standards war lessens, managers can take corrective action by taking on new contracts or opting out of existing contracts.

Figure 3.2 shows the relationship between the correlation $\rho$ and profit-at-risk values for the unconstrained point of profit maximization ($S$ = 51%). The effects of correlation on risk exposure are profound. As the cost factors become negatively correlated, profit-at-risk increases, and thus the firm can expect to achieve higher minimum profit with 95% confidence. These points of negative correlation illustrate the effects of hedging. An IT services provider can make significant reductions in its IT services portfolio risk just by choosing contracts where the risks affecting cost volatility are negatively correlated. On the other hand, the risk positions are magnified if the risks are positively correlated. This latter observation is shown in Figure 3.2 by the increase in risk exposure, *PaR*, as positive correlation increases.

In general, correlation is an important factor to consider when balancing a portfolio. Firms may wish to determine the correlation of risk factors relative to their clients by balancing the industry sectors with which they do business, for example. This is an important consideration since many IT providers have a strong presence in particular industry verticals. In addition, competing technologies are likely to exhibit significant negative correlations. For example, success in one standard may lead to the demise of another.

**Figure 3.2. Profit-at-Risk (*PaR*) vs. Correlation ($\rho$) at the Profit Maximization Point**




**Note:** Each point on the curve represents the profit-maximizing point $S = 51\%$ with the initial model inputs given in Table 3. The base case occurs when the correlation $\rho = 0$. This is shown where the curve intersects the Y axis at the point where $PaR$ = -\$130. When $\rho$ is highly negative, the profit-at-risk (*PaR*) increases. As $\rho$ increases, however, we see that the value of *PaR* decreases below the 0 correlation scenario.

Many of the risk factors in IT services are likely to have *positive correlations* with one another. For example, an increase in labor costs around a particular technology is likely to be seen across labor markets, whether for offshore resources or dedicated resources. However, the impacts are not likely to be equivalent in both labor markets, which would imply nearly perfect correlation. We further observe that even competing standards can exhibit forms of positive correlation in some settings. For example, the standards for digital music of Apple and Microsoft may exhibit positive correlations, as the success in Apple's format, driven by iPod sales, also contributes to growth in Microsoft's standards, given the latter's shear dominance of the desktop platform and recent capabilities in support of digital music and media. This comes, in essence, through broad-based growth in the market. For vendors managing positive correlations in risk factors, it is important to identify how much the technologies are likely to co-vary in their related cost factors due to changes in shared exogenous or endogenous risk factors. Gauging this *shock response* is likely to be challenging for some technologies, since the provider and the clients will have little or no experience with them

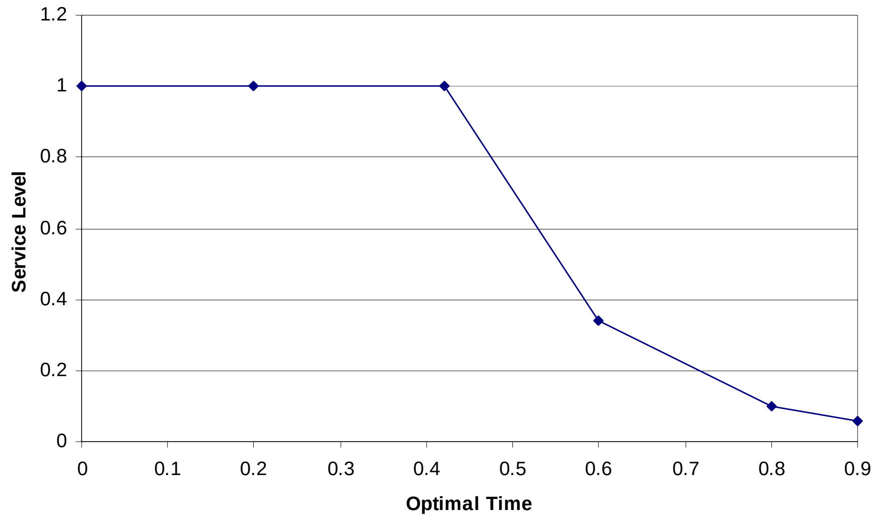
There also are many IT services in which the risk factors will exhibit *low or negligible correlations*. For example, IT security services and software development outsourcing are likely to involve different technologies and related skills. The kind of VaR analysis that we are advocating can help inform vendors as to the markets in which they may wish to expand. Adding additional practices or offerings may allow the vendor to lessen its overall risk position within its portfolio of contracts, depending on the correlation of these new practices to existing service portfolios.

One of the main obstacles to effective correlation analysis for IT services contracts is finding appropriate estimations or proxies for correlations which might be used in the model. Technology diffusion models and simulations may be useful in this endeavor, as we have seen in the research of Paleologo (2006) of IBM. Providers may be able to model firm-level or industry sector correlations through analysis of credit risk. In addition, historical data on labor rates may provide estimates for correlations between the costs of delivering services involving particular skills or skill sets. Managers should carefully scrutinize such estimations and conduct sensitivity analysis to evaluate the impact of deviation from any estimates.

### 3.5.2 Contract Duration

The simulations heretofore all considered a time horizon of one year for which managers evaluated the contract. In other words, we assumed that the time to fulfill the service requirements under the contract was one year. Now we consider the case where the provider can segment the contract, and consider shorter time horizons, which implies fewer hours of contractual obligation. See Figure 3.3.

**Figure 3. 3 Optimal Contract Duration at Service Levels for Profit at Risk > 0**




**Note:** In this case, the inputs of Table 3 and the functional form of the base model are used, except we chose *t* as the variable to optimize, again keeping the *VaR* constrained to be non-negative. As the "high" service levels are demanded by the clients, the provider firm can negotiate a shorter contract duration or buyout clause in order to lesson the risk exposure. The analysis shows the trade-off between time commitments (contract duration) and risk inherent in most services agreements.

Figure 3.3 models the optimal contract duration at a given service-level commitment for a firm which sets its minimum acceptable profit-at-risk to 0. We can see that the optimal time horizon drops as the commitment to the high-level services increases. The intuition is that firms can mitigate their risk exposure for clients who will not negotiate service levels below a certain level of on-site services. This follows the basic intuition of financial economics in that the shorter the time horizon, the lower the risk exposure. Indeed, real options analysis values the flexibility associated with an option to stage or abandon a project. Profit-at-risk analysis provides a unique, but complementary insight. It evaluates the effect on risk exposure associated with various parameters of the contract, and allows providers and firms to reevaluate their relationship at key times in the project. Table 3.8 shows service contract profits for these different time horizons and service levels.

**Table 3.8. The Impact of Contract Duration on Optimal Service Levels and Profit**

| PERCENT HIGH SERVICE LEVEL HOURS (*S*) | *t** | EXPECTED PROFITS | PROFIT-AT-RISK (*PaR*) |
|---|---|---|---|
| 20% | 1.00 | 314 | 121 |
| 42% | 1.00 | 408 | 0 |
| 60% | 0.34 | 139 | 0 |
| 80% | 0.10 | 39 | 0 |
| 90% | 0.06 | 19 | 0 |

**Note**: We optimize profits by choosing the duration of the contract $t$, where $0 \leq t \leq 1$.The intuition is that the client has a hard preference for a particular service level, but is willing to shorten the duration of the contract by staging the project. We used the initial input values shown in Table 3, with the obvious exception of $S$ and $t$, which we vary for this analysis. Expected profits and profit-at-risk are in 000s of dollars.

Table 3.8 shows that it is possible for the firm to add a profitable contract with a minimum of risk by shortening the contract's duration, $t$. The firm can maintain a minimum profit-at-risk by taking on a shorter contract. At service levels of 20% and 42%, describing the mix of high-quality to low-quality service labor, the optimal contract duration is one year; so the firm should accept the full services offered by the company. Note that a service level of .20 is not profit-maximizing in this illustration – note, for example, that a service level of 42% is at $408 – yet the .2 level still offers significant risk reduction opportunities in the portfolio analysis context based on the *PaR* of $121.

In addition, the optimal time horizon can be modeled in the face of portfolio constraints. See Table 3.9. Here we have a portfolio which is set with a profit-at-risk above the threshold of $0. Consider again an important client who requires a 60% service-level mix. Rather than absorb the additional risk of a full duration contract of one year (Table 3.5, far right column), the provider may negotiate a shorter contract to reduce risk (Table 3.9). However, assuming the provider requires a positive *PaR*, the portfolio profit-at-risk position allows for a sizable absorption of risk. The provider is still able to offer the client's preferred service level of 60% dedicated resources over the full one-year time horizon and maintain a positive *PaR*.

**Table 3.9. Optimal Time Horizon for an IT Services Contract in Portfolio, *S* = 60%**

| VARIABLES | VALUE | |
|---|---|---|
| | WITHOUT PORTFOLIO | WITH PORTFOLIO |
| Duration (*t*) | 0.34 | 1 |
| New contract profit | 139 | 409 |
| New contract profit-at-risk | 0 | -293 |
| Initial portfolio profit | | 4,030 |
| Initial portfolio profit-at-risk | | 302 |
| Portfolio with contract profit | | 4,439 |
| Portfolio with contract profit-at-risk | | 72 |

**Note**: Here we consider the impact of time horizon on the firm's portfolio position, in a manner that is similar to the analysis in Table 5. We optimize profits subject to $PaR \geq 0$. In the Without Portfolio analysis, the optimal duration is short ($t = .34$). However, the firm's portfolio of contractual obligations for the same services implies a positive *PaR* of $302. Then, portfolio profit-at-risk is calculated including the new contract. All values stated in 000s of dollars except duration *t*, which is stated in terms of continuous values between 0 and 1, representing the contract time horizon.

## *3.6 Efficiency and Optimality in Profit-at-Risk Analysis*

The range of contracts to be considered by profit-at-risk analysis can be narrowed to a set of *efficient contracts*, defined as those contracts which represent a maximum profit for a given profit-at-risk constraint. We demonstrate that all portfolios are dominated by those in the range of the point between the unconstrained profit maximization service level contract and the maximum profit-at-risk contract. The maximum profit-at-risk contract can be thought of as the *minimum-variance efficient portfolio*. This permits us to show how the firm's risk aversion will affect the choice of efficient portfolio.

In Table 3.10 we evaluate an extended range of service levels, *S*, similar to Table

3.5. We utilize the same inputs from Table 3.4 and functional forms as those used to create Table 3.10.

**Table 3.10. Simulation of Contracts**

| % HIGH SERVICE LEVEL HOURS ($S$) | 10 | 15 | 22 | 30 | 35 | 40 | 45 | 51 | 55 | 60 |
|---|---|---|---|---|---|---|---|---|---|---|
| Expected profit | 192 | 265 | 332 | 375 | 393 | 405 | 412 | 414 | 413 | 409 |
| Profit-at-risk | 53 | 101 | 123 | 101 | 67 | 20 | -41 | -130 | -198 | -293 |

**Note:** These figures are based upon the initial inputs given in Table 2.3, with variations in $S$ as noted in the top row. $S^{(a)}$ = .22 represents the profit maximizing point and $S^{(b)}$ = .51 represents the maximum *PaR* from the dual formulization of our original profit maximization model without profit constraint consideration. The values of costs, revenues and profits are stated in 000s of dollars. The accuracy and precision of the simulated values reported in the table are consistent with the nature of the value estimation and modeling task.

Consistent with the analysis results shown in Table 3.5 and Figure 3.1, we note that the profit maximization point occurs where $S^{(b)}$ = 51%. As we move to columns left of this point, we further note that both the profits and the profit-at-risk are lower than the point of unconstrained profit maximization. That is to say, the contracts at $S$ = 55% and 60% imply greater risk exposure and lower profits. These contracts are dominated by the profit-maximizing contract, and should be removed from the manager's consideration set. To refer back to Figure 3.1, these contracts occur where both profits and profit-at-risk are decreasing in $S$.

Another important case occurs when $S$ is chosen to maximize *PaR*. Formally, we can state:

$$\text{Max}_{(S)} PaR = R(S) - C(S, C_H, C_L)\,[1+\sigma_c(S, \sigma_H, \sigma_L, \rho_{HL})\,\alpha\sqrt{t}] \qquad (9)$$

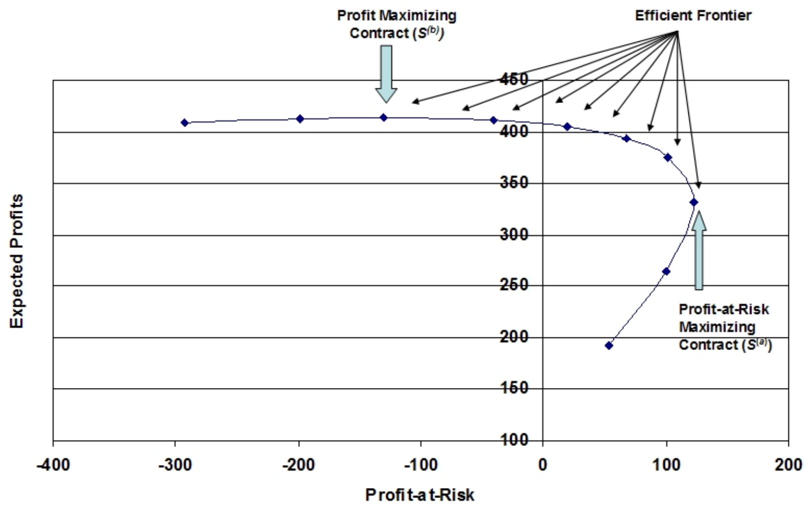
$$\text{Subject to: } 0 < S \leq 1 \qquad (10)$$

Utilizing the same functional forms and inputs as given in the objective function in Equation 4 the *PaR* constraint in Equation 5, and Table 3.4, we find that the solution for the maximum value of *PaR* occurs at $S^{(a)}$ = 22%. As we move to columns left of this point, both the profit and the profit-at-risk decrease. Again, these points are dominated by the maximum profit-at-risk position. These dominated values of $S$ are within the range where profit and profit-at-risk are both increasing in $S$.

We define the *range of consideration*, where marginal profit increases in $S$ and marginal profit-at-risk decreases in $S$, as the *efficient frontier*. We assume the functional forms given by the objective function of Equation 4, and the constraints in Equations 5 and 6. The efficient frontier contains all values of $S$ such that $S^{(a)} \leq S \leq S^{(b)}$. These values for $S$ are represented by the curve connecting $S^{(b)}$ and $S^{(a)}$ in Figure 3.2. Each value for $S$ on the efficient frontier corresponds to a value of $k$, where $k$ falls between the maximum profit-at-risk and the profit-at-risk associated with $S^*$. In Table 3.5, where we varied the value-at-risk constraints, each profit-at-risk constraint represents a point on the efficient frontier. However, the value $S = 60\%$, represented by the right-most column in Table 3.10, does not fall on the efficient frontier; instead, it is dominated by other values for the higher service quality input combinations, per the preceding analysis.

Figure 3.4 illustrates the efficient frontier of IT services contracts. The efficient frontier is a useful guide for managers who have responsibility for portfolios of IT service contracts. If managers have accurate, reliable measures of their customers' willingness-to-pay and cost structures, they will be able to construct an efficient frontier. This will be helpful to narrow down the set of possible IT services contracts to just the set of efficient contracts, which will make for a more productive negotiation provider-customer negotiation process.

**Figure 3.4. Efficient Frontier for IT Services Contracts**




The efficient frontier, as we have defined it for the IT services contract portfolio context, depends upon a key assumption: a strictly increasing, continuous concave willingness-to-pay function. So this extended "frontier" analysis will be more difficult for practitioners to implement in comparison to assessment of contract profit and profit-at-risk in the negotiation setting. Nevertheless, it should be intuitive for an IT services manager <u>not</u> to accept a customer for a contract that is strictly dominated, so in that respect a comparison of relative efficiency should always be made when comparing two contract choices, even if both are below the bounds of a true efficient frontier.

### 3.6.1 Efficient and Optimal Contracts

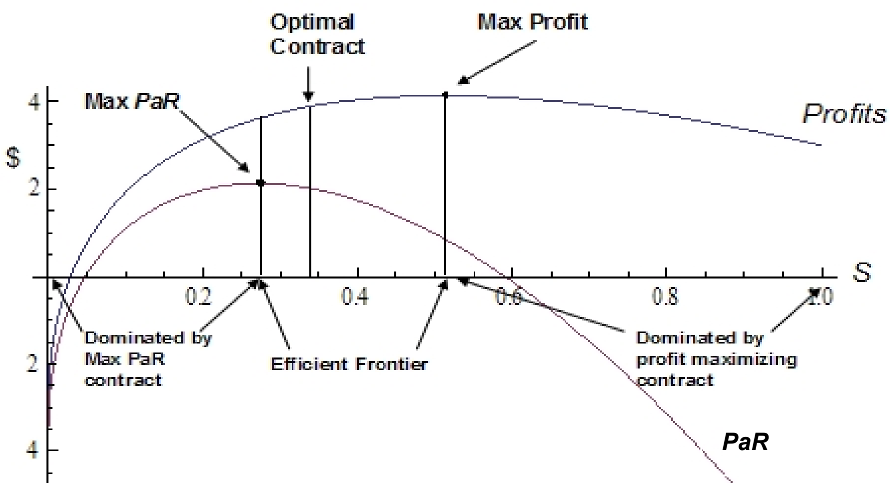
We now turn to provide formal definitions of the efficient contracts and introduce the concept of the optimal contract within the efficient frontier.

- **Proposition 1 (Maximum Profit-at-Risk Proposition)**. *The point of maximum service level agreement profit-at-risk (PaR), $S^{\wedge}$, is less than the profit-maximizing position, $S^*$, and $PaR(S^{\wedge}) < \pi(S^*)$.*

**Proof.** Under the given assumptions, both the profit and profit-at-risk constraint are continuous, concave functions over the interval $0 \leq S \leq 1$. We consider the first-order conditions $R'(S) - C'(S) = 0$ of the primal problem. The first-order conditions of the dual formulation are $R'(S) - C'(S) - C(S)\sigma'(S)\alpha\sqrt{t} - C'(S)\sigma(S)\alpha\sqrt{t} = 0$. Since the term $C(S)\sigma'(S)\alpha\sqrt{t} - C'(S)\sigma(S)\alpha\sqrt{t}$ is positive, when the first-order conditions of the primal problem hold, the *marginal profit-at-risk*, represented by the first derivative of the dual formulation, will be less than zero. ■

We interpret these results graphically in Figure 3.5.

**Figure 3.5. A Representation of the Efficient Frontier and the Optimal Contract**




We can see that the range we are most interested in occurs where the profits are increasing in *S*, and the profit-at-risk is decreasing in *S*. This is important because it shows a lower bound for the ability of the provider firm to mitigate risk. The provider firm will never accept a contract in the range where both profits and profit-at-risk are increasing or decreasing in *S*; the firm will always be able to negotiate a contract with more profit and less risk. We now define an *efficient contract*:

- **Definition 1 (Efficient Contract).** A service level agreement c*ontract is efficient if for a given level of S in the range between $\hat{S}$ and $S^*$, it satisfies the following optimization problem for a unique value of profit-at-risk*, *k.*

$$\text{Max}_{(S)}\ \pi = R(S) - C(S, C_H, C_L) \tag{11}$$

s.t.: $PaR = R(S) - C(S, C_H, C_L)\,[\,1+\sigma_c(S, \sigma_H, \sigma_L, \rho_{HL})\,\alpha\sqrt{t}\,] \geq k$ and $0 < S \leq 1$ (12,13)

The constraint in Equation 2 will hold with equality over the range $S^{\wedge}$ and $S^{*}$, where *PaR* decreases in *S* and profit increases in *S*.

