University of Augsburg
Prof. Dr. Hans Ulrich Buhl
Research Center
Finance & Information Management
Department of Information Systems
Engineering & Financial Management

Universität
Augsburg
University

Discussion Paper WI-254

Sourcing and Automation Decisions in Financial Value Chains

by

Matthias Henneberger, Arne Katzmarzik, Stephan Müller, Frans-Matthis Pleie

in: S. Newell, E. Whitley, N. Pouloudi, J. Wareham, L. Mathiassen, eds.,
Proceedings of the 17th European Conference on Information Systems,
ECIS, Verona, Juni 2009, p. 679-691.

Universität Augsburg, D-86135 Augsburg
Visitors: Universitätsstr. 12, 86159 Augsburg
Phone: +49 821 598-4801 (Fax: -4899)
www.fim-online.eu

SOURCING AND AUTOMATION DECISIONS IN FINANCIAL VALUE CHAINS

Technological progress and globalization foster relocation and automation of business processes. Especially financial services providers oftentimes have the choice either to automate information-processing tasks or to relocate them to foreign sites to profit from differences in wage levels. Both strategies bear enormous economic potential in terms of cost savings. However, with the main focus on cost reduction, risk due to the uncertain development of effective labor costs or future transaction volumes are oftentimes either inadequately considered or completely neglected. This systematically leads to false decisions, in particular since the two strategies – relocation and automation – result into different risk profiles. In this paper, we analyze the conditions for automating or relocating parts of processes and propose a decision model for allocating business processes to these alternatives in a risk/return efficient way. In particular, we consider how uncertainties of the effective labor costs and transaction volumes influence the decision. As shifting tasks to other locations or their automation has effects on the workload at the original location, we also consider costs for social effects. The practicability of our approach is demonstrated with a real world case with data from a major financial services provider.

Keywords*: business process sourcing, relocation, automation, costs for social effects, risk, decision model*

1 INTRODUCTION

Today, globally acting companies that are integrated into world-wide value chains are constantly in demand to make sourcing decisions. This includes relocating business processes entirely or in parts to foreign countries to profit from effects such as increased cost efficiency due to wage differences and opening up new labor pools. Such relocation is accomplished either by outsourcing the business processes to external service providers that are located abroad or by shifting the processes internally from one site to another. Relocating business processes, either kept in-house or outsourced, has become very attractive in the last years and is facilitated by better communication technologies and improved staff skills in emerging countries (Agrawal et al. 2003). Consequently, this trend is predicted to continue in the next years, which is underscored by Gartner (2007), who predict the worldwide market volume for business process outsourcing to grow from $160 bn in 2007 to $235 bn in 2011 with an annual growth rate over 10%.

Another ongoing trend that is facilitated by technological progress is business process automation. As pressure for efficiency increases, firms have to evaluate whether and to what extent business processes should be automated. Most often a mixture of both – automation and relocation – seems to be most reasonable. Gartner (2008b), for instance, conceives a combination of automation and outsourcing as a way to reach the fullest extent of efficiency and cost reduction and predicts process automation to rise from 10% in 2007 to 55% in 2017 of all processes outsourced (Gartner 2008a). Oftentimes, process automation has become a true alternative to relocation. For example, simple tasks in the financial services domain such as entering paper orders in an order processing system could either be accomplished cost effectively by staff members in low-wage countries or those tasks could be (at least partially) automated. Applying, for instance, optical character recognition (OCR) technologies, the paper orders could be automatically scanned and processed. Therefore, for making sourcing decisions, an integrated decision support model considering relocation and automation is crucial.

