



Research Center
Finance & Information Management



Project Group
Business & Information
Systems Engineering

Discussion Paper

Multivendor Portfolio Strategies in Cloud Computing

by

Christian König, Philipp Mette, Hanna-Vera Müller

in: Proceedings of the 21st European Conference on Information Systems,
Utrecht, Netherlands, June 2013

WI-367

University of Augsburg, D-86135 Augsburg
Visitors: Universitätsstr. 12, 86159 Augsburg
Phone: +49 821 598-4801 (Fax: -4899)

University of Bayreuth, D-95440 Bayreuth
Visitors: F.-v.-Schiller-Str. 2a, 95444 Bayreuth
Phone: +49 921 55 - 4710 (Fax: - 844710)

www.fim-rc.de



MULTIVENDOR PORTFOLIO STRATEGIES IN CLOUD COMPUTING^{1 2}

König, Christian, FIM Research Center, University of Augsburg, Universitätsstraße 12, 86159 Augsburg, Germany, christian.koenig@wiwi.uni-augsburg.de

Mette, Philipp, FIM Research Center, University of Augsburg, Universitätsstraße 12, 86159 Augsburg, Germany, philipp.mette@wiwi.uni-augsburg.de

Müller, Hanna-Vera, FIM Research Center, University of Augsburg, Universitätsstraße 12, 86159 Augsburg, Germany, hanna.mueller@wiwi.uni-augsburg.de

Abstract

Cloud computing emerges as a powerful driver of the information technology industry and many companies are willing to exploit the advantages this development bears. However, services provided by the cloud are subject to default which can result in major economic damage for the client. Moreover, different cloud service providers may also bear a conjoint risk and may therefore not default independently. Hence, to implement effective cloud sourcing strategies, this paper postulates requirements for evaluating multivendor sourcing decisions to select cloud service providers, considering cost, cloud computing specific risk, and interdependencies. We develop an analytic model that meets these requirements and quantitatively expresses the specific cost and risk structure of cloud computing sourcing decisions. Our approach is based on Portfolio Theory with regard to the specifics of fungible cloud services by using exponential loss distributions and one-sided risk measures. Thereby, an evaluation and optimization of a client's cloud service provider portfolio is possible. To determine the value added we use a simulation for the evaluation of our approach.

Keywords: Cloud computing, IT portfolio management, service provider selection, decision model.

¹ Grateful acknowledgement is due to the DFG (German Research Foundation) for their support of the project „ITPM (BU809/10-1)“ making this paper possible.

² This version of the paper contains some minor corrections compared to the version published in the ECIS 2013 proceedings.

1 Introduction

The prevailing topic of cloud computing is supposed to reshape the information technology industry during the next years (Leavitt, 2009). Thereby, the economic and practical potential of this technology appears to be tremendous. Cloud computing providers like Amazon or Google are continuously extending their computing infrastructures, platforms, and services. The market-research company International Data Corporation expects expenditures on IT cloud services to ‘account for 25 percent of annual IT expenditure growth by 2012 and nearly a third of the growth the following year’ (Leavitt, 2009). Hence, cloud computing may have the potential to transform large parts of the IT industry (Armbrust et al., 2010). To retain control and thereby overcome adoption reluctance, an economic risk assessment of cloud services and a comparison of different providers are necessary (ENISA, 2009). This includes the evaluation of a provider’s respective availability, recovery rate, and viability (Heiser and Nicolett, 2008). Lee et al. (2003) point out that service providers’ system failure can result in major loss of productivity for clients. Therefore, the clients’ businesses depend on the cloud service providers’ wellbeing. The availability of cloud computing services is a major concern for companies. ‘The interruption of data availability has the same effect as a system failure, because it significantly impedes all processes affected’ (Martens and Teuteberg, 2011). For example, due to a power outage, datacenters of Amazon and Microsoft near Dublin were blacking out resulting in a default of both, the Amazon Elastic Compute Cloud (EC2) platform as well as the Microsoft Business Productivity Online Suite (Miller, 2011). The online storage service called ‘The Linkup’ shut down on August 8th, 2008 after losing access to 45% of customer data. Therefore 20,000 users had to be told that the respective services are no longer available (Brodkin, 2008). Unlike other IT (sourcing) projects, cloud services show a specific asymmetric risk structure with relatively low expected costs but very high economic damage in case of default. To reach an economic valuation of sourcing decisions for cloud sourcing strategies in accordance with general IT governance guidelines, a cloud specific risk assessment as well as the consideration of interdependencies and diversification effects is inevitable. However, Venters and Whitley (2012) state that still many organizations have a poor understanding of their costs, cannot evaluate the benefits, and only have limited ability to quantify the risks of cloud computing. Against this background we develop an analytical model to evaluate the ex ante allocation of shares to multiple cloud service providers, taking into account the service providers’ costs and default risks. Since the economic attributes of cloud services can be very diverse, we chose to tailor our model towards a specific class of cloud services with basic attributes in order to guarantee comprehensible results, i.e. fungible cloud services, which can be independently allocated to different cloud service providers and for which a short-term provider switch is no effective solution to keep the business running. Examples for such cloud services are hosted desktops, hosted exchange and e-mail services, shared workspace systems, the provision of online storage and intra-company file sharing, as well as for hosted Anti-Spam/Anti-Virus solutions for e-mail security in the cloud. What these services have in common is that a provider’s default may result in severe economic damage for the user, since the continuation of operations depends on the services’ availability.