- **Proposition 2 (Efficient Contract Frontier Proposition).** *Every S such that* $S^{\wedge} \leq S \leq S^{*}$ *represents an efficient contract for a unique risk preference, k.*

**Proof.** Since *PaR* decreases in *S* over the interval $S^{\wedge} \leq S \leq S^{*}$ and profits increase in *S* over the interval $S^{\wedge} \leq S \leq S^{*}$, the constraint represented in Equation 2 will hold with equality for each value of *k* on the decreasing portion of the profit-at-risk function. ■

### 3.6.2 Optimal Strategy in IT Services Contract Design

Now that we have established the efficient frontier, a key question remains: How can we develop an optimal strategy for making the trade-off between profit and profit-at-risk? We note that on the efficient frontier, each contract choice is a profit-maximizing optimal solution for a given level of *k*, which can be thought of as an individual's risk preference related to profit-at-risk. However, we can examine the trade-off between the absolute amounts of profit sacrificed relative to the amount of profit-at-risk gained in return. In evaluating this trade-off, we must again consider the risk preferences of the manager. In this case, we ask the additional question: How much profit-at-risk reduction is worth $1 of profits? We evaluate trade-offs between the increasing profit and the decreasing profit-at-risk function. When this marginal exchange is balanced (weighted by risk preferences), the contract is *optimal*, in this way:

- **Definition 2 (Optimal IT Services Contract).** *A contract is optimal over the interval* $[S^{\wedge}, S^{*}]$ *if it satisfies the following conditions:*

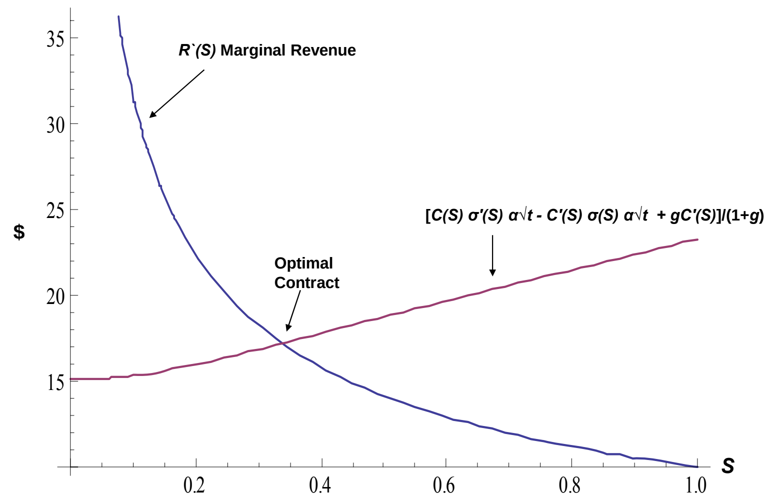
$$g[R'(S) - C'(S)] = -\,[R'(S) - C'(S) - C(S)\,\sigma'(S)\,\alpha\sqrt{t} - C'(S)\,\sigma(S)\,\alpha\sqrt{t}] \qquad (14)$$

$$= R'(S) = [(C(S)\ \sigma'(S)\ \alpha\sqrt{t} - C'(S)\ \sigma(S)\ \alpha\sqrt{t}) + gC'(S)] / (1+g)] \qquad (15)$$

By setting the marginal trade-offs equal in absolute terms, we balance the number of dollars of profits traded with minimum amount of profit associated with a given level of confidence. The parameter *g* is itself subjective, and is be set by management as a means to evaluate the trade-off between profit and profit-at-risk. So, for example, if $g = 1$, then a manager will be indifferent between a dollar of profit and a dollar of profit in the worst case scenario, at a given level of confidence. We note that there is no constraint *k* in this analysis. Standard models of risk-return optimization, such as the Sharpe ratio, assume short selling and a traded asset with a risk-free return (Sharpe 1964). Our model precludes these conditions, so we must capture a measure of risk aversion, *g*, to effectively evaluate optimality.

Equation 15 is noteworthy because it models the conditions under which the marginal revenue is balanced with a trade-off in both marginal cost, and the stochastic component which models the maximum cost increases. Provider managers can utilize this information during negotiations by comparing their cost structure to the price concessions, $R'(S)$, they would have to make in order to place fewer dedicated resources on the client site. Figure 3.6 shows the optimal strategy. The optimal contract occurs where the curve representing the marginal revenue intersects with the curve representing the marginal cost-at-risk.

**Figure 3.6. Marginal Revenues and Optimal Contract Strategy**




### 3.6.3 Comparative Statics

We now explore a specific functional form in order to observe the interactions between the parameters of the model under conditions of optimality, efficiency and profit maximization. Our goal here is to illustrate the effects of risk on the choice of the pooled resources a provider may offer. We show that in addition to scale and scope affects on the cost function, which we assume but do not model dynamically, the provider can significantly reduce its risk exposure by pooling resources among clients.

For clarity in our analysis, we make additional assumptions regarding the functional form, and the value of certain variables. As in the original model, we assume that the client's willingness-to-pay for a particular service decreases as that service is offered as a *pooled resource* ($L$) vs. a dedicated resource ($H$) and $C_H > C_L$. We assume cost function is a linear combination of expected costs of the high and low services as before, however in this instance, we will focus on the risks associated with the project-specific dedicated resources and assume that the pooled resources do not reflect any risk. We assume that the firm's demand and credit risk, as well as its region-specific labor will not be affected by a specifically large pooled resource, since the firm can shift resources among the projects to which it is committed. We expect that pooled resources would in fact face specific risks, such as volatility in costs associated with a particular offshore labor pool or technology that is affected by global demand, but we do not consider them in this instantiation of the model. We model the willingness to pay as $R(S) = VS^{\phi}$. $V$ captures the client's valuation of the service when all of the work is done via dedicated resources. We assume that the client values dedicated onsite resources over pooled off-site resources. $\phi$ measures the client's sensitivity to the pooled resource. In our earlier analysis we assumed $\phi = .5$. The term $S^{\phi}$ still models the degradation value the client experiences as the service-level mix is altered to include more dedicated resource. As $\phi$ approaches 0, the client becomes indifferent between the pooled or dedicated resources. As $\phi$ approaches 1, the client favors the dedicated resources in a linear proportion to S. This functional form allows us to capture a wide range of client preferences, although we are bounded by $\phi < 1$, so our model does limit the range of client sensitivity to pooled resources. The specific objective function then becomes:

$$\text{Max}_{(S)}\ \pi = V S^{\phi} - (S\, C_H + (1\text{-}S)\, C_L) \tag{16}$$

$$\text{s.t.: } PaR = V S^{\phi} - \ [(1\text{-}S)\, C_L + S\, C_H\, (1+\sigma\alpha\sqrt{t}\,)\,] \geq k \tag{17}$$

$$0 < S \leq 1 \text{ and } 0 \leq \phi < 1 \tag{18}$$

We first consider profit maximization, $S^*$, for the simple unconstrained profit function:

$$S^* = \left( \frac{\phi V}{C_H - C_L} \right)^{\frac{1}{1-\phi}} \tag{19}$$

$S^*$ illustrates the balance between marginal revenue and marginal costs as the service level decreases. The marginal costs, $C_H$ - $C_L$ can be thought of as the difference in cost, as a result of labor arbitrage or scale effects, between dedicated and pooled resources. The optimal mix of service represents a proportion of the overall willingness to pay for the dedicated resources and the potential cost savings of using pooled resources.

We next derive $\hat{S}$ , which is the point of maximum profit at risk for a given level of profits, by maximizing the PaR constraint (equation 17).

$$\hat{S} = \left( \frac{\phi V}{C_H (1 + \sigma \alpha \sqrt{t}) - C_L} \right)^{\frac{1}{1-\phi}} \tag{20}$$

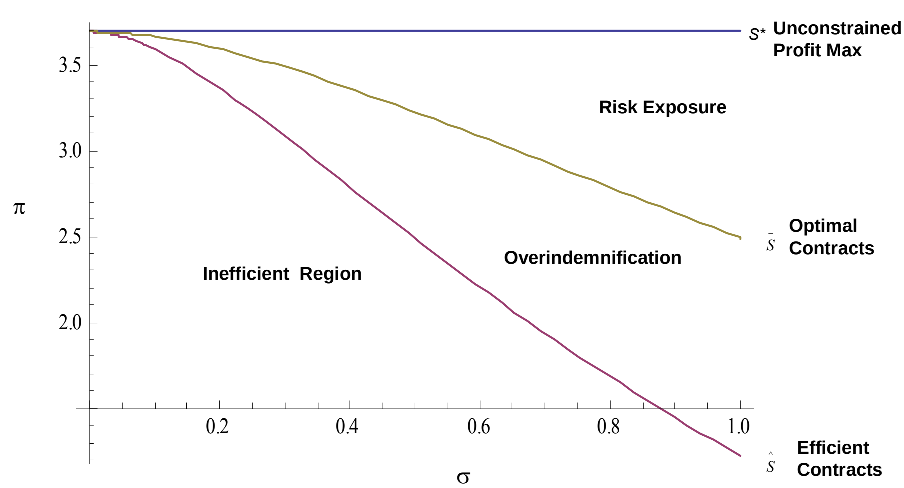
From proposition 2, $\hat{S}$ defines the boundary of the efficient frontier, that is, those set of contracts which maximize profit for a given risk constraint, *k*. Equations 19 and 20 are equivalent in the case that there is no risk or time component to the analysis. Equation 20 shows the effect of risk, duration of contract on the cost parameter $C_H$. Risk magnifies the difference in the costs between the dedicated and pooled resource. In this simplified model, the effect is to increase the cost of the dedicated resource ($C_H$). However, when multiple risk factors interact, the effect of diversification of the standards deviation of cost increases must be considered. The intuition holds in the general case that in the optimal profit-at-risk will be determined now be the proportion of the willingness to pay for the dedicated resource, the cost savings of the pooled resources, and the risk of cost increases of the resources.

$$\bar{S} = \left( \frac{(1+g)\phi V}{C_H(1+\sigma\alpha\sqrt{t}) - C_L + g(C_H - C_L)} \right)^{\frac{1}{1-\phi}} \tag{21}$$

Equation 21 represents the optimal contract we defined in Definition 2. In this contract, the provider states their preferences in terms of expected profits (π) and profit-at-risk (*PaR*) with the parameter *g*. The manager decides how many dollars of certain profits at a given confidence (*PaR*) are worth one dollar of expected profits.

In Figure 3.7 we insert $S^*$, $\hat{S}$ and $\overline{S}$ into the objective function to illustrate the influence of risk on the contract selection strategy and overall profitability.

**Figure 3.7. Risk Affects on Contract Selection Strategy**




First, we note that the graph's upper bound is the unconstrained profit maximization, which is unaffected by contract risk, and remains constant. At the origin of the x-axis, the standard deviation of the cost increases is assumed to be zero. At this point, $S^*$, $\hat{S}$ and $\overline{S}$ are equal, and any deviation from $S^*$ would clearly be sub-optimal, as is shown by the intersection of the three curves. As we increase $\sigma$ along the $x$-axis, three regions emerge.

The first region from the origin is the *inefficient region*. It is bounded by the curve defined by $\hat{S}$ , the maximum PaR contract for a given level of $\sigma$. In this region, the manager would always choose a contract that is both less risky and more profitable. The maximum PaR curve defines the boundary of efficiency for the contract. By *efficient*, we mean those contracts which satisfy the objective function for a given $k$, which we defined earlier as the profit-at-risk constraint.

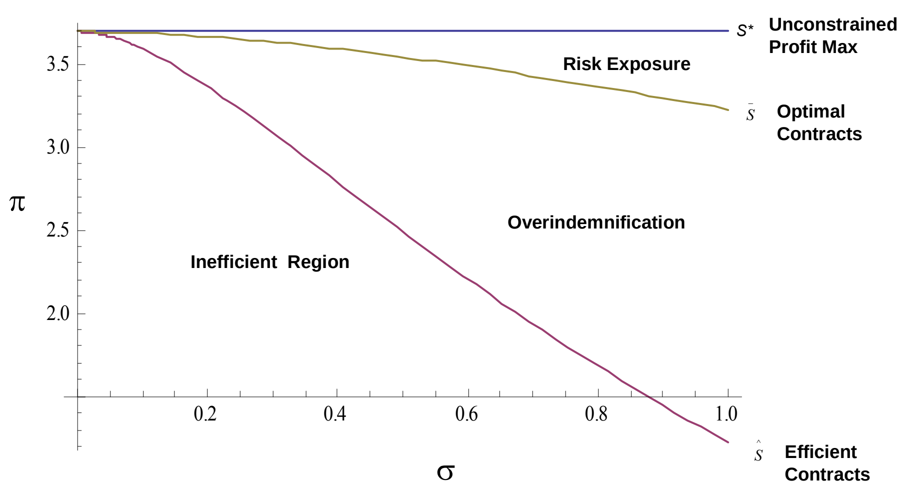
The region between the curves defined by $\hat{S}$ and $\hat{S}$ defines the region of *overindemification*. In this region the provider is choosing contracts which violate the constraint $g$, leading to choice of S that is sub-optimal ($> \hat{S}$ ). Independent of the value of $k$, the provider is sacrificing an excessive amount profits for a relatively modest level of risk indemnification. Indemification in our model equates to a higher PaR. The region bounded by $\overline{S}$ and S* represents an area of *risk exposure*, where the firm has opportunities to further indemnify risk by sacrificing a small amount of profits relative to *PaR*.

In Figure 3.7, $g$ is assumed to be 1, which implies that manager is indifferent between \$1 of profit and \$1 of profit-at-risk. However we would assume that the manager would want compensation greater than \$1 of profit for the certainty of \$1 of profits at an expected confidence. If the confidence level is set at $\alpha$ =90%, then a risk-neutral manager would set $g$ at 1/(1-$\alpha$)= 10. She would be indifferent between \$1 of expected profits and the certainty of \$10 of profits with 90% confidence over the life of the contract, *t*. From equation (21) we note that as *g* increases, it converges to S*.

$$\lim_{g\to\infty} \bar{S} = S^* \quad \textbf{(}22)$$

Equation (21) can be interpreted by considering a manager who places little value on reducing risk exposure by sacrificing profits for any level of *PaR*. This manager would simply choose the unconstrained optimal contract. Figure 3.8 illustrates the shift upwards of the curve defined by $\bar{S}$, where *g*= 1/(1-*α*).

**Figure 3.8.Effects of Increasing *g* on Optimal Contracts**




Here we note that the region of risk exposure is greatly reduced. Thus by restricting the manager's valuation of *PaR* through *g*, the provider firm now has a much narrower window of opportunity to indemnify risk exposure. Note also that the region narrows as σ declines, which serves as a note of caution of using the Profit-at-Risk approach for less risky contract decisions. Any errors in measurement or estimation are likely to result in overindemnification.

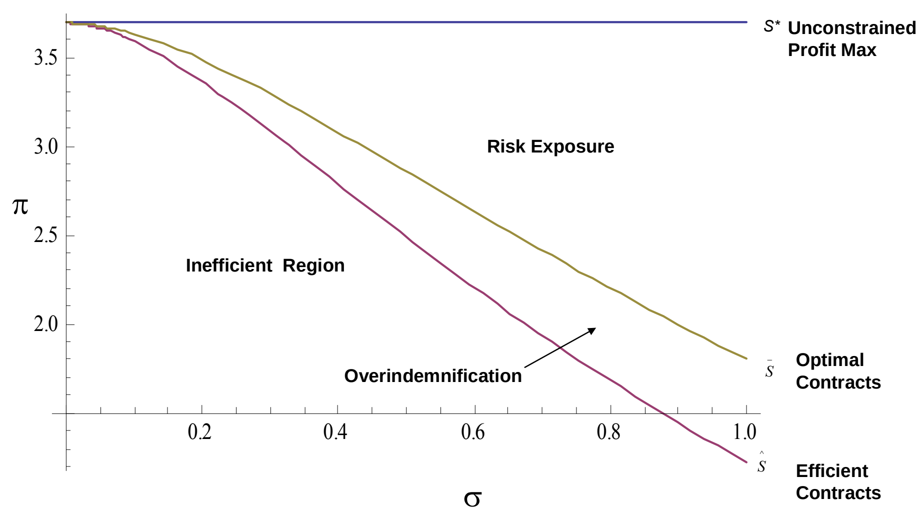
We next consider the effects of reducing *g* on the optimal contract curve defined by

$\overline{S}$ . Again we note that from equation 21:

$$\lim_{g \to 0} \overline{S} = \hat{S} \qquad (23)$$

When *g* is less than 1, the manager is willing to trade greater amounts of expected profit for a reduction in *PaR*. Such a situation might arise when a manager is under pressure to meat earnings expectations. In such cases the provider may be willing to sacrifice expected profits for a relatively modest gain in PaR, if that ensures that it will meet earnings targets at a given confidence level.

**Figure 3.9. Effects of Reduction in *g* on Optimal Contracts**




In Figure 3.9 the region of risk exposure has increased, a natural consequence of increasing *g*. We note the proximity now of the optimal contract curve $\hat{S}$ and the efficient contract boundary $\overline{S}$ . Consistent with Definition 1, the efficient boundary represents the absolute limits of risk indemnification for the profit-at-risk approach.

## *3.7 Conclusion*

Fundamentally, this work deals with the trade-off between risk and return in IT services contract management. The use of the techniques that we have described will be a function of a manager's risk aversion as well as the underlying risk factors to service delivery. From a manager's standpoint, the choice of confidence level may reflect the extent of the risk aversion that the person feels. Risk-seeking managers, as a result, may be more comfortable with lower odds for a minimum profit payoff than risk-neutral or risk-averse managers would be. More important than the choice of confidence level though is the value which managers choose as their minimum profit threshold – what we have referred to as the constant *k* throughout our analysis in this article. This choice will largely be impacted by the pressures faced by the managers from the outside market (e.g., the need to make earnings and to show strong growth in signings relative to their firms' competitors), as well as the levels of risk tolerance that individual managers may exhibit in the context of their own organizations.

### 3.7.1 Contributions

This work provides a contribution to the IS literature in two ways. First, it represents one of the first robust applications of VaR methods, and qualitative risk and reward trade-offs, and begins to move the IS discipline toward the emerging services science area. Second, our research incorporates VaR analysis in an optimization model of IT service parameters in a way that provides useful and actionable managerial decision support. To illustrate why this is the case, we illustrated several scenarios where a profit-maximizing decision is not optimal relative to management's tolerance of risk. In addition, we modeled the impact of contract duration and contract structure to risk exposure, and provided scenarios where managers can reconfigure the timing of contracts to mitigate risk. We developed an evaluative method for IT services contract portfolio assessment involving a new financial construct, *profit-at-risk*, which we believe can be implemented as the basis for a new and deeply insightful decision support tool. With further extensions to the data modeling and financial analytics, our profit-at-risk approach will support IT services contract negotiations and post-contract interactions between service-providers and clients. The beneficial impact in reduced litigation and increased client goodwill associated with fewer service-level breeches goes beyond the quantitative measurements produced here.