Relocation as well as automation bear risk and recent studies show that saving expectations were often not met (Bloch et al. 2003, Lacity et al. 2000). Two effects are especially important when assessing the risk and the expected return of both alternatives. First, uncertainties concerning effective labor costs, wage developments in foreign countries or future transaction volumes have to be considered. If, for instance, the risk of rising wage levels is not taken into account, cost savings intended by relocation cannot be realized. False sourcing decisions are the consequence, leading to higher costs than before (Rouse et al. 2004). Second, social effects that may arise when tasks are relocated or automated have to be considered carefully. For example, relocating the entering tasks outlined in the example above to low-wage countries may have important negative effects (including reputation problems) if at the same time employees are laid off at the original site. While those effects may be unavoidable in bad times, an interesting question is how enterprises can support growth in good times by exploiting the benefits of relocating or automating without provoking negative social effects.

The objective of this paper is to analyze the economic effects of relocation and automation in such a setting and to contribute a normative decision model proposing an optimal allocation of (parts of) business processes in a risk/return efficient way. Thus, we primarily contribute to sourcing theory by providing an integrated view over the alternatives: retention at the origin site, relocation to a new site and automation. We consider the different cost characteristics of the alternatives taking into account also possible negative effects of cutting jobs and analyze how these alternatives relate to each other. We examine the effects of uncertainty of effective labor costs and transactions volumes in a model via simulation. The applicability of our model is shown by studying a real world case with data from a large financial services provider (FSP).

The remainder of this text is organized as follows: In section 2, we give an overview of related literature. Additionally, this section lays the conceptual fundament for this paper (including the definition of important terms). In section 3, the decision model is presented, analyzed and illustrated by an operationalization. Finally, we conclude in section 4 by giving an outlook to further research.

2 LITERATURE REVIEW

Sourcing decisions can be separated into the organizational and the regional dimension which are to a certain extent independent of each other. With respect to the organizational dimension, outsourcing is defined as the procurement of services from sources that are external to the organization (Lankford et al. 1999). With respect to the regional dimension, near- and offshoring refers to relocating jobs to foreign countries without distinguishing whether the provider is external or affiliated with the firm (Levy 2005). In this text, we generally speak of *relocation* (standing both for near- and offshoring) and focus on the regional dimension since the cost reduction potential of relocating to low-wage countries can be realized both with in-house and outsourcing engagements. Furthermore, we consider automation as an alternative action in our decision problem. Automation refers to replacing human work by computers or machines (Bainbridge 1983). In the following, we will discuss the literature on relocation and automation in order to elaborate cost structures and risk factors. Additionally, we will give a review of the literature on social effects, before we conclude this section with an overview of decision models proposed by other authors for sourcing or automation decisions.

In literature, numerous articles on the drivers and criteria for relocation decisions have been published (Farrell 2005, Quélin et al. 2003). Although a number of motives for relocating the execution of business processes such as access to a larger pool of human capital, improved position in global markets, concentration on core business activities or more flexibility in reacting to market changes have been mentioned, the main motive is wage arbitrage due to lower *human resource (HR) costs* (Quélin et al. 2003). This is especially true for countries with high wages such as the US, the UK or Germany because relocation yields enormous cost reduction potential due to large differences in HR costs in comparison to low-wage countries such as India, where wages are about 15 percent of the US HR costs (neoIT 2006). However, regarding only the HR costs may lead to false decisions. Instead the so-called *loaded costs* are significant. The loaded costs per employee consist of costs for HR, benefits, space as well as overheads. In general, the loaded costs only show a difference of about 25-35% (Everest 2005). Relocating business processes (or parts of them) to a new remote location or splitting them up between two locations usually causes *transaction costs* such as management or communication costs. Besides cost types, *productivity levels* differ from site to site resulting in another mitigation of the cost arbitrage (Criscuolo et al. 2005) and have to be considered in the *effective labor costs* which represent the cost efficiency in conducting a process for each site.