Based on existing literature, we postulate three requirements which we consider to be essential for an evaluation of cloud service provider portfolio composition. Then, we provide a brief survey of essential literature with regard to existing valuation methods and describe our research methodology. The article’s novelty is based upon a new approach to model the asymmetric risk structure of specific cloud services with the use of exponential loss distributions and a one-sided risk measure in analogy to technical failure rates to depict a reasonable image of reality. Thereby, we extend existing Portfolio Theory towards the specific characteristics of cloud services. We conclude with a valuation and optimization method for a cloud service provider portfolio. We present a practical example, evaluate our model using a Monte Carlo simulation, and illustrate real world implications of our work, before addressing the prospects and limitations of the model.

2 Research Objectives

Considering a profit-maximizing company, the economic benefits of a technology are in the spotlight of decision-making. Companies are challenged to allocate budget to the most promising combination of IT-services by using methodically rigor valuation methods to assess available IT services (Reyck et al., 2005). Despite this necessity, only 50% of all companies examined by the IT Governance Institute have a clearly defined approach for evaluating IT (IT Governance Institute, 2008). Considering the specifications of cloud computing sourcing investments, we postulate the following requirements.

R1: Cost integration: In general, cloud computing decisions induce costs to a client, e.g. service costs, agency, capital or implementation costs (Martens and Teuteberg, 2011). Thus, a valuation method has to integrate the occurring costs of cloud services.

R2: Consideration of the cloud computing specific risk structure: As mentioned above, providers of cloud computing services bear the risk of default resulting in a temporary service unavailability. The unavailability might be caused by different incidents like technical breakdown, operative errors or natural disasters. In case of default the client is unable to conduct its business processes for the duration of the unavailability of the service and hence has to bear profit setbacks. This one-sided risk structure needs to be adequately considered. In existing IT project/portfolio evaluation methods, risk is often interpreted as a two-sided deviation from a target variable, e.g. the expected costs, like in Fridgen and Müller (2009) and Zimmermann et al. (2008). However, a two-sided risk measure is incapable of depicting the one-sided risk structure of cloud computing services. Therefore, a valuation method has to consider this cloud computing specific risk structure. Requirement R2 is in the focus of this article to enable a cloud specific extension of Portfolio Theory.

R3: Consideration of risk interdependencies and diversification effects: If a client sources a cloud service to multiple providers, the default risks of the service providers are not independent of each other. On the one hand, risk is mitigated through the partitioning of the service provision; on the other hand it is possible that certain risks affect multiple service providers simultaneously. These conjoint risks, affecting for example a certain geographical region, technology, etc., appear in addition to a cloud service provider's specific risk. They occur very infrequent, but may cause high economic damage (Giesecke, 2003). Possible practical examples of cloud computing risk interdependencies are network breakdowns, e.g. by transection of deep-sea cables, large-area electric power breakdowns, or the unavailability of a basic supply service, which is accessed and indispensably required by a certain group of service providers (cascading risk transfer). Different cloud service providers which offer hosted desktops or hosted exchange- and e-mail services might rely on the same infrastructure provider, like Amazon's Elastic Compute Cloud. Since many providers are recently locating their large datacenters in areas where power and cooling are cheap in order to maximize their economic profit from economies of scale (Armbrust et al., 2010), conjoint risks due to geographical proximity are becoming more and more likely. However, if a client obtains a desired cloud service from multiple service providers, whose risks are not perfectly positively correlated, the overall risk is lower than the total risks in case of perfect positive correlation due to diversification effects. For example, a client that uses hosted desktops from two or more cloud service providers keeps its core ability to work at least for a certain part of its employees, even if one provider defaults. This effect has to be considered by a valuation method.

As we will point out more detailed in the next section, to the best of our knowledge, there are no existing valuation methods for cloud computing portfolio management approaches considering all of the three mentioned requirements. To address this issue, our valuation model will answer the following two research questions, thus contributing to a better understanding and exploitation of the economic potential of cloud computing:

How can a cloud service provider portfolio be evaluated considering cost, interdependencies and the cloud computing specific asymmetric risk structure?

How can a client identify the optimal cloud computing portfolio allocation strategy?