### 3.7.2 Future Research

The analytic modeling approach involving value-at-risk that we have presented only scratches the surface in terms of potential applications and methods. Empirical research could be employed to estimate an efficient frontier where firms evaluate their portfolios of obligations as benchmarks against an optimal combination of risk and profitability opportunities in the contracts held in a portfolio. Another interesting approach that is consistent with other evaluative methods that firms use in the management of financial portfolios is to derive an *implied confidence level* by which managers would identify a profit-at-risk level they are comfortable with. They then would be able to use a VaR analysis to calculate the probability that profit levels might dip below a certain level. This is akin to the calculation of *implied volatility* in option pricing, where the analyst computes the variance of returns on the underlying asset consistent with a given option price observed in the market.

Incorporating real option-based thinking will be a key modeling extension. We introduced an initial illustration of how such thinking can lead to the structuring of contracts with value-at-risk constraints. Many parameters of IT services contracts can be thought of as options, for instance penalties and buyout clauses in service level agreements can be priced via real option analysis. These pricing decisions also may be considered in a VaR portfolio context. In addition, contractual liabilities may be conceptualized as corporate bonds, with the *default boundary*, or point at which payback is no longer viewed as viable, priced as an *option to abandon* the contract.

An additional avenue to explore is the impact of risk-mitigating investments which the provider can make. For example, quality control programs such as ISO 9001 and Six Sigma may greatly reduce the uncertainty and risk associated with service delivery. Profit-at-risk analysis could provide a useful means to measure quality improvements that might not translate into measurable cost reductions. Another interesting application would be the effects of capacity investments on the client's risk position. For example, a provider will often make fixed-capacity investments, both in technology and labor, to exploit economies of scale. This additional capacity would likely reduce risk exposures associated with fluxuations in customer demand.

Customers of IT services will also benefit as providers will be more willing to absorb new client risks in their IT services offerings. We expect that the methods that we have described can also be applied in other IS settings, for example, in assessing the risks associated with the bundling of information goods (Bakos and Brynjolfsson 1999) evaluating information security services, and assessing other information practices in the firm. In addition, large firms will be able to leverage the profit-at-risk approach in the context of shared services to more accurately assess transfer costs with considerations for risk exposure.

The ultimate direction for research is the development of decision support tools based on the model we have proposed. Such tools would incorporate the profit-at-risk approach in real-time analysis. Rather than focusing on the impact of additional contracts to the portfolio, active portfolio management could be implemented to enable new decision analysis approaches beyond those that we modeled in this article. This will permit IT services managers to make informed choices about the levels of their investments and contractual decisions, such as extensions and/or withdrawal from services agreements. In addition, firms can use this approach to make strategic choices on headcount requirements and resource deployment decisions. Such analysis will further inform recruiting and retention decision-making, as well as global sourcing strategies.

### 3.7.3 Limitations

The main limitation of the methodology that we have proposed is our use of the delta-normal method and the associated estimation of the standard deviation of costs. However, we expect that decision support tools that implement our proposed approach probably will rely more on historical data-based, full valuation approaches. In IT settings, we believe that labor market data will be a useful basis for providing proxies for standard deviation estimates of wages, and even correlations for costs and revenues across different IT standards. For example, firms can begin to track wages or employment data regarding Bluetooth vs. wireless skills, or a host of other project management, network architecture and systems deployment staff salaries in the marketplace. There are additional issues with the delta-normal method which must be considered too though. Under assumptions of normally-distributed returns, VaR has limitations. In portfolio settings, value-at-risk may not be sub-additive, which could overstate the actual risk position to some degree. In spite of this, however, many financial services firms may be observed to be continuing to use VaR techniques. Jorion (2007), exhibiting an awareness of the underlying issues, has suggested that employing full valuation methods with historical data can reduce the exposure associated with issues of sub-additively and coherence. For example, firms can model the actual distribution of returns for a particular kind of IT service based on historical data, once they build up sufficient experience with tracking the relevant data to do this. Simulation techniques will be important as this work moves towards full-valuation methods (Jorion 2007).

IT services contract data may exhibit kurtosis and/or skewed distributions, which may cause a firm to underestimate its risk positions. The use of *conditional value-at-risk* may reduce the impact of kurtosis and non-normal distributions, which are likely to occur when modeling technology risks (Anderson et al. 2001). Firms should use caution with conditional value-at-risk implementations, since Alexander and Baptista (2004) show that in portfolio selection without a risk-free asset, highly risk averse managers may wind-up selecting riskier portfolio positions under conditional value-at-risk constraints. We expect that as firms implement this methodology, they will build competencies in estimating volatility and other input parameters, which will make it possible to diminish the negative impact of non-normality in terms of the outcomes of the analysis. Luciano and Marena (2002) present a technique to examine portfolio-level value-at-risk without the assumption of normally distributed returns.

Beyond the issues associated with the structure of the data used is the practical ability of firms to gather the data required about their service levels, and detailed cost and revenue data, which are tied directly to each contract. For many service providers, these data occur in disparate areas. A firm's financial recording systems may cover the necessary granularity which contract analysis requires, for example. Fortunately, there are several vendors, such as SAS (www.sas.com) and Digital Fuel (www.digitalfuel.com) have begun to offer service level management (SLM) systems which actively track data regarding the performance of a service provider's contractual obligations (O'Neil and Hubert 2007). IS and OR researchers also have utilized the well-known data envelopment analysis (DEA) methodology to model best practice production frontiers (Sherman and Zhu 2006). We believe that it will soon be possible to develop efficient frontiers for IT services management best practices by utilizing contract data from service level management tools such as those offered by SAS and Digital Fuel. Advanced data mining techniques may also be used on the data from these systems in order to identify "at-risk" clients or service commitments patterns that lead to unacceptable levels of firm risk. In spite of the obstacles, we believe that the future is very bright for the further development and diffusion of managerial use of the methods that we have proposed involving value-at-risk methods, as well the broader tool sets that are being developed for services science.

# Chapter 4. Essay 2: Optimal Timing and Valuation of Price Benchmarks in IT Services Contracts

## *4.1 Introduction*

Contracting for information technology (IT) outsourcing services involves the transfer of risk among parties. In fact, the uncertainties associated with the management, delivery and cost of IT solutions often serve as drivers for a firm to outsource. Clients expect to benefit from a provider's unique expertise and efficiencies in delivering services, albeit at a competitive price. As technology costs fall, and competition increases, *service-level agreement* (SLA) prices that a provider and a client agreed upon at the outset of the contract may not be competitive as time passes. As a result, many clients insist on a provision in their IT services contracts for benchmarking. *Benchmarking* is the process of seeking a third-party estimate of the current market price for the IT solution, as a means to gauge how close the price of the contracted services are to prevailing external prices.

Benchmarking provisions are the result of information asymmetries between clients and providers of IT services. Clients cannot generally track the prevailing market price for IT services. Provider firms, due to their frequent client interaction and negotiation have more accurate market price information than do client or third-party benchmarkers. As a senior executive of EDS stated: "The reality is I have much better information than the benchmarkers do ... we participated in over 9,000 deals last year" Overby (2007a). Though it is believed that benchmark provisions benefit clients more than providers, there has been little analytic or empirical research to determine how much clients benefit from benchmarking and under what circumstances they should negotiate for, and ultimately exercise benchmark provisions. Benchmark data are notoriously hard to come by (Harris 2007), and there is often little incentive for either client or provider firms to share the intricacies of their IT services contracts. In this paper, we seek to build analytic model to extend existing theory in financial economics to provide managerial guidance on the valuation and timing of benchmarks for IT services that will aid in SLA contract design and contract negotiation. Specifically, we ask: what is the value of including a benchmark provision to a client? What is the optimal time and frequency of exercising benchmark provisions in an IT services contract? How will uncertainty about the variety of IT service contract cost drivers affect these decisions?

### 4.1.1 Characteristics of Price Benchmarks for IT Services

The key uncertainty driving the need for benchmarking emanates from the changing future market prices for various inputs that constitute the cost drivers of SLAs. In long-term outsourcing arrangements, *ex ante* price adjustment schedules are often included to account for changes in service scope, inflation or process improvements. Benchmarking works as a means to address the drift of relevant market prices away from the original IT services contract price. This drift often is the result of innovations in service delivery, declining technology costs, and increased competition (Harris 2007). Viewed this way, long-term contracts provide stability benefits for both parties. They also may limit the ability of the client firm to access the most competitive market rates for services though.

Methodology-wise, the process of benchmarking can hardly be considered an exact science in current industry practice. Third-party benchmark firms (which we will refer to as *benchmarkers*) access pricing data on the cost-drivers from various kinds of IT services outsourcing arrangements. One of the market leaders in third-party benchmark firms is TPI (www.tpi.net) that specializes in outsourcing advisory services (Harris 2007). Analyst firms such as Gartner and IDC also provide benchmarking services. In addition, many consulting firms offer benchmark services. Data are collected through surveys of existing IT services clients in the marketplace to get a sample of IT service delivery terms and pricing. Since IT services engagements generally vary in content across client engagements, benchmarking firm must adjust for these differences.  This process is called *normalization*, and it involves adjusting prices for differences in services such as scale, scope or delivery location (Overby 2007a). The normalized data are then compared to the original prices that are stipulated in the SLA agreement. Since the market for IT services is relatively opaque, benchmarkers often struggle to achieve access to the relevant data. SLA contracts also often include predetermined thresholds as a basis for determining whether a price adjustment can take place – either reducing or increasing the price for IT services rendered. Harris (2007) reports that some benchmark provisions hold the provider responsible to be no greater in price than the prices associated with the upper quartile or upper decile of all prices observed in the marketplace, while other contracts may utilize a confidence level around the sample mean. Beyond the fact that IT outsourcing contracts are heterogeneous, the author also mentions that benchmarks are usually conducted with a small sample size, about eight to ten contracts.  This is a cause for concern relative to the overall accuracy. Client firms may benefit through inter-organizational sharing of outsourcing contract data. If the current price does not meet a *designated benchmark threshold*, enforcement mechanisms included in the contract may provide a legal basis for automatically adjusting prices, or allowing the client or the vendor to abandon the IT services arrangement.

### 4.1.2 Benchmarking Strategies and Their Countervailing Benefits to Providers and Clients

It may not be surprising that benchmarking provisions are popular among IT services clients, but they tend to be much less popular among IT services providers. Benchmarks cut into a provider firm's profit when the underlying cost drivers for IT services can be controlled or are headed in the "right" direction (as with a decline in the price of software labor, for a given kind of software development). Also, like warranties on consumer electronics, providers' pricing schemes create profits at the back-end of SLA contracts (Overby 2007a). Seeking to shift the balance of power in IT service relationships away from the provider's side, many client firms have adopted a strategy of employing benchmarking provisions, resulting in micro-price adjustments with frequent invocations of the benchmarks (Harris 2007). Practitioners differ in the advice they give clients regarding benchmark frequency though. Some suggest consistent yearly intervals (Overby 2007b). Others promote the use of infrequent benchmarks after at least eighteen months in contracts with durations of longer than three years (Harris 2007). The latter approach seeks to use the benchmark as a risk mitigation tool, while the former views the benchmark as more of a micro-pricing tool.

Providers have turned to several strategies to mitigate the effects of client-mandated benchmark clauses on their profits. One approach they employ now is to request a cap on the post-benchmark price adjustment. Providers can also seek to limit the timing or frequency of the benchmark decision (Overby 2007b). An emerging trend among providers is to limit the use and reuse of client data for benchmarks (Overby 2007a). By stifling access to data, providers can limit the ability of a benchmark to be carried out, per the terms of the contract. In addition, there is added uncertainty as to whether the benchmark will accurately reflect market prices. Such uncertainty has the potential to affect either party adversely.

The present research is motivated by these considerations. We model the value of contract price information in the context of IT services benchmarks, and answer a number of questions. How much should clients be willing to pay for embedded options for benchmarking in their IT services contracts? How can we characterize how optimal timing choices for benchmarking should be established? Will IT service providers be worse off if their prices for benchmarking services were transparent? What other managerially-relevant findings can be extracted from simple models of benchmarking? We explore different conditions for expected rates of the declining market prices and the related uncertainties, which result in firm preferences for early, frequent benchmarks are preferred to later, more infrequent benchmarks.

### 4.1.3 Existing Theory and a New Approach

Three streams of literature support development of a model of optimal benchmark timing. The first includes Dunn and Spatt (2005), and Agarwal et al. (2007), which describe the methods developed to support consumer refinancing decisions, and lender pricing strategies for home mortgages. They model the optimal timing of refinancing decisions. The basic tenet of the theory is that consumers should be indifferent for refinancing when the net present value (NPV) of the benefits of refinancing is equal to the refinancing costs, plus the difference in value between the option to refinance which one gives up, and the option to refinance which one gains over the remaining life of the contract (Agarwal et al. 2007).

In the case of IT services contracts, we note two important modeling differences. First, with IT services benchmarking, the markets in which relevant SLA contract prices are established are quite opaque. The market prices for IT services contracts generally cannot be observed in the market without costly effort. This lack of market transparency is the *raison d'être* for benchmarking services; the market's willingness-to-pay third-party benchmarkers for their services suggests that there is more than just nominal value associated with their intermediation. As a result, when we model optimal benchmarking for IT services, we must consider the optimal timing, given expectations about the uncertainty about the price trajectories of various aspects of IT services. In contrast, mortgage refinancing strategy is often framed in terms of an *interest rate boundary*, a single key parameter with important value referents, across which it is optimal to refinance. For mortgages, it is unnecessary to specify any limits on the amount of time that must pass before a consumer is able to refinance. This is not possible in the IT services contracting though. For IT services contracts with embedded benchmarking options, it typically will be necessary to make an *ex ante* decision with incomplete information about the optimal time during the lifetime of the SLA contract when it is possible for either or both parties to exercise the option to invoke the benchmark. The incomplete information aspect of this decision-making setting arises based on transparency for the given IT services being analyzed (e.g., software, web hosting, data center operation, and so on).

A second key difference between the mortgage refinance decision and the IT services benchmarking decision comes with whether the embedded option can be exercised once only or more than one time. The mortgage example is obvious: refinancing a mortgage means that the original contract is extinguished, and a new one replaces it. But a borrower always holds the option to refinance the new loan. This is not quite the same for IT services benchmarking though; it is still possible to benchmark an SLA contract more than once, only these will occur at different points in time. For simplicity in the development of our managerial analysis and contract design policy strategies, we will consider one benchmark per contract in our base model, and then extend the model to two benchmarks over a given contract time horizon.

We also consider risk management models that evaluate optimal time to *mark-to-market* (MTM), as discussed by Liao and Theodosophoulos (2005). The authors considered the changes in market values of over-the-counter stock derivative positions with respect to collateral posted at the initiation of the derivate contract. We draw an analogy between marking-to-market financial instruments with the benchmarking of IT services contracts. *Mark-to-market* is the periodic valuation of assets held. TPI[25] refers to its benchmarking approach as an *IT mark-to-market method*. In their model, the stock prices are not observed until the mark-to-market takes place, and substantial expenses for this financial intermediation service are associated with the mark-to-market process. IT services benchmarks share these characteristics. The authors also extend the previous mark-to-market literature by considering the potential of using quantile-based analysis to calibrate different risk exposure levels. In the case of

[25] www.tpi.com

benchmarking, we are evaluating the cumulative price paid throughout the contract life and minimizing this in the objective function of our optimization function. On the other hand, the authors also consider the maximum risk exposure over the life of the stock derivative contract and the probability of default on any given day as their key parameters.

A third theoretical perspective we draw upon is *options pricing theory* (Black and Scholes 1973, Cox et al. 1979). Our challenge is to model the expected price that the client firm will pay for the benchmark when it is exercised. We utilize the *contingent expectations approach* discussed by Whaley (2006). The method considers the likelihood of prices having drifted below the original negotiated value, and the expected price decline at the time of benchmark. While the Black-Scholes equation utilizes conditional expectations, we do not make any assumptions about portfolio replication with a risk-free asset, since IT services contracts are not traded.

We combine elements of refinancing and risk management theory, as well as draw on literature regarding IT investment under uncertainty to build a unique model which values benchmark decisions in opaque markets. To our knowledge, few researchers have considered optimal timing in opaque markets and the value of flexibility under price uncertainty, so we believe this to be a broad contribution to the stream of literature around investment in uncertainty. The next section sets up the modeling concepts. We first consider the results of the model with a known, constant price decline in order to establish a baseline case with which to compare results under uncertainty. We then incorporate the effects of uncertainty. Our modeling results are robust in the face of volatility. We show that firms can leverage uncertainty by exercising benchmarks even when the expected price decreases are modest. We find that increases in the dollar value of the benchmark threshold will tend to reduce the time to exercise and the value of the benchmark option. These findings may be counter-intuitive given the dynamics of conventional options models where the increase in the length of time to expiration increases the value of the option.

## *4.2 The Model*

We introduce a model for optimal timing of price benchmarks for a given expected value of IT services price drift. We present examples of the results and a sensitivity analysis. We extend the model to consider multiple benchmarks in a contract.

### 4.2.1 IT Services Contracts and Benchmarking for Price

Imagine that a provider of IT outsourcing services negotiates a fixed-price, fixed-length contract with a client. Service-level agreements regarding quality and time of service are defined in the contract. The SLA prices are assumed to be index-adjusted for inflation. The provider minimizes the cost of providing the service to maximize profits under the fixed-price contract.

We consider the case with declining costs of IT and increasing competition in the IT services industries, and the market prices of the outsourced service are expected to decline as time goes on. Demirhan et al. (2006) provide a formal model of declining technology costs and the impact on IT investments. The client requests a benchmark provision in the contract. The benchmark provision can cover multiple distinct services, for example, desktop support or network management. Under the benchmark provision, a third-party consultant, agreed to *ex ante* by both the client and the provider, will examine the market prices for IT services and provide a benchmark. According to the terms of the contract, price adjustments for the SLA will be made based upon the benchmark results, but will only result in decreases in price to the clients. We consider first the case of a single benchmark allowed during the contract life cycle. We later extend the model to cover multiple periods.

### 4.2.2 Model Specification

The client and provider agree to a contract with a fixed price at the start of the contract, $P$, for a contract lifetime of $T$. The price $P$ is paid in continuous time over an interval of $dt$. *Continuous time analysis* allows us to obtain more general results and is often more tractable in terms of achieving closed form solutions. We expect the model to be implemented over a discrete schedule of payment intervals (e.g., monthly or quarterly). Our modeling results hold under *discrete time analysis* too, which is examined in Essay 3. The modeling notation is given in Table 4.1.