Relocating business processes bears high risk. In the worst case, underestimating that risk may result in higher costs than expected or may even make backsourcing inevitable, i.e. re-integrating outsourced or relocated tasks to the origin site (Rouse et al. 2004). Due to global sourcing, risk influence factors like cultural differences, environment, communication, financial markets, technology, intellectual property and law have to be considered for the decision (A.T. Kearney 2007, Winkler et al. 2006). As the volume of business processes, which are sourced to low-wage countries, and following the demand at the labor market in low-wage countries is increasing, estimating future wage levels is conjunct with growing uncertainty (Vestring et al. 2005), i.e. especially the effective labor costs are risky. At this point, it is necessary to clarify our perception of risk because this term is oftentimes interpreted in manifold ways in academic literature and in practice: In accordance with financial theory, we understand *risk* as deviation of an expected value. Integrating risk in our decision model consequently means to take into account the uncertainty of input parameters by considering those deviations (in the form of a probability distribution).

Costs for *business process automation* are primarily affected by process-specific soft- and hardware such as acquisition costs or license fees (Alpar 1992). Because of the complexity of some processes, it is not always possible to automate the entire process or it may result in uneconomical high expenses for the latest technologies to rebuild the most complex process steps (Nikolaidou et al. 2001). Thus, by rising degree of automation, the costs increase exponentially. Business process automation bears risk, too. Due to initial investments, particularly uncertain transaction volumes are troublesome because resulting uncertain earnings could lead to reduced revenue and upfront investments may not be amortized. Therefore, one has to evaluate the effects of unstable future transaction volume, which in general cannot be forecasted exactly due to incomplete information.

Relocation and automation of business processes may lead to a reduction of workload at the origin location resulting in costs for reassigning employees to other tasks (including e.g. training costs) or even in layoffs including severance payments (Lee 1997). Furthermore, such situations may result in lower productivities due to decreasing employee motivation (Brockner 1988). Thus, the effects on employees should be considered. In the sequel, we consider severance payments, costs for reassignments as well as trainings and possible effects on productivities as *costs for social effects*.

In literature, most articles dealing with decision support on sourcing of business processes are qualitative approaches (Levina et al. 2008, Rouse et al. 2004). There are only few who propose quantitative models such as Yang et al. (2007). They identify influence factors and propose a decision model using the analytic hierarchy process method. In related research areas, however, such as IT sourcing theory some quantitative decision support approaches can be found. These are, for instance, Dutta et al. (2005), who present a system dynamics based model to find an optimal offshoring degree or Zimmermann et al. (2008), who present a method to allocate software development projects efficiently over sites using Markowitz's portfolio theory. A similar picture can be drawn for automation of business processes. While the majority of authors provide qualitative decision support (Gebauer et al. 1999, Stohr et al. 1997), there are only few quantitative approaches such as Wei et al. (1998), who propose a quantification of the optimal automation degree considering task load and process complexity, or Sheridan et al. (2000) who propose a method to quantify the expected value of the gain of either human execution or automation. Summarizing, we can state that there is a lack of quantitative research considering both sourcing and automation decisions. Additionally, to the best of our knowledge, there is no publication that takes an integrative quantitative approach combining both alternatives simultaneously. Thus, we want to fill this research gap and even include the possible effects of sourcing decisions on employees.

3 A MODEL FOR SOURCING AND AUTOMATION DECISIONS

We now introduce a model to support sourcing and automation decisions. Our leading questions in the following are: *Which degree of relocation and automation is optimal for a business process considering the specific cost structures elaborated in section 2? How do social costs influence the decision? How does a combination of two major risk factors – namely the uncertainty of effective labor costs both at the origin site as well as on the new site and the uncertainty of the future transaction volume – affect the optimal relocation and automation degree?* To answer these questions, we introduce a quantitative decision model that is developed in two steps. We introduce a basic model in section 3.1 and derive the economic effects of the different alternatives including costs for social effects. This provides an in-depth understanding of the underlying optimization problem (under certainty). In section 3.2, uncertainty is included into the model, then. This results into a risk-return integrated decision model. The section concludes with an operationalization including a simulation approach.