3 Literature Overview

Many research articles address cloud computing business models and business-related issues of cloud computing, e.g. Pueschel et al. (2009) and Weinhardt et al. (2009). Companies willing to use cloud computing services need a comprehensive strategy to manage cloud services' cost, its specific risk structure as well as interdependencies. For this purpose, they use the support of decision models. Existing articles examine various aspects of sourcing decisions in general, and are based on several common theories applied in IS research, e.g. Social Exchange Theory (e.g. Kern and Willcocks, 2000), Transaction Cost Economics Theory (e.g. Aubert et al., 1996) or Agency Theory (e.g. Bahli and Rivard, 2003). Since in general sourcing decisions are similar to portfolio decisions on for example risky financial assets or IT projects, cf. Zimmermann et al. (2012), this contribution is based upon Portfolio Theory. In this vein, the 'critical target figures of a portfolio are its expected return and risk' as well as 'its interdependencies to all other investments included in a portfolio' (Zimmermann et al., 2012). Related articles in IS research using this theory are for example Wehrmann et al. (2006), and Zimmermann et al. (2008). They focus on IT outsourcing in general and do not adapt the theory according to the characteristics of cloud services. They use the variance as a two-sided risk measure to capture risk and picture interdependencies by the use of the Pearson's correlation coefficient. Thus, existing approaches based on Portfolio Theory consider both cost (R1) and project dependencies (R3), but fall short in capturing the cloud service specific risk structure (R2) and modeling it adequately. Other normative approaches like for example Martens et al. (2011) therefore provide a selection process for cloud computing providers with special focus on data sensitivity and risk attitude of the decision maker. The article contains an illustration of a respective decision process and does not provide a quantitative method-based decision support instrument. Existing contributions to the field that focus on methodological decision support are for example Martens et al. (2012), who develop a Total Cost of Ownership (TCO) approach for cloud services and thoroughly describe different cloud computing pricing schemes as well as a high variety of cost factors of cloud computing. Fitó and Guitart Fernández (2012) introduce a semi-quantitative risk-management approach, which analyses and prioritizes cloud risks according to their impact on business objectives. Liang et al. (2012) provide decision models for cloud resource allocation focusing on cost and technical aspects like capacity, job turnaround time, latency and bandwidth. Martens and Teuteberg (2011) integrate risk in a decision model and model it by means of common security objectives. However, a cloud computing specific decision model with regard to all of the three mentioned requirements cannot be found. Hence, we analyzed general literature on IT outsourcing and decision theory in order to find approaches which might be suitable for a method transfer. The management of dependencies (R3) among various activities was already examined by Malone and Crowston (1990), who analyzed different types of dependencies and suitable management approaches. Interdependency effects are studied empirically by Mani et al. (2012), who focused on coordination between client and vendor. Bapna et al. (2010) developed an agenda for analytical and empirical research on multi-sourcing, focusing on a setting with multiple vendors who are competitors and co-workers at the same time. They found that due to interdependencies multi-sourcing is 'fundamentally different from single-sourcing' and that occurring cooperation and coordination efforts need to be analyzed carefully. Kundisch and Meier (2011) distinguished between different kinds of interdependencies and presented a structured identification process for resource interactions among IT projects and developed a mathematical decision model which accounts for the identified interdependencies. Probst and Buhl (2012) developed a model for sourcing decisions for IT services explicitly focusing on diversification effects. Lammers (2004) also considered IT service sourcing decision and use a risk-adjusted discount rate to model service provider risks. These approaches model risk by the means of symmetric distributions and therefore use two-sided risk measures. To the best of our knowledge a transfer of these approaches to the specifics of cloud computing is not possible, since risk shall be modeled as one-sided deviation from an expected availability rate to picture the facts of cloud computing more realistically. Martens et al. (2012) state that the 'evaluation and selection process of Cloud Computing Services is frequently conducted ad-hoc and lacks systematic methods to approach this topic'. For this reason, we develop a quantitative

risk/cost based model for cloud computing investment decisions using a one-sided risk measure and considering exponentially distributed losses in case of default. Thereby, our work emphasizes specific characteristics of cloud computing, like easy accessibility and reconfiguration in terms of scalability. Thus, we are able to extend the IS literature based on Portfolio Theory with regard to specific risk modelling of cloud services and derive an economic model that delivers relevant insights supporting the design of cloud computing decision processes in today's businesses.

4 Research Methodology

In the context of this work we adopt a design science approach according to Hevner et al. (2004). Our approach to portfolio selection in cloud computing is designed as an artefact. Since it is a model that enables comparison to other approaches in this research area and it is a method that supports the process of portfolio selection in cloud computing, it is a valid artefact type (March and Smith 1995). We gave a brief overview of descriptive literature on cloud computing and pointed out the need of quantitative decision support for cloud computing vendor selection. Since no adequate solutions exist in the extant knowledge base, the first phase (rigor phase) according to Hevner's DSR Approach (Hevner et al., 2004) is accomplished. For the construction of the artefact we relied on Portfolio Theory, as well as on Decision Theory and mathematical methods and related literature dealing with decision support for sourcing. To evaluate our approach to portfolio selection in cloud computing, we follow the methods proposed by Hevner et al. (2004) using a simulation and demonstrate that it will lead to better results than approaches applied in practice today. Thus, this paper provides a basis for the presentation of this approach to technology as well as management oriented readers. Researchers should feel encouraged to challenge the described limitations as well as to validate the proposed effects by empiricism. The findings derived subsequently should continuously improve the approach and therewith the decision support in today's businesses.

5 Multivendor Sourcing Decision Model

Despite traditional IT outsourcing and cloud computing provide similar basic functions and benefits (Leimeister et al., 2010), many limitations of traditional IT outsourcing do not apply to the concept of cloud computing (Talukder and Zimmerman, 2010). The providers of cloud services are subject to availability risk caused by individual or conjoint default. Both risks constitute the asymmetric risk structure of cloud services with relatively low expected costs but extremely high damage in case of default. In order to receive a specifically tailored model, we picture risk as technical failures, which are, in contrast to general IT outsourcing settings where defaults have a much broader variety of reasons, a very typical default reason of cloud services. Moreover, our model is continuous and considers fungible cloud services, which can be independently allocated to multiple service providers. This is not the case for other cloud services, or SaaS in general, where a service is delivered either by one specific supplier completely, or by multiple suppliers, each with precisely pre-defined scope (e.g., online storage is a fungible service, which can be independently allocated to multiple providers, whereas order entry as a Service is not). Due to these reasons, our model is first and foremost applicable to fungible and independent cloud services and not directly applicable to IT outsourcing settings or SaaS in general. Hence, our model cannot claim to be universally applicable, but intends to provide a realistic modeling approach of the specific risk structure of specific cloud services.