**Table 4.1. Modeling Notation**

| SYMBOL | DESCRIPTION |
|---|---|
| $P$ | Price of the IT service, costs paid by client to provider |
| $C$ | Cost to exercise the benchmark |
| $t$ | Time at which benchmark is exercised |
| $T$ | Total length of the contract |
| $\mu$ | Expected drift rate of IT service |
| $\sigma$ | Standard deviation of IT services prices |
| $\Phi$ | Cumulative distribution function for standard normal variable |
| $W$ | Lambert W function |

### 4.2.3. Baseline Case: Optimal Timing of Benchmark without Uncertainty

We first introduce a baseline case where the drift of IT services prices is constant and known by the client. The baseline model provides the optimal timing strategy of the benchmark without consideration of errors in the forecast of the services pricing, which we later model with the diffusion term using *geometric Brownian motion*. In the deterministic case, the dynamics of $P$ reduce to $dP = \mu P dt$ . The total cost, or sum of money paid over the lifetime of the contract, is specified by the function $F(P)$, given by:

$$F(P) = \int_0^t P_0 dt + \int_t^T P_0 e^{\mu t} dt \qquad (1)$$

where $\mu < 0$

The total cost $F(P)$ is the sum the payments at the original price $P_0$ up till the time of the benchmark, the costs of the benchmark, and the sum of the payments made at the benchmark price. We assume that the price drift $\mu$ is non-zero. If the client observes that the prices will rise with $\mu > 0$, there will be no benefit to exercising the benchmark clause in the future.

To explore the dynamics of the growth rate in the timing decision, we make the simplifying assumption that the discount rate used by the firm is zero. We do acknowledge that the discount rate may affect the timing decision, since clients will want to receive cost savings sooner, rather than later, if we assign a time value to the firm's funds. Thus our results are restricted to the case where the discount rate is zero. The client firm chooses to exercise the benchmark at the time when the total cost of the contract $F(P)$ is minimized. The objective function follows:

$$\underset{t}{Min}\, F(P) = \left(P_0 t\right) + P_0 e^{\mu t}\left(T - t\right) \qquad (2)$$

This permits us to state our first proposition:

- **Proposition 1 (The Optimal Benchmark Timing Proposition).** *Under conditions of a constant, negative exponential decline in prices, the optimal time to exercise a benchmark occurs at:* $t^* = \dfrac{\mu T + W(e^{1-\mu T}) - 1}{\mu}$.

**Sketch of Proof**. The first-order conditions are given by

$\dfrac{dC}{dt} = P_0 - e^{\mu t} - e^{\mu t}\mu t + e^{\mu t}\mu T = 0$. Thus $t^* = \dfrac{\mu T + W(e^{1-\mu T}) - 1}{\mu}$. In this expression, $W$ is the Lambert $W$ function, $\mu \neq 0$, and $t^*$ is a local minimum over the interval where $t$ = [0,1]. [26] In addition, the second-order conditions are also satisfied:

$\dfrac{d^2C}{dt^2} = -2e^{\mu t} + e^{\mu t}\mu^2 - e^{\mu t}\mu^2 T < 0$ , over the interval where $\mu$, $t \in [0,1]$.

From our initial model and analysis, we can further conclude:

- **Proposition 2 (The Optimal Benchmark in the First Half of the Contract Proposition)**. *With a negative drift rate of prices μ < 0, the optimal benchmark period will always occur in the first half of the contract.*

**Sketch of Proof:** From the Optimal Benchmark Timing Proposition (P1), $\mu^- \rightarrow 0$, the term $W(e^{1-\mu T}) \rightarrow 1 - .5(\mu T)$. This term reduces to $\dfrac{\mu T - \frac{1}{2}\mu T}{\mu}$ , which implies that as $\mu^- \rightarrow 0$, $t^* \rightarrow T/2$, where $t^*$ is the optimal time to benchmark the contract and $T$ is the total length of the contract.

The Optimal Benchmark Timing Proposition (P1) and the related Optimal Benchmark in the First Half of the Contract Proposition (P2), along with the assumption that benchmarks do not trigger price increases, imply that the $t = T/2$ is an upper bound to the benchmark decision. Apparently it will never be optimal to benchmark in the second half of the contract. We will show later when we discuss the effect of discounting that the proposition holds in the case of introducing discounting, since a positive discount rate will never increase time to benchmark.

[26] According to PlanetMath (www.planetmath.org), "Lambert's *W* function is the inverse of the function $f$ : **C→C** given by $f(x) := xe^x$. $W(x)$ is the complex-valued function that satisfies $W(x)e^{W(x)} = x$ for all x $\in$**C**. Lambert's *W* function is sometimes also called [the] *product log function*." See also Corless et al. (1996), and Agarwal et al. (2007) who used Lambert's *W* in the case of mortgage refinancing decisions.

### 4.2.4 Value of the IT Services Contract Benchmark Provision

One of the motivating factors in this work is to understand the value of implementing an IT services contract benchmark. Benchmark provisions are often the subject of intense negotiation between the contracting parties, and understanding the value of specific benchmark provisions can inform both the client and the provider as to how to negotiate effectively. Figure 1 shows the optimal timing of the benchmark contract and the value of the across levels of $\mu$ from -10 to 0, where $T = 1$. A value of $\mu$ = -10 with a contract length of $T = 1$ is equivalent to a 10-year contract with -100% drift in price, so it seems like it is a reasonable boundary to the analysis.[27] Figure 4.1 shows contract costs and the optimal time to benchmark.

In Figure 4.1, The y-axis represents both $T$ and $P = 1$, as the upper curve represents costs and the lower curve represents prices. We can see that per the Optimal Benchmark Timing Proposition (P1), when the drift rate, $\mu$, approaches zero, the cost at the optimal benchmark nears $P = 1$. This implies no change in the market price, and as we discuss later, implies no benchmark. The optimal time to exercise the benchmark can be seen to approach $t = .5$ as the drift rate $\mu$ approaches 0, per Proposition 1. The value of $P$ at the optimal benchmark can be interpreted as (1 - %Cost)(Total Contract Costs).

[27] To isolate the effects of the drift rate, and provide general interpretive results, in Figures 1 and 2 we plot the drift rate $\mu$ assuming a contract length of $T = 1$. This allows any combination of contract length and drift rates to be calibrated to any time period considered by dividing the value of $\mu$ where $T = 1$ by the contract length. Thus, the absolute term $\mu$ when $T = 1$ can be calibrated across time periods and drift rates. For example, $\mu = -1$ and $T = 1$ represent the following drift rates and contract lengths: (a) $\mu$ = -20% in a five-year contract ($T = 5$ years), or (b) $\mu$ = -10% in a ten-year contract ($T = 10$ years). We will only use percentages to represent a special case of drift rates calibrated in the model. When $\mu$ is not presented in terms of a percentage, we are referring to the drift rate where $T$ is assumed to be 1.

**Figure 4.1. Contract Costs and Optimal Timing**

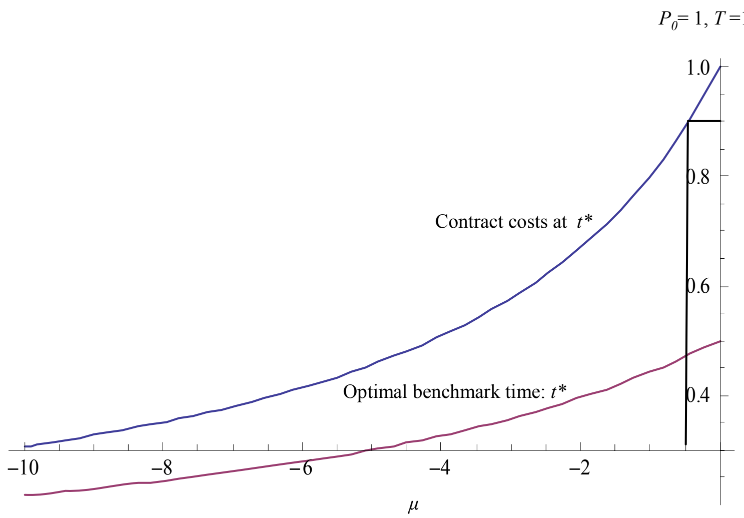



Table 2 shows several contract scenarios for a given values of $\mu$ and $T$. Table 2 calibrates several model input scenarios for given values of $\mu$ and $T$.

**Table 4.2. Cost Savings Associated with Optimal Benchmarks**

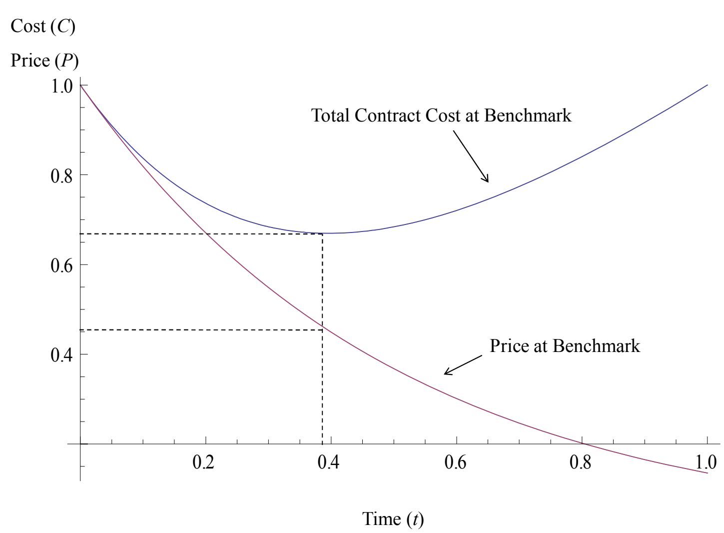
| $T = 1$ | FIRM SLA CONTRACT COST | $T = 5$ YEARS | $T = 10$ YEARS |
|---|---|---|---|
| $\mu$ = -.5 | 88.9% | $\mu$ = -.10 | $\mu$ = -.05 |
| $\mu$ = -1 | 80.1% | $\mu$ = -.20 | $\mu$ = -.10 |
| $\mu$ = -2 | 67.0% | $\mu$ = -.40 | $\mu$ = -.20 |
| $\mu$ = -4 | 50.9% | $\mu$ = -.80 | $\mu$ = -.40 |

**Note:** The left-most column represents values for drift rate $\mu$, where the contract length of 1 is assumed to be unit-less, which is consistent with the scale of Figure 3. The costs represent the percentage of the original contract costs that the client would pay if no benchmark took place. The two right-most columns show the implied drift rate and contract length associated with the optimal benchmark length.

Row 1 of Table 4.2 shows a five-year contract with potential cost savings of 11.09%. For a contract of $1,000,000 dollars, that translates into a savings of $110,900.

For a \$20,000,000 contract, the benchmark provision is worth \$2,218,000. In other words, the larger the contract, the more valuable the benchmark is. Table 2 also shows the role of contract duration and drift rate of IT services costs in determining the timing and ultimate value of the benchmark decision. As the drift rate decreases and SLA delivery prices decline, we see that the contract savings increase. In this case, a client should benchmark earlier in the life of the contract, as shown on Figure 4.1. The client will reap more benefits at the earlier optimal benchmark time. More interesting is the effect of contract length on the benchmark value. As the contract length increases in the presence of a constant drift rate, the firm will benchmark earlier in the contract. Figure 4.2 presents a graphical illustration of contract costs and the expected market prices across time for the scenario where $\mu$= -2, $T$ = 1.

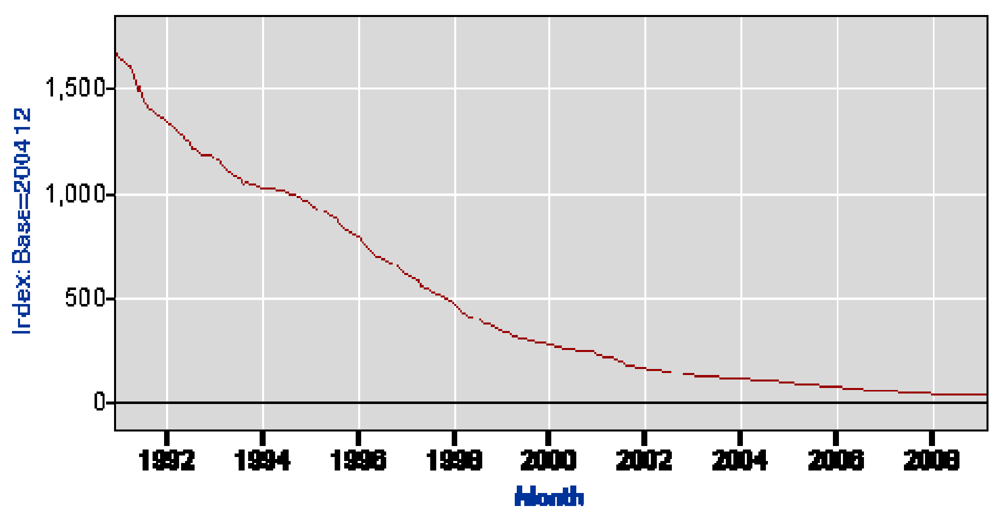
**Figure 4.2. Contract Costs and Price across Time: $\mu$= -2, $T$ = 1**




### 4.2.5 Model Assumptions and Parameterization

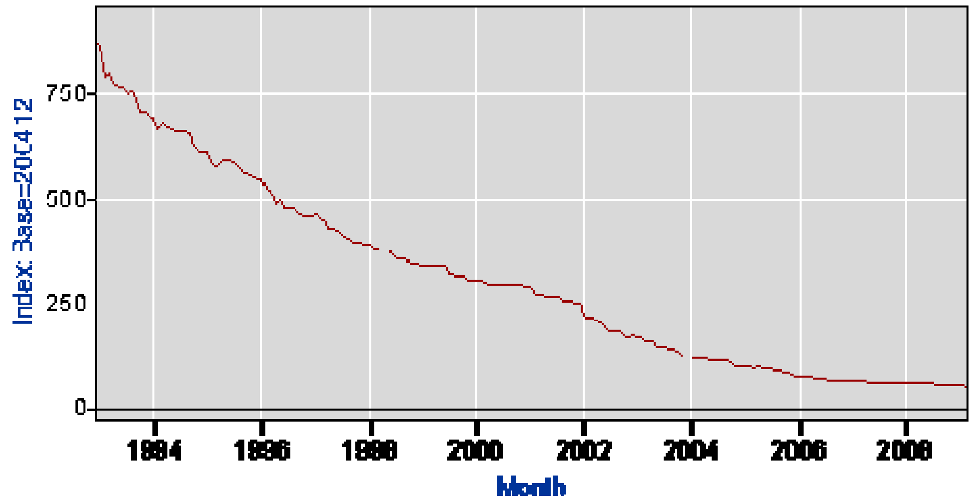
Our baseline assumption for the model is that the market price for IT services follows a constant, continuous, year-to-year price decline. While firm-specific data was not available for our study, we base our assumption on the functional form of the price drift, $P_t = P_0 e^{\mu t}$ on anecdotal evidence from practitioner writings. We also draw on the proposition of Moore's Law (Moore, 1969) that processing power increases at an exponential rate, and this acceleration leads to declines in the per-unit cost of computing. This law has been extended to other technology products such as disk drive capacity and the doubling of pixels per dollar in digital cameras (Gün Sirer and Farrow, 2007). Figures 4.3 and 4.4 plot the Bureau of Labor Statistics Producer Price Index for Computer Equipment Manufacturing (Dec 1990- March 2009) and Computer Storage Device Manufacturing (Dec 1992- March 2009).

**Figure 4.3. Computer Equipment Manufacturing Producer Price Index**




Source: U.S. Bureau of Labor Statistics

**Figure 4.4 Storage Equipment Manufacturing Producer Price Index**




Source: U.S. Bureau of Labor Statistics

We note that this data is at an aggregate level, across many different products. Price index data is not meant as an input to our model. Hardware only makes up a component of the overall IT services price mix. IT services prices are driven many other factors such as labor markets, business process innovation and competitive forces. However, Figures 4.3 and 4.4 do lend support to the claim that at least one component of IT outsourcing prices, technology hardware, follows a price trajectory similar to the one we propose.

Practitioners have also studied price drift of IT services. Gartner (LaVasseur 2001) cites a study where they found that comparable market prices of a client's mainframe outsourcing services fell by 20% year to year over a ten year period. We use this as a base case example in the analysis. Overby (2007a) cited a study by the benchmarker Compass which finds clients end up paying 23% below market value by the end of year three. For a ten year contract in our model, this would indicate a value of μ of about -.23. We note that precision of the inputs is not the goal of our model. Rather, we are interested in the evaluating the decision a firm would make for a given estimate of IT services price drift and uncertainty.

## *4.3 Extended Analysis*

### 4.3.1 Illustrative Example: A Case of One Benchmark

To give the reader a feel for the kind of analysis we are proposing, we develop an illustrative example based on a scenario associated with the Gartner Group, as discussed in LeVasseur (2001). A Gartner client had a data center services outsourcing scenario where service prices were able to be evaluated based on the decline in *million of instructions per second* (MIPS) on a mainframe computer. By the time the client firm engaged Gartner, it was already six years into a ten-year contract, and the firm was paying well over double the market value of the services. Gartner estimated a 20% annual decline in the price of MIPS in the period from 1992 to 1998. In our model, a 50% decrease in market prices, as cited by Gartner, would occur at Year 6, in this case a drift rate of -11.5%. (The $\mu$-equivalent of -11.5% is -1.15.) We will consider both scenarios; together they provide useful intuition into measurement issues and the use of proxies in benchmarking. In Table 4.3 we compare the optimal solution implied by our model with the client's actual choice of benchmarking at Year 6 of the 10-year contract. The scenario in which the client firm found itself paying twice the market rate in support of SLA costs appears in the $4^{th}$ row for $t = 6$ as the implied drift in Table 4.3. The client realized an 80% savings by undertaking the benchmark after the sixth year, based on the recalibration of the contract price with its vendor.

**Table 4.3. Value of Optimal Benchmarks**

| BENCHMARK STRATEGY | ACTUAL DRIFT | *T* IN YEARS | FIRM SLA CONTRACT COSTS |
|---|---|---|---|
| Implied drift optimal | $\mu$ = -11.5% | 4.35 | 77.6% |
| MIPS drift optimal | $\mu$ = -20.0% | 3.96 | 66.7% |
| MIPS drift optimal under implied drift conditions | $\mu$ = -11.5% | 3.96 | 77.9% |
| $t$ = 6, implied drift | $\mu$ = -11.5% | 6 | 80.1% |
| $t$ = 6, MIPS drift | $\mu$ = -20.0% | 6 | 72.1% |

**Note:** Firm SLA Contract Costs represent the percentage of contract value the firm pays under the benchmark strategy. The drift rate in IT service delivery cost is expressed in annual terms, with a 10-year duration. The left column shows the drift rates used to compute optimal time to benchmark.

Had the firm benchmarked at the optimal time (as shown in Table 4.3, Row 1), it would have saved an additional 2.4% of the total contract value, which may be a significant amount on a ten-year contract. Had the drift rate mirrored the mainframe MIPS price decline (as shown in the bottom row), then the firm would have saved 5.65% compared to its for the optimal time under the MIPS drift rate (as shown in Row 2). We can also see that had the firm applied the MIPS drift optimal rule for benchmarking (as in Row 3), then it would only have missed out on about .03% of the cost savings compared to the case where the client firm benchmarked at the optimal time. From this analysis, we can see that the benchmark model is fairly robust to changes in the drift rate when optimal conditions are applied.

### 4.3.2 Benchmark Considerations with Transaction Costs

In addition to understanding the optimal timing of the benchmark decision, it is useful to determine the conditions under which a benchmark should be considered. Specifically, we will look at what drift rate of the market price of IT services would need to be in the market before a benchmark would be undertaken.