3.1 Basic Decision Model

We start by introducing the notations and assumptions, before describing and analyzing the model.

Notations and Assumptions

In our one-period model, we consider a FSP that currently conducts a business process at its origin site (in general a high-wage country such as the US or Germany). For each transaction processed, the FSP receives a fixed income E. Due to economic constraints, the FSP plans to reengineer and to re-evaluate the sourcing strategy for the business process. The business process (or a part of it) can be carried out at the origin site, it can be relocated to a new low-wage site or it can be automated. More precisely, we assume that the overall work required to conduct the process can be performed with any possible combination of the alternatives (retention, relocation and automation). To model this, we introduce the decision variables ω, κ and λ $(\omega,\lambda,\kappa \geqq 0)$, which are normalized to 1 $(\omega+\lambda+\kappa=1)$, i.e. their sum represents the complete workload and where ω represents the degree of work conducted at the origin site (retention), λ represents the degree of relocation and κ represents the degree of automation.

The cost structures of the alternatives differ significantly: "Manual" work at the origin or at the new site causes costs that are assumed to be variable and proportional to the amount of work. For the new site additionally transaction costs T arise due to international coordination. Automation causes a fixed upfront investment depending on the specific degree of automation chosen. These costs are assumed to grow exponentially by γ ($\gamma>1$) with the degree of automation and with a maximal amount of money A for full automation.

At present, the FSP processes an amount of transactions V_0 at its origin site. In the following period, the FSP has to conduct a number of transactions V_1, i.e. the total earnings in the following period can be calculated by $V_1 \cdot E$. As outlined in the introduction, we are especially interested in situations where the transaction volume is expected to grow, i.e. $V_1>V_0$. If – due to relocation and/or automation – the new transaction volume conducted at the origin site falls below V_0, costs for social effects S, which represent the estimated costs for a complete shutdown of the origin site, as discussed in section 2 have to be considered.

Model Description

To reduce writing overhead in the following, we introduce the index n to denote the different sites, work can be conducted at. The origin site (n=1) and the new low wage site (n=2) are characterized by their productivity P_n and their loaded costs LC_n. To determine the effective labor costs of the business process at a site, we calculate the ratio of loaded costs and productivity as shown in equation 1).

1) $$L_n = \frac{LC_n}{P_n}$$

The overall effective labor costs can be calculated either for the origin site by $\omega \cdot V_1 \cdot L_1$ or the new site by $\lambda \cdot V_1 \cdot (L_2+T)$. Depending on the degree of automation κ, the maximal expenses for automation A and the exponent γ, automation costs are calculated by $\kappa^{\gamma} \cdot A$.

Costs for social effects only arise, if the share of volume retained at the origin site falls below the original volume because in this case the workforce on the origin site would be larger than required. The costs are increasing proportionally depending on the reduction in volume. We model this applying the maximum function, i.e. $\max\left(\frac{V_0}{V_1}-\omega,\, 0\right)\cdot S$.

Finally, we substitute ω by $1-\kappa-\lambda$ and express the return only depending on κ and λ as described by the following objective function:

2) $$R(\kappa,\lambda)=V_1 \cdot E-\left((1-\kappa-\lambda)\cdot V_1 \cdot L_1+\lambda \cdot V_1 \cdot (L_2+T)+\kappa^{\gamma} \cdot A+\max\left(\frac{V_0}{V_1}-(1-\kappa-\lambda),0\right)\cdot S\right) \rightarrow \max!$$