5.1 Setting and Assumptions

To conduct business, a client decides on deploying a specific service obtained through the cloud. As mentioned above, we focus on cloud services which are fungible, can be independently allocated to multiple service providers, and for which a short-term provider switch is no effective solution to keep the business running. We refrain from a technical investigation of cloud computing related problem solving. Instead, we examine the use of multiple cloud providers as a strategic or project management

related means to deal with the problem of cloud computing service availability. Therefore, n multiple cloud service providers exist which render the desired service either completely or to some extent. The client has to decide ex ante on the respective share w_i of the service that will be obtained from provider i , with $\sum_{i=1}^n w_i = 1$. Considering a possible default of a service provider, clients are generally able to switch to an alternative provider, which in such cases might be a lengthy and complex migration project. However, even a fast provider switch cannot avoid unavailability of a service, since it takes time until a client notices the default, gathers information about possible courses of action, chooses an alternative solution and switches to the respective provider. During this entire time span, economic damage accrues due to the interruption of business operations. Hence, we omit short term provider switches for our model and state the following assumption:

A1: The possibility of a short term change of the service provider is neglected for the considered period of time.

Referring to R1: Cost integration:

Each provider i offers a service to the client at certain costs c_i , whereas c_i being the costs for the provision of the complete service, i.e. $w_i = 1$. We consider the present value of all costs, e.g. initiation costs, negotiation cost, agency costs, coordination costs (Martens and Teuteberg, 2011), to be integrated in c_i .

Referring to R2: Consideration of the cloud computing specific risk structure:

The service offered by provider i is subject to default. This risk is modeled by the random variable t_i , which indicates the duration of unavailability of the service of provider i within the considered period. We infer that the longer the duration of unavailability, the higher the economic damage. Therefore, we state the following assumption:

A2: The economic damage D increases linearly with the duration of unavailability t_i of a service, i.e. $D(t_i) = t_i \cdot d$, with $d > 0$ being the client-specific damage rate and will be denoted as D_i .

Since D_i is functionally dependent on the random variable t_i , D_i is also random. In practice, the economic damage may also stand in other than a linear relation to the duration of unavailability, e.g. convex, quadratic or exponential, relations. The model could easily be tailored to such other relations by adapting the factor d to be any desired function of t_i . We use assumption A2 as simplification which does not alter the model's findings. In case of unavailability of the service, providers are typically obliged to render compensatory payments specified by their SLAs. For example, if a client of Amazon's cloud service EC2 drops below the guaranteed duration of availability, the client 'is eligible to receive a service credit equal to 10% of their bill' (Amazon Web Services, 2008). Since the uncertain economic damage D_i on behalf of the client is unknown to and not influenceable by providers like Amazon, it is not appealing to them to grant a higher compensation. Related to the compensatory payment, the economic damage e.g. due to loss of customer data and thereby delayed business processes is likely to be much higher, which makes the risk of default almost completely born by the client. Venters and Whitley (2012) state that unlike regular outsourcing SLAs, cloud service SLAs 'are often weak and ineffectual' and 'currently poor vehicles for customers'. Durkee (2010) finds that 'in the cloud market space, meaningful SLAs are few and far between, and even when a vendor does have one, most of the time it is toothless'. Therefore, and for reasons of simplicity, we state the following assumption:

A3: Compensatory payments are neglected.

To model the distribution of the duration of unavailability \tilde{t}_i we have to consider the fact that cloud providers do not have an incentive to publish empirical data for their services' unavailability times. Thus, we follow an established method of modeling technical failure rates with an exponential distribution, with shorter durations of unavailability like e.g. due to power outages or server outages being more likely than longer ones like e.g. bankruptcy of a provider.

A4: The duration of unavailability t_i of a service is influenced by the provider-specific risk, modeled by an exponential distribution determined by the recovery rate $\lambda_i > 0$.

The recovery rate λ_i defines the capability of a cloud service provider to fix a service in case of default. Thereby, a high recovery rate refers to a broad expertise of a service provider to decrease the duration of unavailability.

Referring to R3: Consideration of risk interdependencies and diversification effects:

Besides the provider-specific risk, conjoint risks affect multiple cloud service providers i and j simultaneously. Following Duffie and Garleanu (2001) and Marshall and Olkin (1967), we model these conjoint risks according to the following assumption:

A5: Dependencies between the durations of unavailability of two services are pictured by the conjoint risk, modeled by an exponential distribution determined by the recovery rate $\lambda_{ij} > 0$. All dependencies are assumed to be linear.

The recovery rate λ_{ij} defines the existing external capability to fix a service in case of default, which is for example influenced by a certain region's electricity grid and respective support. Again, a high recovery rate refers to a broad expertise to decrease the duration of unavailability. The provider i 's duration of unavailability t_i can now be described by a bivariate exponential function $t_i \sim \text{Exp}(\lambda_i, \lambda_{ij})$ considering both the provider-specific risk as well as the conjoint risk. Since the service provider's statement of its duration of unavailability DU_i given by the respective SLA, e.g. 'we guarantee 99.5% availability', is the best information accessible, we state the following assumption:

A6: The statement of duration of unavailability DU_i equals the expected value of the bivariate exponential distribution $E(t_i)$.