The cost of the benchmark itself is expressed as *X*. Benchmark costs depend largely on the size of the contract. Most benchmarks cost \$100,000 but can run as high as \$1,000,000 according to Overby (2007a). Inserting the Optimal Benchmark Timing Proposition (P1) into the objective function gives the cost of the contract at the optimal time of the contract. We then weigh the cost savings of the optimal benchmark versus the transaction costs, *X*.

- **Definition 1 (Cost Savings Threshold for Benchmarking).** *The client firm should only benchmark if the cost savings exceed the transaction costs of conducting the benchmark:*

$$P_0T - [P_0t^* + P_0e^{\mu t^*}(1 - t^*)] > X \tag{5}$$

The left-hand side of Definition 1 represents the cost savings, that is, the total costs with no benchmark less the total cost with a benchmark exercised optimally. If these savings exceed the transaction costs, then the benchmark should be considered. Figure 1 shows the relationship between contract costs, optimal timing and the drift rate of expected market prices. The value for $t^*$ approaches .5 (the halfway point of the contract) as $\mu$ approaches 0 (which is a neutral drift rate), as we noted ought to be the case in the Optimal Benchmark in the First Half of the Contract Proposition (Proposition 2). The transaction costs, *X*, are represented on the price axis labeled *P*. The intersection of the horizontal line drawn from *X* to the drift axis (labeled $\mu$) implies a maximum value for $\mu$ of the expected drift rate of IT services prices where the benchmark should take place. As shown in Figure 1, the benchmark would cost 10% of the total contract value. In order for the benchmark to even be considered, the firm would need to expect a drift rate less than or equal to -.5. Consider the following calibration of a small contract for 5 years with an annual payment of \$120,000. The firm would be looking at paying \$60,000 (10% of the total contract value of (\$600,000) for a benchmark. For the benchmark to be profitable, the firm needs the market price to decline by 10% per year. That may be a reasonable assumption, but nevertheless it is something the manager must consider when making a decision to exercise the benchmark option.

**4.3.3. Sensitivity Analysis of Drift Rate Assumptions**

We model the sensitivity of our model with two issues in mind. First, we consider the potential gain if the client were to gamble and exercise the benchmark at the optimal time, given a scenario of rapidly decreasing costs of the IT services that underlie the SLA contract. This is considering the effects if the forecast underestimated the magnitude of the price drift. We also compare this to the value of the optimal timing decision under different drift rate scenarios. Table 4 shows the sensitivity of the drift forecast on the benchmark strategy. We infer the probabilities from quantiles of the normal distribution, corresponding our stated assumption that IT services prices follow a *geometric Brownian motion* stochastic process.

In the Table 4.4, we calibrate the model such that the firm faces the same expected drift rates in the costs of MIPS as in the earlier example, where the drift rate was -20%. This time we include a volatility of $\sigma = .35$ surrounding the drift. This represents the uncertainty associated with the client firm's forecast of prices. The volatility level represents a two-thirds likelihood that the price will go 35% above or below the estimated mean. The first row illustrates a strategy in which the firm optimizes for the $90^{th}$ percentile of the expected drift rate. With this strategy, the firm will only end paying 35.55% of the original contract costs. Thus, the firm has a 10% chance of saving an additional 35% of total contract costs, as compared to the scenario where IT service prices decline by 20%. However, as the third row shows, if the firm benchmarks according to the strategy where the IT service costs decline by 20% when the drift is actually -78.5%, the firm will realize a cost saving of 42.31% of total contract costs. The firm still reaps significant savings.

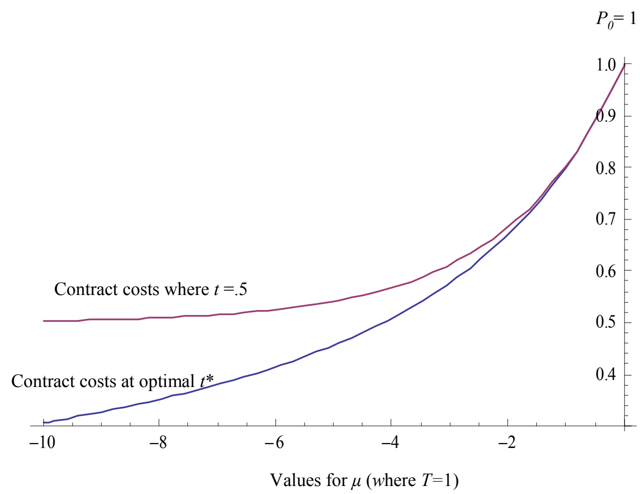
**Table 4.4. Sensitivity Analysis of Benchmarks**

| OPTIMIZE ACCORDING TO DRIFT | ACTUAL DRIFT | FIRM SLA CONTRACT COST |
|---|---|---|
| At 90th percentile = -78.5% | -78.5% | 35.5% |
| | -20.0% | 70.7% |
| For a 20% IT service cost decline | -78.5% | 42.3% |
| | -20.0% | 67.0% |

Note: Firm SLA Contract Cost represents the percentage of contract value the firm pays under the benchmark strategy. The *drift rate* is expressed in annual terms, with a duration of 10 years ($T = 10$). The left column shows the drift rate in IT service prices under which the firm chooses the optimal time to benchmark.

Figure 4.5 compares an optimal strategy where the expected drift rate is zero ($t = .5$) to optimal strategies at hypothetical drift rates of IT service prices. The upper curve in Figure 4.5 demonstrates the contract costs when $t = .5$ across all possible scenarios of service price declines in the interval $-10 \leq \mu \leq 0$, when $T = 1$. The reader should recall that the drift rate $\mu$ can be presented in a general, although it can be calibrate as a IT service price decline percentage for any contract length. The bottom curve represents the costs of a contract when optimized according to the Optimal Benchmark Timing Proposition (P1) at every instance of $\mu$. At drift rates near zero, the contract costs are nearly identical. As the drift rates go more negative there may be a benefit to benchmarking earlier in the period.

**Figure 4.5. Contract Costs at Optimal $t^*$ and $t$ =.5**




There is little difference between the two approaches until the drift rate of IT services prices goes well below -2. Note from Table 2 that $\mu$ = -2 implies a 20% annual rate of IT service price decreases in a 10-year contract in the market. In a 5-year contract, this represents a 40% annual rate of decline over 5 years. One can draw the conclusion that in short contracts, with relatively high rates of forecasted price declines, a firm may do well to benchmark at $t$ = .5. As the drift rate and duration of the IT service contract decrease beyond $\mu$ = -5, we see substantial potential savings. $\mu$ = -5 implies an annual decline in prices of 100% for 5 years, 50% for 10 years, or 25% for 20 years, depending upon the contract length. While unlikely, in this scenario, benchmarking at the half-way point involves missing out on savings of about 9% of total contract value. The client is better off choosing the optimal solution according to their forecast of IT services prices.

### 4.3.4 Multiple Benchmarks within a Contract

Heretofore we have only considered the case of one benchmark provision in a contract. In practice, clients often request multiple benchmarks over a contract's duration. The issue of benchmark frequency is a common subject of contention in negotiations between clients and providers, according to Overby (2007a). We now extend our baseline model to account for the possibility of two benchmarks over the duration of the contract and compare the results to the case with one benchmark. We examine conditions under which a client firm chooses a single-benchmark versus two-benchmarks ($t_1$, $t_2$), with the following objective function:

$$\underset{t}{Min}\, C = P_0 t + P_0 e^{\mu t_1}(t_2 - t_1) + P_0 e^{\mu t_2}(T - t_2) \tag{3}$$

In the case of two benchmarks the firm must choose optimal $t_1^*$ and $t_2^*$ to minimize the total cost over both periods. The contract with provisions for two benchmarks can be thought of as consisting of three periods. Initially, the client pays the original price agreed to in the IT services contract, which is seen in the first term in the above equation. The second term represents the period where the first benchmark prices prevail. The last represents the third period, where the client pays the price identified by the second-period benchmark.

We do not consider a closed form solution for the two-period case. Instead, we apply backwards induction to solve for the optimal benchmark schedule ($t_1^*$, $t_2^*$). To solve for the optimal benchmark schedule, we consider the cost intervals separately. We first calculate second-period costs, given by the last two terms in:

$$C(t_2) = P_0 e^{\mu t_1}(t_2 - t_1) + P_0 e^{\mu t_2}(T - t_2) \tag{4}$$

We select a candidate value of 0 to $t_1$, which we denote as $t'_1 = 0$. With this candidate, we define an optimal value for $t_2$, which we denote as $t'_2$. We apply the same technique and refer back to the proof for the Optimal Benchmark Timing Proposition (P1) to solve for an optimal $t'_2$, given a candidate value $t_1$, as follows:

$t'_2 = \frac{\mu T + W(e^{1-\mu T + t'_1 \mu}) - 1}{\mu}$. We then insert $t'_2$ into the objective function defined in Equation 4 for a total cost at $(t'_1, t'_2)$ of:

$$C(t'_1, t'_2) = P_0 e^{\mu t_1}\left(\frac{\mu T + W(e^{1-\mu T + t_1 \mu}) - 1}{\mu} - t_1\right) + P_0 e^{\frac{\mu T + W(e^{1-\mu T + t_1 \mu})}{\mu}}\left(T - \frac{\mu T + W(e^{1-\mu T + t_1 \mu}) - 1}{\mu}\right)$$

(5)

On the first iteration, if we consider the period one benchmark candidate, $t_1' = 0$, the $t_2'$ value will be equal to the optimal one-period benchmark. From this point, the solution is iterated until an optimal benchmark schedule $(t_1^*, t_2^*)$ is identified. Consistent with the single-period benchmark, the optimal time to the first benchmark $t_1^*$ increases as the value for $\mu$ and $T$ increase. See Table 4.5.

**Table 4.5. Optimal Timing and Value of a Two-Period Benchmark**

| | **Two-Period Benchmark** | | | **One-Period Benchmark** | | |
|---|---|---|---|---|---|---|
| **$\mu$ ($T = 1$)** | **$T^*_1$** | **$t^*_2$** | **Firm SLA Contract Cost** | **$t^*_{One\_Benchmark}$** | **Firm SLA Contract Cost** | **Difference** |
| -0.5 | .31 | .64 | 85.41% | .47 | 88.90% | 3.49% |
| -1.0 | .28 | .61 | 74.16% | .44 | 80.01% | 5.85% |
| -2.0 | .24 | .56 | 58.15% | .40 | 66.95% | 8.80% |
| -4.0 | .21 | .48 | 40.20% | .33 | 50.89% | 10.79% |

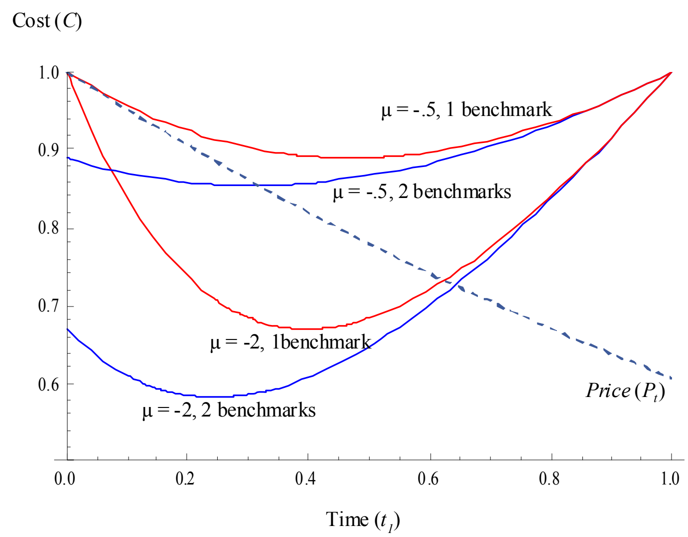
**Note:** The Firm SLA Contract Cost represents the percentage of contract value the firm pays under the benchmark strategy. The left column shows the drift rate in IT services costs, $\mu$, where $T$ =1.

Table 4.5 shows the relationship between the single-benchmark and the two-benchmark contract cases. As the drift rates of IT service prices in the market nears zero, the difference in cost savings between the two approaches narrows for the client.

Two-benchmark strategies are more valuable as the drift rate in IT service prices decrease. For example, Row 1 shows a contract with a drift rate in the IT services price of $\mu$ = -.5, which is equivalent to a 5% price decline over a ten-year contract. Depending on the total costs of the benchmarks, a firm may find the additional 3.49% savings over the contract life an insignificant amount. For a large contract this might make sense, however, in smaller contracts, the cost of the benchmark could easily exceed the expected gains. At lower drift rates of IT services prices, the differences are more pronounced, as Rows 3 and 4 illustrate. Row 2 represents the 20% price decline that we used in the earlier MIPS case. In this example, the client would have realized close to 5.85% cost savings over the total contract, which would likely be significant in a multi-year data center outsourcing scenario.

Figure 4.6 graphically compares the one- and two-benchmark scenarios. The figure plots the total costs as a proportion of the contract value on the vertical axis, and the time to the first benchmark on the horizontal axis. The two curves which intersect at $C$ = 1.0 represent the single-benchmark scenarios. The curves which intersect where $C$ =.89 and .67 represent the two-period benchmark at $\mu$ = -.5 and -2, respectively. If the first benchmark is not undertaken, the second benchmark collapses to the single-benchmark optimum. The optimal total costs can be inferred from the lowest cost point which the curves reach, and we note that the cost differences can be seen to increase as the drift rate for the IT services price moves from -.5 to -2. From our earlier discussion of benchmark timing, we see that, as intuition suggests, multiple benchmarks will be most useful in situations where the duration is longer.

**Figure 4.6. Comparison of One vs. Two Benchmarks**




With downward future adjustment of prices, benchmark provisions cut into the profits of the service provider. Providers often claim that the benchmarks do not accurately reflect the market price of services (Harris 2007). To shield themselves against this uncertainty, service providers often insist upon a reasonable discrepancy between the price identified in the benchmark and the current price of the contract. A common tool is a *pre-identified threshold* that must be met, usually 10% or 15% before price adjustments take place (Harris, 2007). Therefore, the providers are shielded against any downward bias in the benchmark sampling data.

The dashed line in Figure 3 represents the prices over the interval $0 \leq t \leq 1$, where $P_t = P_0 e^{\mu t}$, $P_0 = 0$, and $\mu = -.5$. If the benchmark threshold were set at .80, the first-period benchmark would result in no price adjustments since the price of the IT services is equal to .85. However, the price at the single-benchmark optimum is .79. This illustrates a case where a provider can benefit by granting the client firm the option to benchmark twice, but negotiate a higher threshold for price adjustments.

The benchmark threshold is especially interesting given situations of uncertainty around the expected drift rate of market prices for IT services or the accuracy of the benchmark. It adds the possibility of potential losses for the firm when it exercises the benchmark. If the threshold is not met, the client risks losing the investment costs associated with the benchmark. If there is significant volatility and the drift rate is relatively close to zero, a client may insist on a two-benchmark provision, but conduct the benchmark at a later date than the optimal $t_1^*$, where there is more certainty that the cost savings threshold may be met, while still benefiting from a second benchmark.

## *4.4 Optimal Timing of Benchmark with Price Drift Volatility*

We now turn to the case where the price drift is not known with certainty. We assume that the managers make a *price drift forecast*. The forecast gives an expected value of price drift along with a value of uncertainty. We will consider two-cases. First, we will consider the general case where the price drift forecast is negative: that is to say, the client firm expects the prices to fall over time according to an assumption of functional form, an exponential drift rate. We will then consider the special case where the price drift is zero. In addition to an environment where market prices are expected to remain stable, a zero-drift scenario could occur when the provider and client negotiate growth a priori to reflect the expected price decline. We will later show cases where the client will benchmark under conditions of a zero growth rate when volatility is sufficiently high.

### 4.4.1. Model of Price Benchmarks Under Uncertaitny

We assume that prices for the IT services evolve according to a geometric Brownian motion stochastic process, $dP = \mu P dt + \sigma P dz$ .

In addition, we assume that the client will not incur price increases should the benchmark findings report a price where $P_t > P_0$.

$$F(P) = P_0 t + Min[P_t, P_0](T - t) \tag{6}$$

The fact that the client is not exposed to price increases when the benchmark provides additional incentive to the client to benchmark. The client's overall loses are capped at the cost of the benchmark. This is a unique feature of the benchmarking option. In a traditional call option, the holder of the option is indemnified against the downside risk when the stock price drops below the strike price, in other words, when the option is out of the money. In these cases, the investor's losses are capped at the price of the option. We note that while we use the analogy of an option, we point out that this is not a pricing model. We do not assume that underlying benchmark is a tradeable asset.

We infer the overall value of the contract $F(P)$ from a benchmark exercised at time $t$ by evaluating the expected price of the IT services at a proposed exercise date $P_t$. We utilize the approach of Whaley (2006) to calculate the *conditional expected prices.* The conditional expected price, $E[P_t \mid P_t < P]$ is the expected price time $t$, conditioned on $P_t < P$. The conditional expected price is then multiplied by the probability that $P_t < P$. The total expected price at time $t$ adds the probability-weighted conditional expectations for the range of both $P_t < P$ and $P_t > P$. So we have the expected price at time $t$:

$$E[P_t] = E[P_t \mid P_t < P][\Pr(P_t < P)] + E[P_t \mid P_t > P]\Pr P_t > P \tag{7}$$

Equation 7 simply states that the unconditional expectation of the price at time t is equal to the sum of the probability weighted conditional expectations. Using the properties of the geometric Brownian motion with drift (Dixit and Pyndick 1994, Whaley 2006), we assume that the IT services price changes over time follow a log-normal distribution. Using this property allows us to calculate the probability of the price of IT services reaching a particular threshold, [pr ($P_t < P$)], as well as the expected price of the IT service conditioned on the prices not reaching the predetermined threshold, E[$P_t$ | $P_t < P$] and E[$P_t$ | $P_t < P$] (Whaley, 2006). In the application of our model, we are interested in the expected price of the IT service conditioned on it falling below the original price, $P_0$.

### 4.4.2. Conditional Expectations of IT Services Prices

The conditional expectations of the IT services price gives us the expected price of the IT services at time $t$ weighted by the probability of the services price being below the initial price of the service $P$ (Whaley 2006). The partial expectation is the conditional price weighted by the probability that the price does not exceed or fall below a threshold on which the conditional price is based. Stone (2007) derives an approximation of the Black-Scholes equation using a partial expectation approach. In addition, conditional expectation approaches have also been utilized in engineering to study reliability and hazard rates (Blischke and Murthy 2000). We calculate conditional expectations based on Whaley's approach (2006). The conditional expectation if $P_t > P$ is given by: $E[P_t \mid P_t > P] = Pe^{\mu t}\dfrac{\Phi[d_1]}{\Phi[d_2]}$, where $d_1 = \dfrac{\ln\left(\dfrac{P_t e^{\mu t}}{P}\right) + \dfrac{1}{2}\sigma^2 t}{\sigma\sqrt{t}}$ ,

$d_2 = \dfrac{\ln\left(\dfrac{P_t e^{\mu t}}{P}\right) - \dfrac{1}{2}\sigma^2 t}{\sigma\sqrt{t}}$ and $\Phi$ is the cumulative density function of the normal distribution and $E[P_t \mid P_t < P] = Pe^{\mu t} \frac{\Phi[-d_1]}{\Phi[-d_2]}$. The probabilities of $P_t$ exceeding and falling below a threshold $P$ are given by: $\Pr[P_t > P] = \Phi[d_2]$ $\Pr[P_t < P] = \Phi[-d_2]$.