$$s.t.: \lambda \geqq 0;\ \ \kappa \geqq 0;\ \ \lambda+\kappa \leqq 1$$

The optimization problem can be solved by differentiating between the two cases: no costs for social effects occur and costs for social effects occur. In the first case, it is sensible to automate process steps until the marginal costs of automation reach the marginal costs of human conduction (relocation or retention). Interestingly, an automation degree of κ=0 is not a feasible solution, i.e. under the given assumptions it is always reasonable to automate at least a marginal share of the process. Since the costs of relocation increase proportionally with λ and the costs of retention increase proportional with $\omega(=1\text{-}\kappa\text{-}\lambda)$, the relationship between relocation and retention is rather simple: If the sum of effective labor costs at the new site and transaction costs is higher than the effective labor costs at the origin site ($L_2+T > L_1$), then the maximal possible volume (considering of course the part that is to be automated) should be kept at the origin site. Otherwise, the maximal possible volume (in case no costs for social effects occur: $\lambda = 1 - \kappa - \frac{V_0}{V_1}$) should be relocated. In the second case, costs for social effects occur. Generally, the directions of the relationship between the alternatives are equal in this case. Comparing the solutions of the two cases, finally delivers the solution to the optimization problem. A general (and not very surprising) finding is that with prohibitive high costs for social effects and in case costs for relocation are smaller than costs for retention, the optimal automation degree and the optimal relocation degree are chosen so that social costs just do not occur.

Having understood these fundamental relationships, we can now extend the model and analyze the effects of uncertainty.

3.2 Analyzing the Effects of Uncertainty on the Decision via Simulation

Since unpredictable effects may occur during the planning horizon, we have to consider uncertainty. We simultaneously consider two important risk factors, uncertainty of the effective labor costs and of the transaction volume, in the model. For this integrated approach, we introduce Assumption 1:

Assumption 1: *To model risk, the effective labor costs $\widetilde{L}_n$ and the transaction volume $\widetilde{V}_1$ are assumed to be normally distributed (N(μ,σ)) random variables. Risk is hereby understood as possible negative or positive deviation from the given expected value $E(\widetilde{L}_n) = \mu_{L_n}$, $E(\widetilde{V}_1) = \mu_{V_1}$ and is quantified by the given standard deviation $\sigma(\widetilde{L}_n) = \sigma_{L_n}$, $\sigma(\widetilde{V}_1) = \sigma_{V_1}$, respectively.*

As the input parameters $\widetilde{L}_n$ and $\widetilde{V}_1$ for the return function are now uncertain, its result $\widetilde{R}$ is uncertain, too. This uncertainty has to be considered by the decision maker. This is accomplished using a preference function integrating return and risk, i.e. each allocation represented by its specific risk/return position shall be valuated with a preference function. A prerequisite to the preference function is the decision maker's utility function that puts possible alternatives in an order according to its risk aversion. This is expressed by the following assumption:

Assumption 2: *There exists a utility-function $u(\widetilde{R})$, which assigns a specific utility to every random variable $\widetilde{R}$ and which is compatible with the Bernoulli-principle. We assume a risk averse decision maker that maximizes utility.*

3) $u(\widetilde{R}) = 1 - e^{a\widetilde{R}}$

Based on this utility function, one can derive a preference function that integrates return and risk in a classical μ-σ-rule and is compatible – under the constraints of normally distributed random variables (Assumption 1) and a risk averse decision maker – with the Bernoulli-principle (Assumption 2) is given by the following equation (cp. Freund 1956):

4) $\Phi_R(\kappa, \lambda) = \mu_R - \frac{1}{2} \cdot \alpha \cdot \sigma_R^2 \quad \rightarrow \quad Max!$

This function calculates a preference Φ_R based on the expected value of the return $\mu_R=E(\widetilde{R})$, the risk $\sigma_R=\sigma(\widetilde{R})$ in realizing the return, quantified by the standard deviation of the expected value, and the risk aversion of the decision maker *α,* which is represented by the Arrow-Pratt parameter and is expressed by a positive value (Arrow 1971).

The optimization problem is far more complex than the problem described by equation 2). The expected return μ_R and the variance σ_R^2 can be derived from equation 2) and from the distribution parameters of the input parameters $\widetilde{L}_n$ and $\widetilde{V}_1$ (μ_{L_n}, σ_{L_n} and μ_{V_1}, σ_{V_1} respectively).