As the expected value of the bivariate exponential distribution can be calculated according to (Giesecke, 2003) as

$$E(t_i) = \frac{1}{\lambda_i + \lambda_{ij}},$$

we can state that

$$DU_i = \frac{1}{\lambda_i + \lambda_{ij}}$$

Since a cloud service provider tries to avoid contract violations, the information DU_i given by the provider might not equal the true expected duration of unavailability, which might be derived from empirical values. The integration of this factor, as is, might therefore be a very cautious calculation. Empiricism could therefore come up with industry specific corrective factors, which could easily be integrated in the model.

Referring to all three listed requirements:

To picture the risk of unavailability of a service appropriately, we use the concept of lower partial moments (LPM), which measure one-sided deviations from a certain threshold, i.e. downside-risk. Therefore, the risk of unavailability of a provider i is measured by the second order lower partial moment $LPM_{2,i}(0; t_i)$. To evaluate a portfolio with respect to all requirements mentioned above, we compose an objective function as the client's decision criterion that integrates the portfolio's expected costs (denoted as μ_{PF}) and risks (denoted as $LPM_{2,PF}(0; t_{PF})$, with $t_{PF} \sim \text{Exp}(\lambda_i, \lambda_j, \lambda_{ij})$) weighted by the individual risk aversion of the decision maker, measured by the parameter γ . We state assumption A7:

A7: The client determines the risk-adjusted costs of a cloud computing portfolio PF using the following objective function: $\Phi(\mu_{PF}, LPM_{2,PF}(0; t_{PF})) = \mu_{PF} + \gamma \cdot LPM_{2,PF}(0; t_{PF})$. The client is risk-averse, i.e. $\gamma > 0$.

We assume a risk-averse decision maker, which means that the higher the unavailability risk of a service, the lower the client's willingness of choosing it. The exact determination of parameters of risk aversion is difficult and subject to further research. Similar objective functions are used by other

authors within the IS discipline, e.g. Fridgen and Müller (2009), Probst and Buhl (2012), Zimmermann et al. (2008).

5.2 Portfolio Selection of Cloud Computing Providers

The client's objective is to minimize the risk-adjusted costs of the portfolio, i.e. the value of the objective function. For this purpose, we derive the objective function's constituent parts for a cloud service provider portfolio μ_{PF} and $LPM_{2,PF}(0; t_{PF})$. The expected costs μ_i for provider i 's complete service are measured by the costs for the provision of the complete service c_i plus the expected damage $E(D_i)$, which consists of the expected duration of unavailability $E(t_i)$ multiplied by the client-specific damage rate d :

$$\mu_i = c_i + E(D_i) = c_i + E(t_i) \cdot d = c_i + \frac{1}{\lambda_i + \lambda_{ij}} \cdot d$$

The expected cost of a portfolio of cloud service providers μ_{PF} is the sum of the expected costs for all providers μ_i weighted with their respective shares w_i : $\mu_{PF} = \sum_{i=1}^n w_i \cdot \mu_i$

Furthermore, the unavailability risk of a portfolio of providers is measured by the $LPM_{2,PF}(0; t_{PF})$. Following Wojt (2009) and using the second order lower partial moment considering both the provider-specific risk as well as conjoint risk, we get:

$$LPM_{2,PF}(0; t_{PF}) = \sum_{i=1}^n \sum_{j=1}^n w_i \cdot w_j \cdot CLPM_{1,i,j}(0, t_i, t_j)$$

Thereby, $CLPM_{1,i,j}(0, t_i, t_j)$ is the first order co-lower partial moment between the service providers, with

$$CLPM_{1,i,i}(0, t_i, t_i) = LPM_{2,i}(0, t_i)$$

and

$$CLPM_{1,i,j}(0, t_i, t_j) = LPM_{1,i}(0, t_i) \cdot LPM_{1,j}(0, t_j) \cdot \rho_{ij}$$

ρ_{ij} pictures a correlation coefficient and therefore is a measure of the coherence between the respective risks of unavailability of the service providers, which is determined by the provider-specific risks as well as the conjoint risk. Following Marshall and Olkin (1967), this linear dependency can be pictured as

$$\rho_{ij} = \frac{\lambda_{ij}}{\lambda_i + \lambda_j + \lambda_{ij}}$$

If the conjoint recovery rate $\lambda_{ij} = 0$, the providers' durations of unavailability are independent of each other, in this case the correlation $\rho_{ij} = 0$. Furthermore, as $\lambda_i \geq 0$ and $\lambda_j \geq 0$, we find that $\rho_{ij} \geq 0$. This implication of the model is reasonable, since a setting where the duration of unavailability of one service provider negatively affecting the duration of unavailability of another one is very unlikely. Given the correlation coefficient and the service providers' statements for the duration of unavailability from the SLAs, the relevant parameters λ_i , λ_j and λ_{ij} can be derived mathematically.