### 4.4.3 Valuation of the Benchmark under Price Uncertainty

In order to find the expected value of the IT services under conditions of uncertainty, we utilize the conditional expectation approach. In our original model, (Equation 2) we utilized the unconditional expected price to value to contract costs after benchmark. However, under conditions of uncertainty, there is chance that the market price of IT services could price could rise beyond the initial threshold, $P_0$. Since the price of the IT services will not increase with a benchmark, we limit the upper bound of the IT services prices to not exceed $P_0$. Thus the value of the IT services price benchmark can be determined by:

$$F(P) = P_0 t + (Min[E[P_t \mid P_t > P_0], P_0] * \Pr[P_t > P_0] + E[P_t \mid P_t < P_0] * \Pr[P_t < P_0])(T - t)$$

### 4.4.4 Total Contract Value and Optimal Timing under Uncertainty

Since the partial expectations depend on $t$, we cannot solve for a closed-form solution in terms of $t$ as we did in Section 2. However, our approach does allow us to compute numerical solutions for the optimal timing. Ultimately we are interested in finding the valuation and optimal timing decision of the benchmark under IT services price volatility.

Table 2 shows simulation results with the optimal timing and contract valuation across time and for different uncertainty levels. It highlights some interesting effects of volatility on the benchmark decision. First, for ranges of relatively low volatility like $\sigma < 1$, we observe that the optimal timing decision moves forward. However, there is little real effect on the value of the contract. For example, when $\mu$ = -2.0 (the case of the 10-year mainframe example from Gartner) and $\sigma$ < .5, the overall contract benefit is not impacted by benchmarking early, according to the optimal time to benchmark under volatility considerations. We plot the scenarios for growth where $\mu$ = 0, -.5 and -2 for the three levels of volatility ($\sigma$ = 0, .5 and 1) across values of time to illustrate the optimal time to benchmark in Figures 4.7, 4.8, and 4.9. In Table 4.6, we provide numerical analysis of the optimal timing at under these modeling inputs.

**Table 4.6. Cost Savings Associated with Optimal Benchmarks under Uncertainty**

| $\mu$, WHERE $T = 1$ | $\sigma$, WHERE $T$=1 | OPTIMAL TIMING | FIRM SLA CONTRACT COST |
|---|---|---|---|
| $\mu$ = 0.0 | $\sigma$ = 0.0 | $t$ = NA | 100.0% |
| $\mu$ = 0.0 | $\sigma$ = 0.5 | $t$ =.33 | 92.3% |
| $\mu$ = 0.0 | $\sigma$ = 1.0 | $t$ =.33 | 84.9% |
| $\mu$ = -0.5 | $\sigma$ = 0.0 | $t$ =.47 | 88.9% |
| $\mu$ = -0.5 | $\sigma$ = 0.5 | $t$ =.41 | 88.4% |
| $\mu$ = -0.5 | $\sigma$ = 1.0 | $t$ =.36 | 80.2% |
| $\mu$ = -2.0 | $\sigma$ = 0.0 | $t$ =.45 | 67.0% |
| $\mu$ = -2.0 | $\sigma$ = 0.5 | $t$ =.40 | 67.0% |
| $\mu$ = -2.0 | $\sigma$ = 1.0 | $t$ =.32 | 58.7% |

**Note:** The left-most column represents values for drift rate $\mu$, where the contract length of 1 is assumed to be unit-less, which is consistent with the scale of Figure 3. The costs represent the percentage of the original contract costs that the client would pay if no benchmark took place. The two right-most columns show the implied drift rate and contract length associated with the optimal benchmark length.

From Figures 4.7, 4.8, and 4.9 we can see that when the expected price drift nears zero, the dispersion between the valuations of the optimal contracts at various levels of uncertainty increases. At low levels of drift, the optimal benchmarking decision, in terms of valuation, is much more sensitive to volatility. However, as we noted from Table 2, the timing decision is rather insensitive to the valuation. This supports one of our key managerial insights: the decision of *whether to benchmark* is more important than *when to benchmark*. Higher volatility increases the expected value of the benchmark option. Higher volatility also implies benchmarking earlier in the contract, but the marginal benefits of the early exercise are slight. For example, if we refer to Figure 4.8, where $\mu$ = -.5, the optimal time to benchmark is $t$ = .36 when $\sigma$ = 1, and the expected contract cost falls to 80.2% of the original value. If we benchmark according to the optimal time when the expected price drift is zero though (with $t$ = .47), then the expected benefits will remain at around 81%. This difference of 0.08% could be significant in a very large contract, but as a measure of sensitivity, we can see that the timing decision is not sensitive to the benchmark. On the other hand, we can see from Figure 4.9 that there is a significant increase in the value of the benchmark when there is uncertainty. If a manager had assessed the total benchmark costs at about 12% of contract value, then the decision of whether to benchmark would be impacted by the levels of volatility in the expected price drift.

**Figure 4.7. Contract Value over Time for $\mu$ = 0**

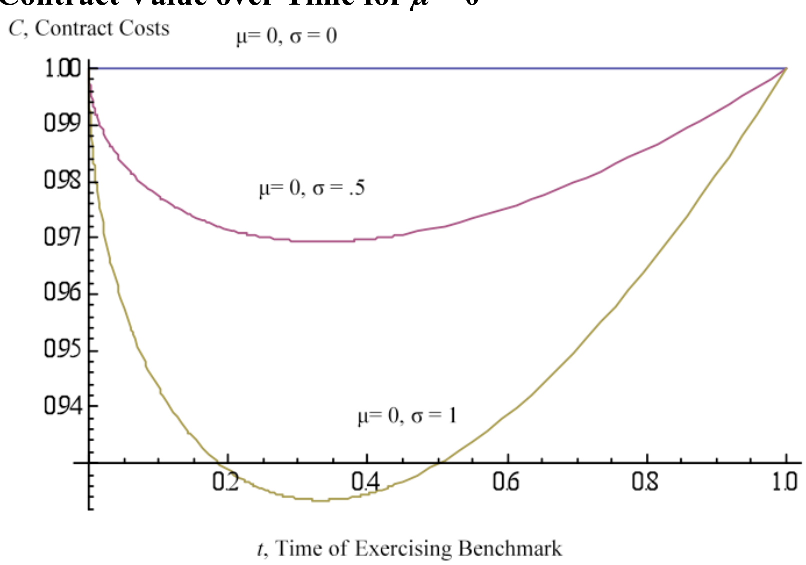


**Figure 4.8 Contract Values across Time for $\mu$ = -.5**

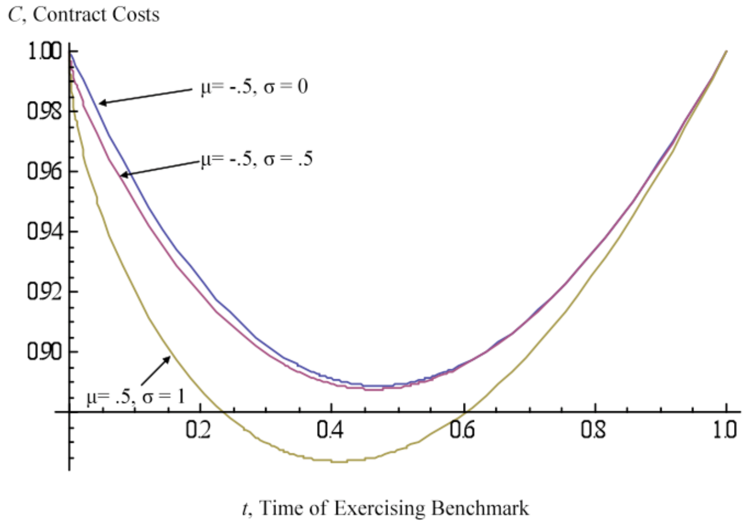
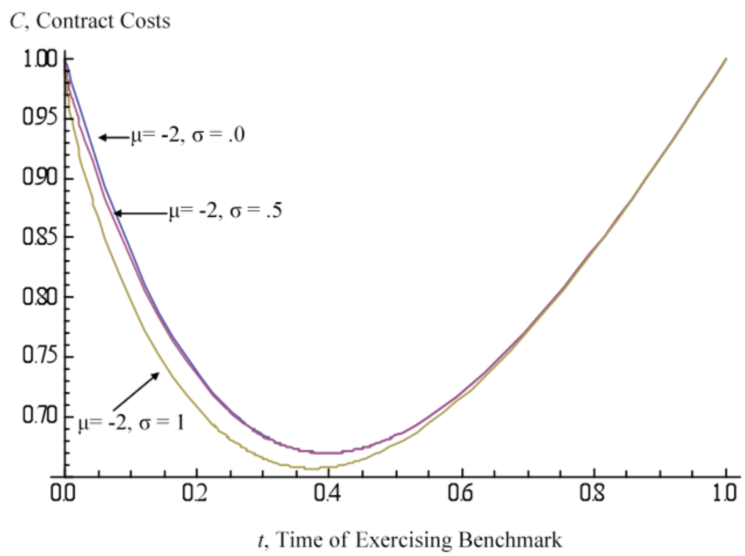



**Figure 4.9. Contract Values across Time for $\mu$ = 2**

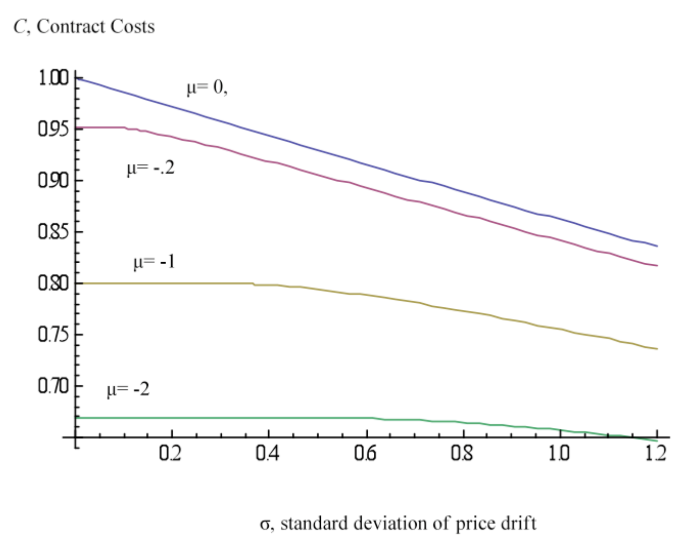



### 4.4.5 Benchmark Valuation under Conditions of Zero or Near-Zero Price Drift

We now turn to the special case where there are zero or near-zero values of price drift in the IT services pricing, but there is significant volatility associated with the price drift. This is the case modeled in Figure 4.7 and the first three rows of table 4.6. If firms pre-negotiate price changes based on an agreed-upon expected drift rate in IT services, then a scenario with a zero expected drift rate in IT services pricing could occur.

Figure 4.10 shows the effects of price drift volatility on contract value. We highlight two main points. First, we can see that at the high expected drift rate of $\mu$ = -2, the volatility associated with the forecast of expected price drift has little bearing on the decision to benchmark. The contract value is relatively unchanged whether $\sigma$ is 0 or 1.2. The most interesting case occurs where $\sigma$ is relatively low, and an expected $\mu$ of -.2. For example, this would be equivalent to a five-year contract with expected drift of -4%. If we assume the benchmark costs are at 5%, the firm would not benchmark under this growth scenario. However, the firm would benchmark if the standard deviation of the price drift was .5. In other words, if the firm felt there was about a 25% chance of the price drift falling below -.5, benchmarking would be a profitable decision.

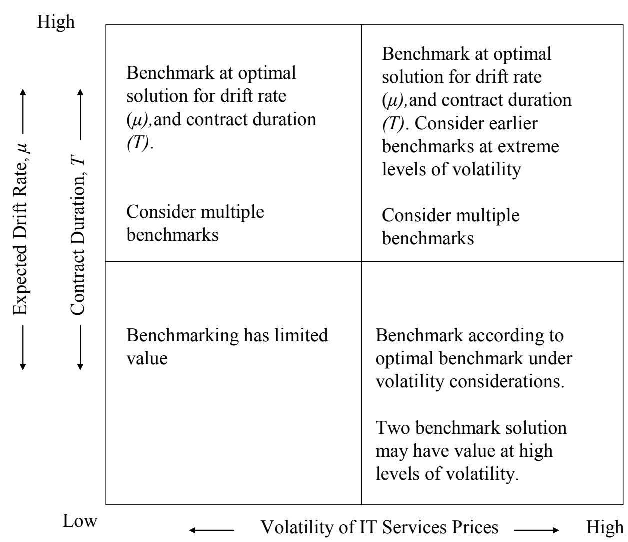
**Figure 4.10. Effects of Price Drift Volatility on Contract Value**



## *4.5 Managerial Implications*

Our approach gives useful insights for managers. Recall that our model assumes an exponential drift rate for the market price of IT services, so its implications for practice are not generalizable. Several other drift rate scenarios for IT services prices could be modeled with different shapes over time, including the possibility of delayed diffusion of services or market shocks. With those caveats acknowledged, we summarize our findings in Figure 4.11.

**Figure 4.11. Managerial Guidelines for Benchmark Considerations**




One of the main findings of this research is that our exponential model is quite robust to volatility in the estimates or the drift rate of IT service prices. When the volatility of the expected decline in IT prices is high, the effects of benchmarking early to leverage volatility are minimal. Even if the drift rate is lower than expected, the firm still benefits substantially from benchmarking at the optimal point according to the forecast for IT service prices. The more intriguing example is shown in the lower left box. Client firms can leverage the fact that benchmark provisions do not expose them to the downside risk associated with a price increase. Therefore, like an option, the client firm's financial exposure is limited to the transaction costs and the threshold set by the provider.

When the expected drift rate of IT service prices is near zero, multiple benchmarks have limited value. Volatility may influence the decision to pursue multiple benchmarks in the contract. We find that the first benchmark in a two-benchmark contract should be earlier than in the single-benchmark case. Under modest expected declines in the price of IT services, this could expose the firm to benchmarking when the price does not meet the threshold of cost savings. To remedy this exposure, the client can exercise the first-period benchmark later in the contract. This gives the client greater confidence in meeting the price thresholds while still creating benefits from the two-period benchmark.

## *4.6 Conclusion*

### 4.6.1 Contributions

We developed a new model to quantify the value of benchmarking strategies for IT services contracts. We devised a method for setting benchmark timeframes *a priori* under conditions of opaque market pricing. Our model considers a unique financial instrument: *IT services price benchmarks*. While our model shares characteristics of mortgage refinance and credit risk models from financial economics, to our knowledge, there has been no prior work evaluating benchmarking intervals with opaque pricing, and hence our analytic model makes a unique contribution to the literature.

We modeled the effects of uncertainty in the drift rates of IT service prices, and derived a solution for the optimal timing under a range of price drift forecasts and volatility. We showed that a firm can leverage the option value of exercise benchmark provisions that would have been forgone when the drift rate of the price of IT services is near zero. We extended our model to two periods and saw that a client firm is better off considering the two-period model, except when the rate of decrease in expected market prices for IT services is modest – not so large that it causes substantial cost changes. We demonstrate how provider firms can leverage this model to negotiate thresholds at which price adjustments are made after comparison with market prices for IT services identified by the benchmark. Our results can influence managerial decision-making, especially when managers are aware of the value of collecting this kind of data in support of contract management.

#### 4.6.2. Limitations

This initial work is subject to several limitations. First, we have conducted a financial analysis of benchmarking provisions for IT outsourcing contracts. There are several non-quantifiable factors that need to be considered before a firm exercises a benchmark though. Clients and providers with a high level of trust may be able to accommodate price adjustments without going through a formal benchmarking process, saving money along the way. The benchmarking process is often contentious and there are hidden costs associated with loss of goodwill between the parties when a benchmark is conducted. Client firms must realize that it is in their long-term interests to have providers who earn reasonable profits.

On the modeling side, we assumed a constant exponential drift rate for IT service prices. This was a reasonable starting point in the analysis since the assumptions are consistent with other asset pricing and investment under uncertainty models on which our theoretical perspective is built. Moore's Law (Moore 1965) provides some validation that computing costs have followed an exponential drift pattern. We expect IT services prices may follow other distributions. An intriguing possibility is that IT services may follow diffusion similar to what is observed with the Bass (1969) model, where competition and innovation affect adoption, and thus market prices for the IT services. We are likely to run into issues with data availability as well. Likely sources are outsourcing providers or benchmarking firms. In either case, researchers will need to work with a snapshot of the market data. So the question of *generalizability* will arise from empirical work based on this model.

**4.6.3 Future Research**

This work represents an initial attempt at financial analysis of IT services contract benchmarks. We will extend the work analytically and empirically. A major issue that separates IT services contracts from others is the availability of accurate benchmark prices. We will explicitly consider the availability of market pricing information in our model and the associated effects on competition. As we mention earlier, we believe that a key extension will occur in the design of effective incentive-compatible mechanisms which will ultimately lead to better contractual provisions for both providers and clients.

We will also consider the service life-cycle in future work. We are interested in the effects of economies of scale and scope on services pricing and the benchmark process. Provider firms often initiate large contracts with clients with the hopes of replicating the services across a broad customer set. As these services diffuse through the market place, competition may arise to erode profits, not only for new customers, but among the “beachhead” clients where the provider firm presumably can earn high margins due to innovation. This analysis will help quantify some of the effects of a replication strategy by IT service innovators.

We will extend this work to develop predictive models of IT services pricing and diffusion. This empirical work will allow us to extend the value of information analysis of IT prices in the context of forecasting and benchmarking. In addition, an algorithm-based optimization model can provide insights into the optimal number of benchmark provisions a client would wish to include in a contract. This analysis also can offer useful information for provider firms in negotiation for multiple benchmark provisions.

# Chapter 5. Essay 3: Visibility of IT Services Prices and the Benchmarking Decision

## *5.1. Introduction*

Entering into long-term IT outsourcing agreements presents challenges to both clients and vendors. IT services are often commodity-type offerings, such as cloud computing services from Amazon.com, Google and others. In most cases, the prices of these services are published, and clients and vendors enjoy a certain degree of price transparency. On the other hand, some offerings, such as business process outsourcing, are often tailored specifically to the clients, and in such cases there may be no comparable service with which to gauge prices. Many IT services fall somewhere in between a commodity and a specialization. Some hardware components and commoditized processes such as desktop support do not necessarily have published prices available. However, some firms such as TPI and Probenchmark collect data on certain pillars of IT services, such as mainframe-outsourced services, print support or desktop support (Harris, 2007). These benchmarking firms offer assessments of market prices to clients outside the boundaries of the benchmark. In this work, we investigate the valuation and timing decision associated with clients' purchase of market price information during the contract prior to benchmarking. We compare this to the scenario where firms benchmark without such market price information (the scenario modeled in Essay 2).

### 5.1.1 Snapshot of IT Market Prices

One option available to the client firm is to purchase a market analysis of the prices of IT services, which we refer to henceforth as the *snapshot of IT services*. Firms may chose to purchase the snapshot the time the benchmark would have been exercised according to the optimal timing of the benchmark with no market price information. We refer to this as the *blind benchmark* because we assume the client has no information regarding market prices at the time of the benchmark. Alternatively, the client could purchase the snapshot at any time over the life of the contract.