In case only one risk factor exists (σ_{L_1} and either σ_{L_2} or σ_{V_1} equals 0), it is even possible to determine an analytically closed solution to the optimization problem. For lack of space, we do not include the entire mathematical analysis here and only summarize the most important results: It can be shown that rising uncertainty of the effective labor costs at the new site (i.e. higher σ_{L_2}), e.g. caused by unpredictable wage developments or productivity deviations, in tendency fosters automation as the less risky alternative. In contrast, rising uncertainty of the transaction volume (i.e. higher σ_{V_1}) leads to a higher share of human work (either retention or relocation) and less automation. This is due to high upfront costs for automating a process and in turn probably lower earnings resulting from uncertain transaction volumes. Interestingly, however, if processes are not automated at all (automation degree equals zero), then the uncertainty of the transaction volumes may also affect the relocation degree.

Determining a closed analytical solution to the optimization problem is not possible anymore, if more than one risk factor is considered at a time because the integrated risk-return model contains several stochastic random variables that are multiplied. Thus, we employ a simulation approach.

3.3 Operationalization and Simulation

Now, we demonstrate how to apply the model in a real world case. It refers to a typical decision situation and is based on real business cases of a FSP. The names as well as all possible identifying details are omitted and the business case data have been anonymized for reasons of confidentiality.

The A-BANK, a large European FSP, operates all over the globe and plans to reengineer and reorganize several of its business processes. For reasons of clearness, we consider only the process for handling high value payments and checks for business clients which consists of 23 process steps. Besides cost reduction, the reason for reorganizing the process is motivated by an expansion and the number of transactions is expected to grow from presently 1,210,000 to 2,200,000 in the next period.

The following alternatives have been identified by A-BANK for the process under consideration:

- Site 1 – Germany: Up to this point, A-BANK processed their checks at its origin site characterized by high wages, but also high productivity. If less transaction volume than at the beginning is handled at this site, it would result in layoffs and/or partial reassignment of staff to new tasks requiring additional training. Both may result in increased costs and resistance of staff. A complete shutdown of the process at the site is estimated to result in costs for social effects of about €2.5 mn.
- Site 2 – India: A-BANK runs a large shared service center in India. This offshore site has become very popular due to the large and mature talent pool. A disadvantage lies in the cultural differences to Western countries. The labor costs are significantly lower than in Germany, but with a considerable large rate of increase. In addition to labor costs, transaction costs due to international distribution arise. Thus, the total costs for each transaction consist of labor and transaction costs.
- Process Automation: A-BANK is able to implement several process steps with a new software system and can install OCR systems for check handling. There are different levels that differ in the scope of the automation and in the recognition quality. The latter influences the manual effort required in subsequent process steps. For instance, low recognition quality means that (manual) controlling steps are still required in the process. By rising degree of automation, the costs are expected to increase exponentially.

The introduced model should be utilized to find an optimal allocation of the process steps to the different alternatives. One of the major challenges was to parameterize the model (concerning e.g. automation costs). For this purpose, we used data of the business case. For each process step, automation costs were estimated. Similar process steps were clustered by complexity and costs together with experts of the A-Bank. The analysis revealed that some process steps were easy and inexpensive to automate whereas others were extremely complex or difficult resulting in very high automation costs. Five different types could be differentiated with estimated costs for the automation as shown in Table 1 and Figure 1.