To provide a suitable evaluation method for cloud computing service providers in terms of our first research question, we combine expected costs and risk in the decision maker's objective function:

$$\phi(\mu_{PF}, LPM_{2,PF}(0; t_{PF})) = \sum_{i=1}^n w_i \cdot \mu_i + \gamma \cdot \sum_{i=1}^n \sum_{j=1}^n w_i \cdot w_j \cdot CLPM_{1,i,j}(0, t_i, t_j)$$

The decision maker can use this objective function to evaluate a possible allocation of services w_i with regard to the resulting risk-adjusted costs under consideration of the decision maker's specific risk aversion. However, it still has to be identified which combination of shares of the cloud service providers is best for the decision maker. To address this issue in terms of the second research question, we use the deduced evaluation method as a basis and formulate the problem as

Min $\phi(\mu_{PF}, LPM_{2,PF}(0; t_{PF}))$. Here we face a nonlinear optimization problem with a vector of decision variables $\vec{w} = (w_1, \dots, w_n)$ subject to two constraints: $\sum_{i=1}^n w_i = 1$ and $w_i \geq 0, \forall i \in N$. The analytic solution of such problems is possible but rather complex and would go beyond the scope of this contribution. However, to provide an analytical optimum in this paper, in the following, we concentrate on a setting with two service providers. This implicates a minimization of the risk-adjusted costs, resulting from the chosen optimal portfolio weights for $n = 2$ providers with $w_2 = 1 - w_1$. To fulfill the first order condition for optimality we set the first derivative with respect to w_1 equal to 0. By solving $\frac{\partial \phi(\mu_{PF}, LPM_{2,PF}(0; t_{PF}))}{\partial w_1} = 0$ for w_1 we get a candidate for optimality \check{w}_1 . To fulfill the second order condition for optimality, we examine the second derivative with respect to w_1 $\frac{\partial^2 \phi(\mu_{PF}, LPM_{2,PF}(0; t_{PF}))}{\partial w_1^2} > 0$. For reasons of convenience, we do not depict the mathematical terms of the optimization. Considering all parameters in the previously defined domains, the second derivative is always positive and therefore the second order condition is always fulfilled. In case of optimization outcomes outside the interval $[0,1]$ we apply 0 at minimum and 1 at maximum. Hence, $w_1^* = \check{w}_1$ and $w_2^* = 1 - w_1^*$ represent the optimal shares. The decision maker's optimal portfolio allocation strategy is to choose the shares according to the computed w_1^* and w_2^* thus minimizing the risk-adjusted costs.

6 Example of two cloud computing providers

A company decides to obtain the service of hosted desktops and therewith realize advantages like easy access from different locations, provider support, less energy consumption, and no high investment costs. The company wants to split the provided desktops between two service providers SP1 and SP2. If SP1 provides all hosted desktops, the costs of the service are $c_1 = 13,000$ monetary units (MU), whereas the costs of full service provisioning of SP2 are $c_2 = 15,000$ MU, including initiation costs, adoption costs and other. The economic damage D_i increases linearly with the duration of unavailability t_i which is the time in which the affected employees cannot access their desktops. The client-specific damage rate is $d = 110,000$ MU. The company's parameter of risk-aversion is $\gamma = 4$. The recovery rates given in the providers' SLAs are 99.95% (SP1) and 99.96% (SP2), respectively. Since both service providers are located in the same geographical region and natural disasters and electric power breakdowns might have simultaneous impact on the availability of both providers, the correlation coefficient is assumed to be $\rho_{12} = 0.25$. Given this data, the provider-specific recovery rates $\lambda_1 = 1,100$ and $\lambda_2 = 1,600$ as well as the conjoint recovery rate $\lambda_{12} = 900$ can be derived mathematically. To compare the results of the optimization to more pragmatic approaches, we examine the respective risk-adjusted costs for each of the following allocation strategies.

- optimization: The optimal shares, identified by the method described above, are allocated to the respective providers.
- cost-based decision: The provider who charges less for the respective services is chosen to conduct the service entirely no matter what risk the service bears.
- risk-based decision: The provider with the higher availability is chosen to conduct the service entirely no matter what price the provider charges.
- equal shares: Each service provider conducts the same fraction of the service.

To picture the calculation outcomes: according to allocation strategy 1 (optimization), the portfolio composition with optimal shares $w_1^* = 0.42$ and $w_2^* = 0.58$ leads to risk-adjusted costs of 20,127. Allocation strategy 2 (cost-based decision) recommends a selection of provider SP1, as the costs are lower than the costs of SP2, which implies risk-adjusted costs of 25,155. Allocation strategy 3 (risk-based decision) recommends a selection of provider SP2, as its risk (reflected by the LPM) is lower than the costs of SP1, which implies risk-adjusted costs of 22,788. Allocation strategy 4 (equal shares) leads to risk-adjusted costs of 20,220. Hence, the optimization outcome of the model presented above delivers the best results in this example. We use a Monte Carlo simulation to verify these results.