A snapshot of market price information prior to the benchmark has three components of value to the client. First, the client avoids the possibility of benchmarking if the benchmarking threshold has not been reached. The benchmark threshold refers the amount that the *observed price at benchmark* must exceed the current contract price before a cost adjustment is made. Harris (2007) recommends calculating a simple mean of the sample data and applying a threshold of around 10-15% at which vendors prices must fall before an adjustment is warranted. The possibility of benchmarking and not reaching this threshold is real. In 2005, Hydro-One, a Canadian energy company benchmarked IT services from the vendor, Inergi. The benchmarking firm found that a sample mean of $50,341,054 vs. $50,855,770, which was within 1%, and no price adjustments were made (Hydro-One 2005). The costs associated with benchmarks were high, and there was value to avoiding them. Practitioners quote figures of $100,000-$500,000 for third-party consulting services (Harris 2007, Overby 2007). There may be additional costs of firm resources to provide the third-party access and inventory of the current client services environment too. A second source of value is that the client holds the option to benchmark at a later date. If the client decides not to benchmark based on the available market price information, there is a chance that the client can exercise the benchmark at a later time. Finally, if the firm purchases a snapshot of the market prices of IT services, it will still retain the option to benchmark at a later time.

### 5.1.2 Information Asymmetry and IT Services Contracts

Of interest in the phenomenon of IT outsourcing is that the vendors may enjoy an advantage of information asymmetry over the clients (Overby, 2007). As stated in the motivation for Essay 2, benchmarks are complicated and expensive propositions. We investigate three mechanisms which clients and vendors utilize to avoid benchmarks. First, at the prospective time of benchmarking, the client and vendor may choose to negotiate a price adjustment. In this case, the vendor may choose to avoid going through the benchmark process if the price adjustment is expected. Second, *a priori*, the provider may offer the client a price adjustment in exchange a benchmark clause in the contract. A third mechanism includes offering price adjustments while the benchmark clause is still in place. The motivation for the latter is to account for productivity increases in the delivery of IT services, while still indemnifying the client against risk exposures.

The following research questions motivate this work: What is the value of market price information throughout the life of the contract for the client firm? When should a client purchase these services? How does the availability of market pricing information to affect the participants' decision to benchmark or negotiate contractual terms? First, we extend the model of benchmark evaluation under uncertainty in Essay 2 to incorporate assessments of IT services market pricing, and examine contract costs under different price diffusion scenarios. We then consider the effects of avoiding benchmark provisions. The final analysis considers the vendor firm's price negotiation under conditions of IT services price visibility vs. a blind approach.

## *5.2 Model*

The model of benchmarking under volatility from Essay 2 provides us with the valuation for holding the benchmark provision under conditions of IT services price drift with volatility. Modeling notation is presented in Table 5.1. Under price visibility, at any point in time, *t*, the client can choose between benchmarking at the observed price and the client gets the cost savings associated with that benchmark with certainty. Therefore, at each observed price/time pair, $p^*$, $t$ the client will weigh weather the benchmark is worth more now or in the future.

**Table 5.1. Modeling Notation**

| SYMBOL | DESCRIPTION |
|---|---|
| $P$ | Price of the IT service, costs paid by client to vendor |
| $C$ | Cost to exercise the benchmark |
| $t$ | Time at which benchmark is exercised |
| $T$ | Total length of the contract |
| $\mu$ | Expected drift rate of IT service |
| $\sigma$ | Standard deviation of IT services prices |
| $\Phi$ | Cumulative distribution function for standard normal variable |
| $\tilde{E}[P_t]$ | Expected value of the IT services conditional on $P_t$ not exceeding $P$ |

### 5.2.1 Critical Price Point of Early Exercise

If the client firm has access to market prices, it must establish a critical value of IT services prices at which to exercise the benchmark. Under transparent market prices the client has two main considerations. First, the client must access the value of benchmarking at the observed price. Second, the client must consider the value of holding the benchmark option and exercising at a later date. The *critical price point of early exercise* is defined as the point at which the value of exercising the benchmark provision is equal to the value of holding the benchmark.

As with the benchmark with no visibility, a closed form solution is not available. A decision rule can be defined where the client will benchmark under visible prices. This occurs when the value for benchmarking exceeds the value for waiting and benchmarking at a different time, as follows:

$$Pt + P_t(T-t) > P(t+\Delta t) + E[\widetilde{P}_{t+\Delta t}](T-t-\Delta t) \tag{1}$$

where

$$E[\widetilde{P}_{t+\Delta t}] = Min[E[P_{t+\Delta t} \mid P_{t+\Delta t} > P], P] * \Pr[P_t > P] + E[P_t \mid P_t < P] * \Pr[P_t < P])(T-t) \tag{2}$$

The client weighs the value of benchmarking at the observed price vs. the value of waiting until the next period. The left-hand side of the equation represents the value the client can obtain by benchmarking at time *t*, after observing price $P_t$. The right-hand side represents the value of waiting. $E[\widetilde{P}_{t+\Delta t}]$ represents the expected value of the IT services at time $t + \Delta t$ conditioned on *P* not exceeding $P_t$. We note that we can make this evaluation at any point in the contract; the evaluation where $P = P_0$ represents looking forward at the start of the contract. The client will benchmark at time *t* if the benefits of doing so outweigh the benefits of waiting and benchmarking under the expected prices at $t + \Delta t$. In order to implement a numeric solution, we assume a discrete time approach, that is, $\Delta t$ is a measurable value. This assumption would likely hold in practice, where the client would likely call benchmarks at discrete intervals such as a monthly or quarterly billing cycle. The discrete time approximation of the critical price $\hat{P}_t$ can be obtained by the following:

$$P_0 t + \hat{P}_t (T - t) = P_0 (t + \Delta t) + E[\widetilde{P}_{t+\Delta t}](T - t - \Delta t) \tag{3}$$

$$\hat{P}_t = \frac{P_0 (\Delta t) + E[\widetilde{P}_{t+\Delta t}](T - t - \Delta t)}{T - t} \tag{4}$$

**5.2.2. Analysis of Critical Price Approach**

Consider a client engaged in a five-year contract for outsourced mainframe services. We assume that the expected price decline is 10%. This translates into a drift value, $\mu$ equal to -.5, with $T = 1$. We further assume that the standard deviation of the price drift, $\sigma = .5$. The client can benchmark only after a quarterly billing cycle, which translated into $N = 20$ periods. The optimal timing of the benchmark with no visibility occurs at $t = .4$ which would occur at the beginning of Year 2, and result in approximate savings of 14% of the total contract cost.

The client purchases a snapshot of the market prices at $t$ =.4. Rather than benchmark blindly at the optimal point with no visibility, the client chooses to gauge the market prices before actually engaging in the benchmark. This allows the client to avoid the cost of a full benchmark while preserving the option to benchmark at a later date. The critical value at $t = .4$ is:

$$\hat{P}_t = \frac{1(.05) + .76(1 - .4 - .05)}{1 - .6} = .78 \tag{5}$$

At this observed price, there is no benefit to the client waiting until the next period or any period thereafter. The option to benchmark is worthless after $t = .4$ at this price point. Table 5.2 shows the value of benchmarking at the observed price $P_t$ vs. waiting to benchmarking in the future.

**Table 5.2. Benchmark Decision at Observed Prices at $t$ = .4**

| OBSERVED PRICE $P_t$ FOR $t$ =.4 | CONTRACT COST AT $t$ = .40 | EXPECTED CONTRACT COST AT $t + \Delta t$ = .45 | OPTIMAL EXERCISE TIME $t^*$ | VALUE AT OPTIMAL TIME $t^*$ |
|---|---|---|---|---|
| 1 | 1 | .97 | .65 | **.94** |
| .90 | .94 | .93 | .60 | **.92** |
| .79 | **.87** | **.87** | .4 | .87 |
| .60 | **.76** | .77 | .4 | .76 |

The first row in Table 5.2 illustrates an example where the market prices have not changed. Of course, the client will not choose to exercise a benchmark provision in this scenario. However, the option to benchmark remains alive. Based on the observed price at $t$ = .4, the firm could wait and exercise a benchmark in 15 months at $t$ = .65, and could expect an overall contract cost of 94% of the original value. At this price point, and those above 1 where market prices have increased, the firm will have to consider whether the later option to benchmark is worthwhile, by weighing the total costs and thresholds to the benchmark against the savings associated with the benchmark.

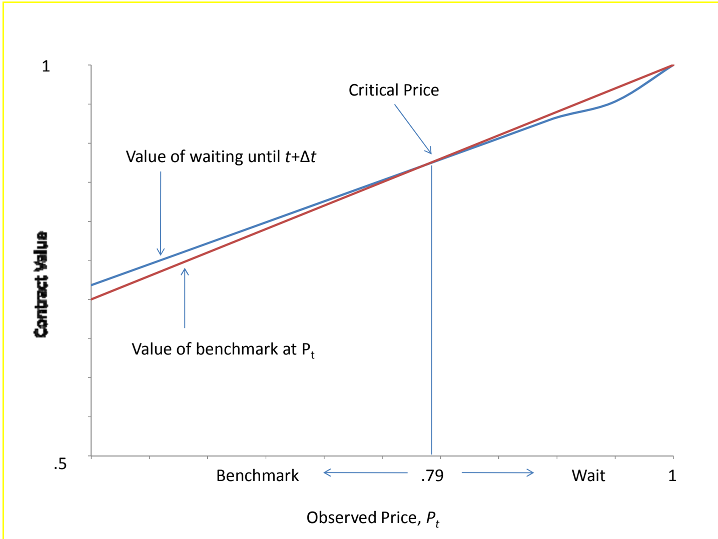
When the observed price is .9 (Table 5.2, Row 2), the client is faced with difficult decision. Here a benchmark at $t$ = 4 provides a total contract cost of 94% of the original cost with no benchmark. Assuming the 6% savings exceeds the cost of the benchmark, the firm may choose to wait and exercise the benchmark at a later time. The next period costs are expected to decline by 1%, and the expected time to benchmark occurs one year later at $t$ = .6, where the total contract costs are reduced by 2%. The critical price approach implies the costs of the contract, on average, will go down.

Under the conditions of drift and uncertainty of this example, at $t$ = .4, and $P_t$ = .9, there is a 39% chance that the contract costs could actually go up. A risk-averse manager may choose to take the certain cost savings at $t$ =. 4, rather than waiting for the next period prices which could drop.

The critical price of .79 is shown in Table 5.2, Row 3. At this point, there is no gain for the client to hold on to the benchmark. Prices are still expected to go down. However, waiting the additional period to reap the benefits of the benchmark leads to the same expected value as exercising the benchmark at $t$ = .4.

Finally, Table 5.2, Row 4 shows a situation where the firm also will benchmark. Waiting to benchmark in the later period will lead to paying slightly more (77% vs. 76%) over the contract life. This occurs because waiting one more period to realize the cost savings is outweighed by realizing them immediately, regardless of the expected price decline in subsequent periods. The reader should note that $t$ = .4 is likely not the cost minimizing time to exercise this benchmark. If the client firm had been tracking market prices at each quarter, they may have exercised at an earlier critical value. This case will be examined in the next section.  Figure 5.1 illustrates the prior example. The horizontal axis represents a range of potential prices, from .5 to 1, the client could observe at $t$ = .4. The vertical axis represents the total contract value. The top line on the left-hand side of the figure represents the value of waiting one period to benchmark. The bottom line on the left-hand side represents the value of benchmarking at $P_t$.

**Figure 5.1. Contract Values at Observed Prices: Benchmark vs. Waiting**




From all points to the left of the critical value, the cost minimizing strategy is to benchmark at $t$ = .4. For observed prices higher than the critical price, the cost-minimizing strategy is to wait. The curve in the line associated with the value of waiting at as $P_t$ nears 1 represents the indemnification the client enjoys against price increases. At these values, if expected prices do in fact increase from $P_t$, they would increase to a value higher than 1, which is the current price paid by the client. Since the client does not receive price increases from the benchmark, there is increased value to waiting. However unlikely, the prices may in fact decline, and the client is better off waiting in these scenarios to see if these a price decline does indeed materialize.

## *5.3 Timing and Frequency of Market Snapshot.*

### 5.3.1 Valuation and Timing of Single Snap Shot

In this section we examine the value expected with a snapshot occurring at a single interval. If the price of snapshots across time was prohibitive, the client could chose to purchase a single, or select few market snapshots throughout the contract. In order to assess the value of the snapshots, we assess the value associated with the benchmark at the critical price, weighed by the probability of the critical price being reached. As we noted in previous sections, if the critical price is not reached, the client will still retain the value to benchmark at a later date, but that value would have to be calculated based on the observed prices at the snapshot. Table 5.3 presents the critical price, contract cost and probability falling below the critical price. We assume initial inputs of $\mu$= -.5, $\sigma$ = .5, and $P = P_0$, the only observed price by the client is the current price paid. We then weigh the probability of $P_t$ falling below the critical value with cost savings associated with the contract, which is 1- $F(P)$ where $F(P)$ is the expected contract cost if the critical price is reached.

**Table 5.3. Value of Benchmark**

| t= | Crit. $P^{\wedge}$ | Contract costs | $Pr[P_t<P^{\wedge}]$ | Value of Snapshot |
|---|---|---|---|---|
| .05 | .692 | .708 | .001 | <.001 |
| .10 | .704 | .734 | .034 | .009 |
| .15 | .717 | .759 | .108 | .026 |
| .20 | .730 | .784 | .198 | .043 |
| .25 | .743 | .807 | .287 | .055 |
| .30 | .757 | .823 | .370 | .063 |
| **.35** | **.771** | **.851** | **.445** | **.066** |
| .40 | .768 | .872 | .512 | .066 |
| .45 | .802 | .891 | .572 | .062 |
| .50 | .818 | .909 | .624 | .057 |
| .55 | .825 | .926 | .670 | .049 |
| .60 | .853 | .941 | .711 | .042 |
| .65 | .871 | .955 | .747 | .034 |
| .70 | .890 | .967 | .779 | .026 |
| .75 | .910 | .978 | .807 | .018 |
| .80 | .926 | .985 | .828 | .012 |
| .85 | .939 | .991 | .845 | .007 |
| .90 | .960 | .997 | .853 | .003 |
| .95 | 1 | .988 | .888 | .001 |

In Table 5.3, we note that the contract costs are lowest at $t$ =.35. The value of purchasing a snapshot at t = .4 is slightly less (.0656 vs. .0661) of purchasing the snapshot at $t$ =.4. While $t$ = .4 is the optimal blind benchmark, the optimal time to purchase a single snapshot is at $t$ =.35. This makes sense, since the under the critical value approach, the client weighs the option of holding the benchmark at the next period. Purchasing the benchmark at $t$ = .4 would weigh the value of holding the benchmark at $t$ = .45, which is beyond the optimal timeframe.

A second point of interest is that the value of the early snapshots is quite small. This is also intuitive, since the probability of reaching the critical value early in the contract is quite small. In the scenario where snapshots are purchased across the life of the contract, the client may wish to wait a few periods until the initial snapshot is worthwhile. We should point out that once a client purchases a snapshot and the critical value is not reached, the value for waiting must be updated. If for example, the observed price is still near the original price late in the contract, the client may decide that the value of the benchmark is so low that further snapshots are not warranted and the firm will not exercise a benchmark. The snapshots will have shown that the client is receiving a fair market price for the IT services.

**5.3.2 Critical Price Approach across the Life of the Contract**

In the following analysis, the client firm purchases snapshot market price information quarterly. The client follows the same approach for calculating the critical price at each time period, and the client benchmarks the first period in which the critical price is reached. The same initial conditions of the previous example are used to calculate critical values, which are shown in Table 5.4.

**Table 5.4. Critical Values across Time Periods, $\mu$ =-.5, $\sigma$ = .5**

| Time period, *t* | Critical Price, $P_t$ | | Time period, *t* | Critical Price, $P_t$ |
|---|---|---|---|---|
| .05 | .69 | | .55 | .84 |
| .10 | .70 | | .60 | .85 |
| .15 | .72 | | .65 | .87 |
| .20 | .73 | | .70 | .89 |
| .25 | .74 | | .75 | .91 |
| .30 | .76 | | .80 | .92 |
| .35 | .77 | | .85 | .94 |
| .40 | .79 | | .90 | .96 |
| .45 | .80 | | .95 | 1 |
| .50 | .82 | | 1 | |

Table 5.4 shows the increase in the critical values as the time increase. At $t$ = .05, the first quarter, the critical value is .69. This implies that the firm will only benchmark if the prices in the first quarter have dropped by 31%. This is a highly unlikely scenario, with a probability of about .1% chance of occurring. As the critical price increases, the likelihood of reaching that value also increases: at $t$ = .40, there is a greater than 52% chance that the critical value will be reached. A client would be inclined to forgo the first period snapshot, since the expected value is . 01%* 30% = .03% of contract value. The critical values for increased uncertainty in future price drift are given in Table 5.5.

**Table 5.5 Critical Values across Time Periods, $\mu$ =-.5, $\sigma$ = 1.5**

| Time period, *t* | Critical Price, $P_t$ | | Time period, *t* | Critical Price, $P_t$ |
|---|---|---|---|---|
| .05 | .69 | | .55 | .79 |
| .10 | .70 | | .60 | .79 |
| .15 | .72 | | .65 | .80 |
| .20 | .73 | | .70 | .81 |
| .25 | .74 | | .75 | .82 |
| .30 | .76 | | .80 | .84 |
| .35 | .77 | | .85 | .86 |
| .40 | .77 | | .90 | .91 |
| .45 | .78 | | .95 | 1 |
| .50 | .78 | | 1 | |

Table 5.5 illustrates the effects of increased uncertainty in the IT services price drift. First, note that the critical prices are the same as in Table 2 until $t = .40$. This occurs because low prices early in the contract diffuse such that conditional values of the expected price increases do not exceed the initial price point of 1. Thus expected price adjustment, if a benchmark is made, will be the same in either scenario. Once $t = .4$, the expected price increases under the high volatility scenario reach a value greater than 1, and the client reaps additional benefits to waiting, since benchmarking does not lead to price increases over the initial price, $P_0 = 1$. This is the effect seen in the curve of the value to wait line in figure 1, which is amplified under higher levels of uncertainty. The discrepancy between the values from Table 5.4 and Table 5.5 increase as the snapshots occur later in the contract, as shown in the right hand side of both tables. In the high-uncertainty scenario of Table 5.5, there is more value to waiting for possible future price decreases than in Table 5.4.

**5.3.3 Simulation**

To illustrate the value of the transparency of market prices, a simulation was run of 1000 contracts under the parameters of the example. We follow Whaley's (2006) approach to Monte Carlo simulation with an estimate of the price at $t$ of

$$P_{t+\Delta t} = P_t e^{(\mu - \frac{\sigma^2}{2})\Delta t + \sigma\sqrt{\Delta t}\varepsilon} \tag{6}$$

Scenarios with expected price drift $\mu = -.5$ and standard deviation of price drift $\sigma = .5$, 1.5 are simulated in Tables 4 and 5. Two sets of results are given. The first is the critical price approach, when the client benchmarks at each time if the observed price is lower than the critical price. The second result is the blind approach where the optimal time to exercise is utilized with no visibility. This optimal time occurs at $t$ = .4 when $\mu$ = -.5, $\sigma$ = .5, and $t$ =.35 when $\mu$ = -.5 and $\sigma$ = 1.5. The results are given in Tables 5.6 and 5.7.

**Table 5.6. Simulation of Critical Value and Blind Benchmark $\mu$ = -.5, $\sigma$ = .5**

| Critical Value Approach (Visibility) | Average | Std Error | 95% Upper Bound | 95% Lower Bound |
|---|---|---|---|---|
| Price $P_t$ at benchmark | .719 | .004 | .727 | .710 |
| Time $t$ of the benchmark | .532 | .010 | .551 | .513 |
| Contract value | .839 | .003 | .846 | .833 |
| **Benchmark at $t$ = .40 (Blind)** | | | | |
| Contract value | .863 | .003 | .869 | .856 |
| **Difference** | **.023** | **.002** | **.027** | **.020** |

**Table 5.7. Simulation of Critical Value and Blind Benchmark $\mu$ = -.5, $\sigma$ =1.5**

| Critical Value Approach (Visibility) | Average | Std Error | 95% Upper Bound | 95% Lower Bound |
|---|---|---|---|---|
| Price $P_t$ at benchmark | .584 | .005 | .593 | .575 |
| Time $t$ of the benchmark | .300 | .009 | .317 | .283 |
| Contract value | .688 | .005 | .697 | .678 |
| **Benchmark at $t$ = .40** | | | | |
| Contract Value | .737 | .007 | .750 | .724 |
| **Difference** | **.050** | **.005** | **.059** | **.040** |

The results in Table 5.6 and 5.7 confirm that benchmarking according to the critical value approach leads to reduced costs for the client. As one would expect, client firms benefit from visibility of IT services prices when faced with uncertainty in the path those prices will take. The benefits may seem modest, but even the 2.3% cost savings under the scenario of less uncertainty in IT service price drift (Table 5.6) could be substantial. Consider the contract of HydroOne (2005), a Canadian Energy company that paid $50,000,000 over three years for IT services. A reduction of 2.3% would equate to $1,150,000. In such a scenario a client may be willing to pay a substantial amount for a market snapshot service. This analysis does not consider those benchmarks which would have been undertaken in the blind scenario that led to no price adjustment. The avoidance of such benchmarks is an additional source of value we examine in a later section.

The value of price visibility increases as the volatility surrounding the market price drift increases, as evidenced by the 5% average differences between the blind and critical price approach in Table 5. Of particular interest is the average time at which the benchmarks are undertaken in each scenario. In the lower volatility scenario of Table 5, the average time is .532, which is later than the optimal time of the blind benchmark, $t = .4$. Conversely, in Table 5, the client is benchmarking at an average time of .300, which is earlier than the optimal time of the blind benchmark at $t = .35$. Clients in the lower uncertainty case benefit from benchmarking later in the contract, picking up those benchmarks they would have either missed because the price had not decreased, or would have benchmarked before the time that minimized costs. In the higher volatility scenario, the clients are picking up those price adjustments that happen infrequently at earlier time. This can be explained by the fact that the critical value is the same for each scenario up until $t = .4$, so it is expected that on average, the higher volatility scenario will trigger more early benchmarks.

### *5.4 Additional Benefits of Visibility of IT Service Prices*

In the previous section, we illustrated the critical value approach of a single benchmark occurring in lieu of the actual benchmark. In this section, we examine additional benefits associated with IT services price visibility.

### 5.4.1. Value of Avoiding Benchmarks

If a client calls a benchmark, and no price adjustments are made, the client has made an investment in a benchmark that has paid zero. We refer to this as a *worthless benchmark*, in that the client did not receive a price adjustment. Avoidance of a worthless benchmark not only saves the firm the cost of the benchmark services, but also the costs associated with utilizing resources. If the benchmark is near a threshold for price adjustment, and the client and vendor contest the outcome, these costs could skyrocket in terms of resources, loss of goodwill among parties and even litigation.

In order to calculate the value of benchmark avoidance, we first determine the likelihood that a calling a benchmark does not lead to a price increases, given the information the client has on market prices, presumably at $t = 0$, the onset of the contract. The partial expectation approach used to calculate the blind benchmark provides the probability that the market prices exceed $P_0$, $\Pr[P_t > P_0] = \Phi(d_2)$.

Thus for any benchmark we assess the expected costs associated with benchmarks that do not results in price reductions. In Table 5.8, we model the two scenarios used throughout this paper. Per the analysis in the previous sections, we assume the client benchmarks one period prior to the optimal blind benchmark. For illustrative purposes, we assume a total benchmark cost assessed by the client of $500,000.

**Table 5.8. Value of Avoiding Worthless Benchmarks**

| | $\mu = -.5, \sigma = .5$ | $\mu = -.5, \sigma = 1.5$ |
|---|---|---|
| $t^*$ | .35 | .30 |
| $\Pr[P_t < P_0]$ | .230 | .276 |
| Cost of benchmark | $500,000 | $500,000 |
| Expected cost avoidance | $115,000 | $138,000 |

The value of avoiding benchmarks increases as the volatility increases; this is to be expected since the optimal benchmark occurs in the earlier in the contract time period. In addition, the increased uncertainty in the diffusion process leads to a greater likelihood of prices above the cost adjustment threshold, assumed to be $P_0$. Vendor firms often insist on a threshold on which price adjustments would be made. For example, that threshold may be 10% within the simple mean (Harris, 2007), or based on a quantile of the samples. In these cases, the client will consider the probability the prices do not reach the specified threshold, rather than the initial price used in the example given.

### 5.4.2 Value of Information and Price Adjustments

As mentioned in Essay 2, benchmarks can be ugly, complicated, costly affairs. In the preceding examples, the main costs of benchmarks are to be absorbed by the client and are limited in scope. In cases where price adjustments are to be made as a result of the benchmark and the vendor contests these price adjustments, the process can be extremely costly, in terms of client and vendor resources and the delay in the client receiving benefits. If the client and vendor know the prices going into the benchmark, the benchmark will be avoided if the vendor can offer a price reduction that is equal to the expected benefits of the benchmark at the expected price less the costs of the benchmark. Solving the original objective function for the price adjustment gives $P_{adj} = P_t - \frac{C}{T-t}$, where: $P_t$ = the client expected costs at time, $t$; $C$ = client cost of the benchmark; and $P_{adj}$ = the vendor's offer of an adjusted price. This expression states that a client will benchmark if the value of the price adjustment is equal to the benefits of benchmarking under the expected price less the costs of the benchmark.

If the actual prices are known by the client above $P_{adj}$ then the vendor may make a price offer of $P_{adj}$ - $C_{vendor}$, where $C_{vendor}$ is the vendor's cost associated with the benchmark process. If the actual market prices exceed $P_{adj}$ - $C_{vendor}$, the benchmark will take place.

Of special interest is the case where the actual prices are below the client's expected prices. In this case, the vendor will still offer $P_{adj}$, which the client will accept based on its expectations of the blind benchmark. In this instance, the firm will wind up paying above market prices for the IT services. This *conditional expectations approach* can be used to evaluate the potential price paid in excess of the market prices, and thus assess additional value to visibility of market prices.

In order to assess the potential cost savings forgone if the client accepts a benchmark based on expected prices, the conditional probability that the actual price at time is less than the expected price. Then the conditional expectation is plugged into the initial objective function to calculate the contract value if the prices had indeed fallen below expectations. This is then subtracted from the expected contract value and the difference is weighed by the probability of the price drop. Table 5.9 illustrates this valuation for the base case example where $\mu$ = -.5, $\sigma$ = .5.

In the example of Table 5.9, the client may see considerable benefits to having information before negotiating a price reduction from the vendor. This example does have significant assumptions behind it, namely that the vendor and client would be willing to negotiate a price adjustment. Even in the blind scenario, the client could conduct this analysis, and ask for this concession given the price adjustment by the vendor. Such analysis extends into the realm of game theory, and we have work in progress on that front. The purpose of the analysis is to highlight another source of potential value, and reinforce a key takeaway: information, under conditions of market uncertainty, allows the client to make more accurate benchmarking decisions than in the blind scenario.

**Table 5.9. Negotiation Value of Market Price Information Snapshot**

| PARAMETER | VALUE |
|---|---|
| Expected price blind E[$P_t$] | .77 |
| Expected contract cost blind | .86 |
| E[$P_t$\| $P_t$ < E[$P_t$]] | .61 |
| Contract cost if $P_t$ < E[$P_t$]] | .77 |
| Difference | .09 |
| Pr[$P_t$ < E[$P_t$]] | .49 |
| **Negotiation value of information** | **.045** |

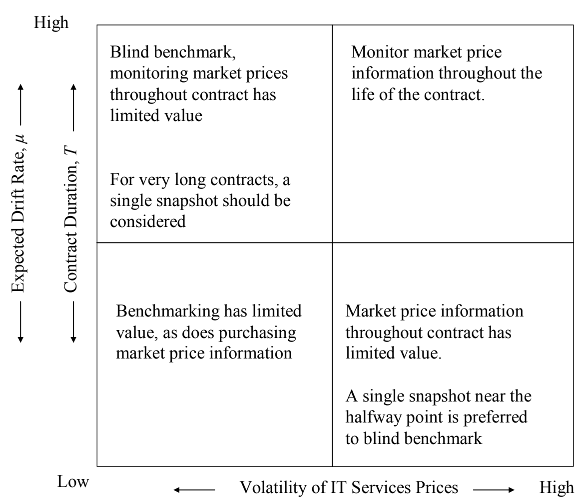
## *5.5 Conclusion*

### 5.5.1 Managerial Implications

The results of this research should be interesting to managers considering the purchase of snapshot services. These snapshot services are themselves expensive; a practitioner quoted the author of a broad range of about $75,000 vs. $100,000 for a comparable services pillar. However, as we noted the true cost of the benchmark process is much higher than the services fees, so, as shown in the example of benchmark avoidance, reducing the risk of a 20% chance of conducting a benchmark where no price adjustment takes place may be of considerable value to the firm.

The ongoing snapshot is another interesting case. We show that, under the assumption of our model, a firm can receive significant benefit, in terms of cost reduction. While these benefits were shown to be significant in the simulation, practitioners should note that the overall magnitude of the cost savings, as compared to the overall cost savings of the contract, may not be enough to entice the client to purchase an ongoing service. The manager could get the benefit of the benchmark avoidance with the single snapshot prior to actually calling the benchmark. In such a case, the client still benefits from the avoidance of the benchmark.  Consistent with Essay 2, we find that volatility affects not only the blind benchmark, but also the valuation of and type of market snapshot price information. Figure 5.2 offers some managerial guidelines based the availability of market price information.

**Figure 5.2. Managerial Guidelines for Benchmarks with Price Information Considerations**




In the upper right quadrant of Figure 5.2, the firm experiences a high rate of drift of IT services prices. In these cases, the services prices are rapidly falling, and the volatility effects amplify this descent, so a client firm will find many opportunities to benchmark early with the market price visibility throughout the life of the contract. In cases of low drift rates, this amplification does not occur. Prices are likely to rise or fall throughout the contract, thus there will be few opportunities for early exercise. If a firm was considering a blind benchmark low volatility considerations with low price drift (Figure 5.2, lower-right quadrant), it will value a market snapshot of IT services since the likelihood of triggering a worthless benchmark under the low drift scenario is high. The upper-left hand quadrant represents an instance where the firm may prefer the blind benchmark. When volatility is low, the chances that the market prices divert from the expected path are low, so the opportunity for early exercise is limited. In addition, the likelihood of triggering a worthless benchmark is low, since prices are assumed to rapidly decline throughout the life of the contract.

### 5.5.2 Limitations

This analysis was limited to the scope of a relatively long discrete time interval of one-quarter. It is likely that the cost savings of a market snapshot of benchmark services would be greater if the discrete time interval under which the firm could decide to benchmark was shorter. In the case of IT services benchmarks, the price trigger is not automatic, but if this model was extended to other service (or product) domain, the client firm could find benefit to purchasing a near continuous time "ticker" of the prices to be benchmarked.

This model is also limited by its underlying assumptions. As with earlier work (Esasy 2) this model assumes IT services prices follow a constant exponential drift with a uncertainty characterized by the Geometric Brownian motion. There may be additional distributions which characterize observed market prices of IT services. In addition we do not explicitly model a discount rate, which a firm may want to consider when evaluating the timing and valuation of market price information.

Finally, the analysis of contract negotiation and information asymmetry is limited in scope. In the case where the client negotiates under blind conditions, we assume the client does not factor expectations of price declines when weighing the vendor's offer. We do not consider accuracy of the benchmark in this analysis, the expectations of which will likely affect client vendor negotiations. Finally, we consider the costs of the benchmark as a single figure, when in reality the true costs are more nuanced, which include client resources, provider stalling tactics and potential litigation.

**5.6.3 Future Research**

The problem space of IT services benchmarks offers several interesting research opportunities. A rich avenue for future research is to delve deeper into the game-theoretic dynamics between the client and the vendor. In the cost adjustment negotiation prior to the benchmark, the client may view the benchmarker's price offer as a signal. This would enable a decision to be made based on the probability that service prices had fallen lower than the client themselves might have expected, as described in my analysis of the negotiating value of the snapshot.

The fact that benchmarks are inherently imprecise offers another topic for research. If the client provides the snapshot of IT services prices from the firm that would conduct the benchmark, the client may be confident that the benchmarker will come back with a similar price once the benchmark is conducted. This price may be lower than what the provider firm had anticipated. In this case the client may enjoy an information asymmetry advantage over the provider. This may lead to cases where the client will prefer sharing market price information with the client or third-parties in the marketplace in order to remedy this risk. The lack of precision may also affect the valuation aspects of the benchmark in our model.

This work also assumes market prices are given, when in reality they are determined by competition. Competition is likely a major factor in the drift rate and diffusion of IT services. In addition, if the vendor firms decide to share data with a third-party to make prices transparent, this could lead to tacit collusion among vendors of IT services. Drivers of uncertainty and drift in IT services prices may be measurable, and an empirical analysis could be conducted to see what drives the adoption of IT services benchmarks in contracts, which may lead to some verification of aspects benchmark valuation presented in this model.

# Chapter 6. Concluding Remarks

## *6.1 Summary of Contributions*

This dissertation is comprised of three essays which address specific research questions in the context of information technology contract design and management. Essays 1 and 2 consider *a priori* contractual decisions from the provider and client perspective respectively. In Essay 3, I show how client access to information may affect the valuation of a contractual clause, and hence terms of the contract. Each essay demonstrates a key value tenet I explore in my research: how a firm understands the risks affecting IT services contracts can affect the overall value and risk exposure to the firm.

In Essay 1, I consider a provider firm's risk exposure to contractual obligations which constrain flexibility in service-delivery. I develop a method, the profit-at-risk approach, to evaluate the trade-off between a provider's contract profits and the risk of cost overruns. I show that under varying conditions of risk aversion, the profit-maximizing contract may not be the optimal choice for managers. I further develop the efficient contract frontier, which provides a boundary for firm contract negotiation with its clients. Finally, I extended the model to inform portfolio analysis, where a firm can leverage its overall portfolio of contracts to provide custom terms to its most attractive clients.

In Essay 2, I explore the client's risk of paying above-market prices throughout the lifetime of the IT services contract. I develop a model of the optimal timing of price benchmarks and valuation of price benchmarks. I show that price benchmarks are best to exercise sometime in the first half of the contract, but that the overall timing decision may not be as critical to the client as the valuations. The decision of whether to benchmark (driven by valuation) is more important then when to benchmark. I extend the model to consider timing and valuation under uncertainty. This approach represents a theoretic contribution as a new model of contract valuation under uncertainty. Finally, I provide a framework for managerial decision making, bounded by the model's assumptions, that provides guidance for the adoption and timing of contract benchmarks.

Essay 3 represents a crucial extension to the research problems identified in Essay 2. I consider the value of market price information. I develop a critical price approach, which allows for the determination of when to benchmark when given market price information. Through Monte-Carlo Simulation, I show that the critical value approach offers an improvement over the blind approach of Essay 2, and this improvement increases as the uncertainty surrounding market price drift. The extended model provides guidance on when and whether a client would want to purchase third-party pricing information. I consider other sources of value, including the avoidance of unnecessary benchmarks and the value of market price information in contract negotiation. Finally, I provide an extended framework to inform managerial decision making regarding the purchase of market price information.

### *6.2 Future Research*

I look forward to continuing research on risk management and contract design in information technology services and investments. I see three main streams of research to pursue in the future. First is the incorporation of real-world historical data to build predictive models of IT cost, delivery and price risk. Second, the models themselves may be subject to future empirical validation. Third, the models can be extended to consider the dynamics of competition.

As with any analytic models, the results and managerial guidelines are subject to the assumptions underlying the model. I expect to engage with practitioners to evaluate real-world data and build predictive models which are accurate to the client or provider environment. This will no doubt necessitate modification of the models to incorporate the empirical distributions observed. For example, in the profit-at-risk model of Essay 1, the portfolio approach is especially sensitive to the assumption of normally distributed returns. I will need to modify the approach to conditional value-at-risk, or extreme value distribution approaches in order to present an accurate assessment of provider risk. It is my hope that I can demonstrate the efficacy of my models from a design perspective by showing they improve managerial decision making in a real-world setting.

There may be opportunity to extend this research to empirical validation. For example, Essay 2 and 3 imply different valuations of contractual provisions along assumptions of price visibility, expected price drift and uncertainty of market prices. An interesting study would measure benchmark occurrences in contracts, and determine if there is a relationship between a measured price drift, expectations of uncertainty in future IT prices, or visibility of the market prices of IT services. Likewise, the profit-at-risk approach could be examined to determine to what extend managers consider risk when assessing contractual terms.

Finally, all three essays have treated costs and prices as endogenous, when in fact they are likely shaped by competitive forces. These models could be extended to assess how competitive factors shape the diffusion of IT services prices. One interesting question to address would be the effect of competition on a provider firm's investment in its overall contract portfolio. Providers may face a choice between innovating new services to create value, or exploiting efficiencies of commodity-like services to create value. In addition, the negotiations among clients and providers could be informed by game theoretic approaches. For example, mechanisms may be available to incent provider firms to share market price information in order to avoid the complications associated with price benchmarks.

### *6.3. General Impact of this Research*

We are living in a world where firm have access to more data on their operations, clients, and markets than ever before. In their book Competing on Analytics, Davenport and Harris (2006) present a vision where a main source of firm value is leveraging information about their clients and operations. Not unlike a CRM-based analytics, it is my expectation that provider firms will utilize information about clients to inform contract negotiation and timing. In fact, a recent IBM research study utilizes client data to predict which clients are likely to renegotiate or terminate outsourcing contracts (Mojsilovic, et al. 2007).

As data regarding services performance, cost and pricing becomes available, firms will be able to make accurate and reliable predictions of future services costs, quality, and pricing. My research provides an avenue for firms to leverage these predictions and make effective decisions while negotiating and managing contracts. It is my hope that this research will have an impact informing how future decision support systems are design and implemented, and ultimately how clients and providers manage their business.

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