7 Model Evaluation based on a Monte Carlo Simulation

According to Hevner et al.'s (2004) design science approach, we provide an analytical optimization and simulation as legitimate means to evaluate a model. Since it is almost impossible to acquire real world data to survey the value added of our allocation approach empirically, we derive realistic results via the simulation of scenarios. Each scenario was created by a variation of the basic parameters cost, recovery rates, and damage. To picture the availability of 99.95%, which is frequently given in cloud provider's SLAs we set the sum of the conjoint and provider-specific recovery rates equal to 2,000.

parameter	range	distribution
cost (c_i)	0 – 20,000 (+/- 20% for different providers)	equal
conjoint recovery rate (λ_{ij})	0 – 2,000	equal
provider-specific recovery rate (λ_i)	2,000 - λ_{ij} (+/- 100% for different providers)	equal
client-specific damage rate (d)	0 – 200,000	equal

Table 1. Monte Carlo input data

We generated 50,000 different project settings and derive the following results: The allocation of cloud services according the optimization outcome dominates all of the three other allocation strategies, especially the magnitude of the improvement obtained through optimization is considerable. Compared to the cost-based decision, the optimization leads to an average improvement of 13.56% relating the respective risk-adjusted costs. Compared to the allocation decision of equal shares, the optimal allocation leads to an average improvement of 10.28%. Compared to the risk-based decision, the optimized allocation saves an average of 6.92%. By varying the parameter of risk aversion γ by steps of 25% in both directions, we performed an additional sensitivity analysis.

parameter of risk aversion γ	$\gamma = 2$	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$	$\gamma = 6$
optimization vs. cost-based	9.93%	11.42%	13.56%	15.61%	17.80%
optimization vs. risk-based	5.75%	6.23%	6.92%	7.42%	7.90%
optimization vs. equal shares	9.66%	10.06%	10.28%	10.47%	11.31%

Table 2. Monte Carlo results: average improvement through optimization

These results have been statistically tested with the Mann–Whitney–Wilcoxon test and are highly significant, i.e. all p-values $\ll 0.01$. Hence, we can state that our findings hold irrespective of the value of γ . Therefore the application of our model features a significant potential to reduce risk-adjusted costs and enables companies to fully reap the benefits this technology bears.

8 Practical Implications, Limitations and Outlook

In this paper, we derive an analytical model to extend existing Portfolio Theory to quantitatively evaluate a client's cloud computing portfolio composition with regard to three requirements. Altogether, the following practical implications can be derived:

- The characteristics of cloud computing require an economic valuation approach with regard to costs, the specific risk structure and risk interdependencies.
- The model developed in this paper fulfills all of these requirements and provides decision support to evaluate cloud computing strategies as well as to determine the optimal provider selection.
- The allocation of cloud services according the model's optimization outcome delivers better results than approaches applied in practice today.

Considering the limitations of this approach, despite the underlying assumptions, one has to mention, that the model pictures ex ante decisions only. The development of an integrated model considering the existing cloud computing portfolio as well as the decision on additional services obtained through the cloud might be of great significance to practitioners as well as to researchers and is subject to

further research. Furthermore, the relation between the announced duration of unavailability of a cloud computing provider, e.g. derived by SLAs, and its actual duration of unavailability, should be further examined. We focus on cloud computing services, which are very likely to be infinitely divisible and deliver constant merits no matter which service provider is chosen. The further examination of such services of which some real world examples are given above, along with the examination of other services, as well as the extension of the model to consider more than two providers analytically is subject to further research. Future empirical research has to further verify the validity of our hypothesis and go beyond the simulation based evaluation, to show that the developed model produces better results than approaches applied in practice today.

References

- Amazon Web Services (2008). Amazon EC2 Service Level Agreement.
<http://aws.amazon.com/de/ec2-sla/>.
- Armbrust, M., Fox, A., Griffith, R., Joseph, A.D., Katz, R.H., Konwinski, A., Lee, G., Patterson, D.A. and Stoica, I. (2010). A view of cloud computing. *Communications of the ACM*, 53 (4), 50-58.
- Aubert, B.A., Rivard, S. and Patry, M. (1996). A transaction cost approach to outsourcing behavior: Some empirical evidence. *Information & Management*, 30 (2), 51-64.
- Bahli, B. and Rivard, S. (2003). The information technology outsourcing risk: A transaction cost and agency theory-based perspective. *Journal of Information Technology*, 18 (3), 211-221.
- Bapna, R., Barua, A., Mani, D. and Mehra, A. (2010). Cooperation, coordination, and governance in multisourcing: An agenda for analytical and empirical research. *Information Systems Research*, 21 (4), 785-795.
- Brodkin, J. (2008). Loss of customer data spurs closure of online storage service 'The Linkup',
<http://www.networkworld.com/news/2008/081108-linkup-failure.html>.
- Duffie, D. and Garleanu, N. (2001). Risk and Valuation of Collateralized Debt Obligations. *Financial Analysts Journal*, 57, 41-59.
- Durkee, D. (2010). Why cloud computing will never be free. *Queue*, 8 (4), 20.
- ENISA (2009). Cloud Computing Risk Assessment.
<http://www.enisa.europa.eu/act/rm/files/deliverables/cloud-computing-risk-assessment>.
- Fitó, J.O. and Guitart Fernández, J. (2012). Introducing risk management into cloud computing.
- Fridgen, G. and Müller, H. (2009). Risk/Cost Valuation of Fixed Price IT Outsourcing in a Portfolio Context. In *Proceedings of the 30th International Conference on Information Systems*, Phoenix.
- Giesecke, K. (2003). A simple exponential model for dependent defaults. *Journal of Fixed Income*, 13 (3), 74-83.
- Heiser, J. and M. Nicolett (2008). Assessing the security risks of cloud computing. Gartner Report,
<http://cloud.ctrls.in/files/assessing-the-security-risks.pdf>.
- Hevner, A.R., March, S.T., Park, J. and Ram, S. (2004). Design Science in Information Systems Research. *MIS Quarterly*, 28 (1), 75-106.
- IT Governance Institute (2008). IT Governance Global Status Report.
- Kern, T. and Willcocks, L.P. (2000). Exploring information technology outsourcing relationships: Theory and practice. *Journal of Strategic Information Systems*, 9 (4), 321-350.
- Kundisch, D. and Meier, C. (2011). A new perspective on resource interactions in IT/IS project portfolio selection. In *Proceedings of the 19th European Conference on Information Systems*, Helsinki.
- Lammers, M. (2004). Make, buy or share combining resource based view, transaction cost economics and production economies to a sourcing framework. *Wirtschaftsinformatik*, 46 (3), 204-212.
- Leavitt, N. (2009). Is Cloud Computing Really Ready for Prime Time? *Computer*, 42 (1), 15-20.
- Lee, J.N., Huynh, M.Q., Kwok, R.C.W. and Pi, S.M. (2003). IT Outsourcing Evolution: Past, Present, and Future. *Communications of the ACM*, 46 (5), 84-89.

- Leimeister, S., Riedl, C., Böhm, M. and Krcmar, H. (2010). The business perspective of cloud computing: actors, roles, and value networks. In Proceedings of the 18th European Conference on Information Systems, Saint Louis.
- Liang, H., Huang, D. and Peng, D. (2012). On economic mobile cloud computing model. *Mobile Computing, Applications, and Services*, 329-341.
- Malone, T. W., Crowston, K. (1990). What is coordination theory and how can it help design cooperative work systems? In Proceedings of the Conference on Computer-Supported Cooperative Work, 357-370, New York.
- Mani, D., Barua, A. and Whinston, A. (2012). An empirical analysis of the contractual and information structures of business process outsourcing relationships. *Information Systems Research*, 23 (3), 618-634.
- March, S.T. and Smith, G.F. (1995). Design and natural science research on information technology. *Decision Support Systems*, 15 (4), 251-266.
- Marshall, A.W. and Olkin, I. (1967). A multivariate exponential distribution. *Journal of the American Statistical Association*, 62 (317), 30-44.
- Martens, B., M. Walterbusch and Teuteberg, F. (2012). Costing of Cloud Computing Services: A Total Cost of Ownership Approach. In Proceedings of the 45th Hawaii International Conference on System Sciences, Maui.
- Martens, B. and Teuteberg, F. (2011). Decision-making in cloud computing environments: A cost and risk based approach. *Information Systems Frontiers*, 14 (4), 871-893.
- Martens, B., N. Zarvi, F. Teuteberg and Thomas, O. (2011). Designing a Risk-based Partner Selection Process for Collaborative Cloud Computing Environments. In Proceedings of the 4th International Workshop on Enterprise Modelling and Information Systems Architectures, Hamburg.
- Miller, R. (2011). Outage in Dublin Knocks Amazon, Microsoft Data Centers Offline. <http://www.datacenterknowledge.com/archives/2011/08/07/lightning-in-dublin-knocks-amazon-microsoft-data-centers-offline/>.
- Probst, F. and Buhl, H.U. (2012). Lieferantenportfolio-Management für IT-Services unter Berücksichtigung von Diversifikationseffekten. *WIRTSCHAFTSINFORMATIK*, 54 (2), 69-81.
- Pueschel, T., A. Anandasivam, S. Buschek and Neumann, D. (2009). Making money with clouds: Revenue optimization through automated policy decisions. In Proceedings of the 17th European Conference on Information Systems, Verona.
- Reyck, B.D., Grushka-Cockayne, Y., Lockett, M., Calderini, S.R., Moura, M. and Sloper, A. (2005). The impact of project portfolio management on information technology projects. *International Journal of Project Management*, 23 (7), 524-537.
- Talukder, A.K. and Zimmerman, L. (2010). Cloud Economics: Principles, Costs, and Benefits. *Computer Communications and Networks*, (4), 343-360.
- Venters, W. and Whitley, E.A. (2012). A critical review of cloud computing: researching desires and realities. *Journal of Information Technology*, 27 (3), 179-197.
- Wehrmann, A., Heinrich, B. and Seifert, F. (2006). Quantitatives IT-Portfoliomanagement: Risiken von IT-Investitionen wertorientiert steuern. *Wirtschaftsinformatik*, 48 (4), 234- 245.
- Weinhardt, C., Anandasivam, A., Blau, B., Borissov, N., Meinl, T., Michalk, W. and Stöber, J. (2009). Cloud Computing – A Classification, Business Models, and Research Directions. *Business & Information Systems Engineering*, 1 (5), 391-399.
- Wojt, A. (2009). Portfolio Selection and Lower Partial Moments.
- Zimmermann, S., Katzmarzik, A. and Kundisch, D. (2008). IT Sourcing Portfolio Management for IT Service Providers - A Risk/Cost Perspective. In Proceedings of 29th International Conference on Information Systems, Paris.
- Zimmermann, S., Katzmarzik, A. and Kundisch, D. (2012). IT Sourcing Portfolio Management for IT Services Providers - An Approach for Using Modern Portfolio Theory to Allocate Software Development Projects to Available Sites. *DATA BASE for Advances in Information Systems*, 43 (1), 24-45.