Type	Quan-tity	Estimated workload share concerning the process [%]		Estimated automation costs [€ mn]	
		per step	per type	per step	per type
I	9	4	36	0.14	1.26
II	7	4	28	0.62	4.34
III	5	4.8	24	1.40	7.00
IV	1	5.5	5.5	4.00	4.00
V	1	6.5	6.5	4.40	4.40
∑	23	-	100	-	21.0

Table 1. Breakdown of the automation costs

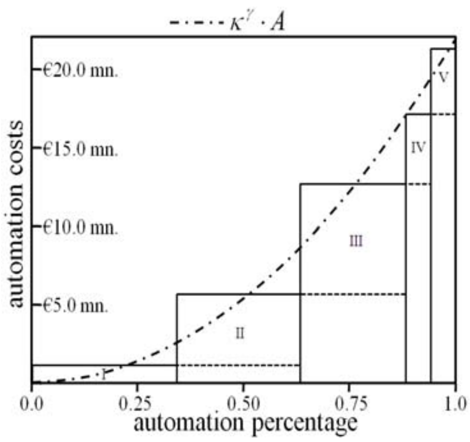

Figure 1. Derivation of A and γ

Based on the cost estimations, we approximated automation costs to increase exponentially with an exponent γ of about 2.0 (cp. Figure 1). The maximal automation costs (parameter A) were determined by the sum of the costs for automating all steps, which were estimated to €21 mn.

Besides the estimations for A and γ, the estimation of the risk aversion parameter α is a major challenge. To this end, we compared the cost estimations and risk surcharges of the business case with the estimated variances of our approach. Based on the ratio of investments over estimated risk, we assume a constant risk aversion parameter α with the value of 0.0001 to be reasonable.

Table 2 summarizes the input parameters for the simulation:

	V_0	V_1	E	P_n	LC_n	T	S	A	γ	σ_{V_1}	σ_{L_n}
Site 1	1,210,000	2,200,000	€4.8	1.1	€5.0	-	€2.5 mn	€21 mn	2	0-20%	3%
Site 2				0.7	€1.9	€0.8					0-20%

Table 2. Model parameters for the simulation

The simulation works as follows: For each possible κ-λ-combination (we iterate over the possible interval [0,1] for both κ and λ in 0.01 steps), we draw values for the normally distributed random variables $\widetilde{L}_n$, and $\widetilde{V}_1$ using the Monte-Carlo method (according to the distribution parameters σ_{V_1} and σ_{L_n}). With these values, we calculate the return $\widetilde{R}$ according to the return function 2). This procedure is repeated 10,000 times (denoted by *i*). With the resulting 10,000 values for $\widetilde{R}$, we can calculate the mean μ_R and their standard deviation σ_R:

$$5)\ \mu_R = \frac{1}{i} \cdot \sum_{i}^{10000} \widetilde{R}_i \quad \wedge \quad \sigma_R = \sqrt{\frac{1}{i-1} \sum_{i}^{10000} (\widetilde{R}_i - \mu_R)^2}$$

These values are inserted into the preference function (equation 4)[1]). Repeating this procedure for each possible κ-λ-combination, we get a value Φ_R for each κ-λ-combination. Consequently, the κ-λ-combination with the highest value of Φ_R is the optimal allocation for the current constellation of input parameters.

To analyze the influence of increasing risk to the optimal κ and λ, we repeat this procedure with different values for σ_{V_1} and σ_{L_2}, where we increase both σ_{V_1} and σ_{L_2} from 0% by 0.5% until 20% and determine for each σ_{V_1}-σ_{L_2}-combination the optimal κ-λ-combination as described above. σ_{L1} always has to value of 3% during the whole process.

Figure 2 depicts the change of the optimal automation degree (κ) (left plot) and relocation degree (λ) (right plot) for increasing both σ_{V_1} and σ_{L_2}. For illustration purposes, we extracted profile cuts I, II, III and IV (cp. Figure 2) and show them in Figure 3 and Figure 4:

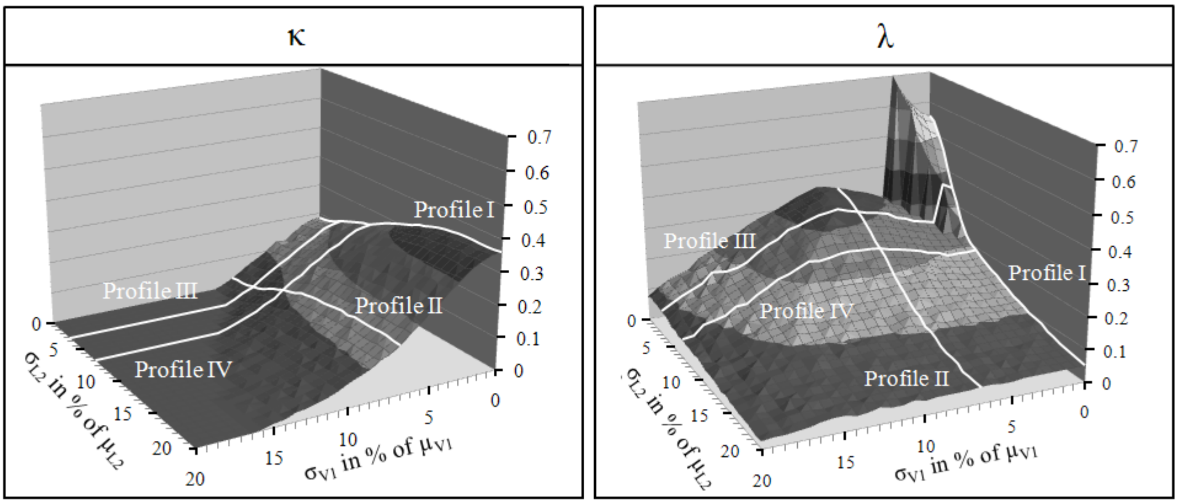

Figure 2. Graphical representation of the results of the simulation

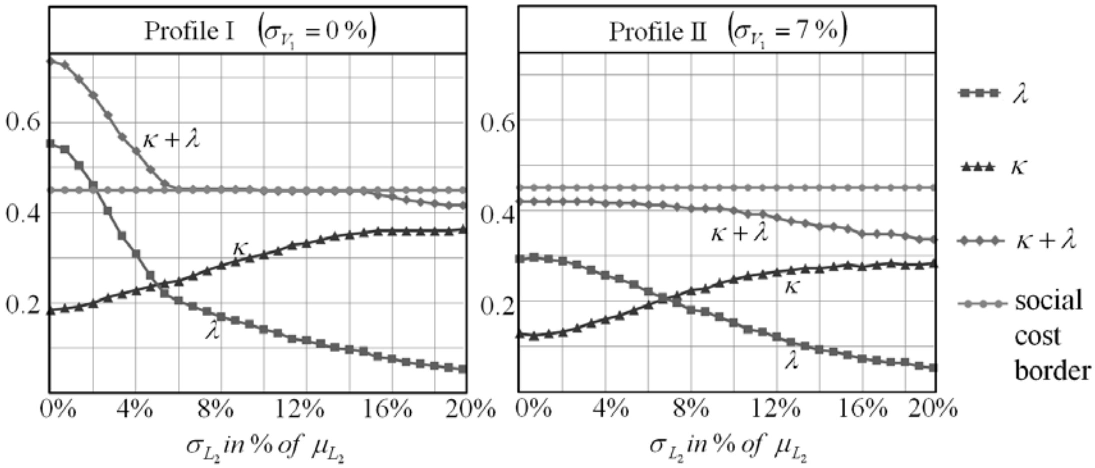

Figure 3. Profile cuts of Figure 2 (Profiles I and II)

[1] We are aware that the return R as specified in the objective function (cp. equation 2)) may not be normally distributed in any case (because we multiply several normally distributed random variables and a maximum function), thus, violating the Bernoulli-Principle. However, an analysis of the distributions in the simulation approach has shown that R is at least approximately normally distributed, i.e. the differences cause little and acceptable deviations in the results.

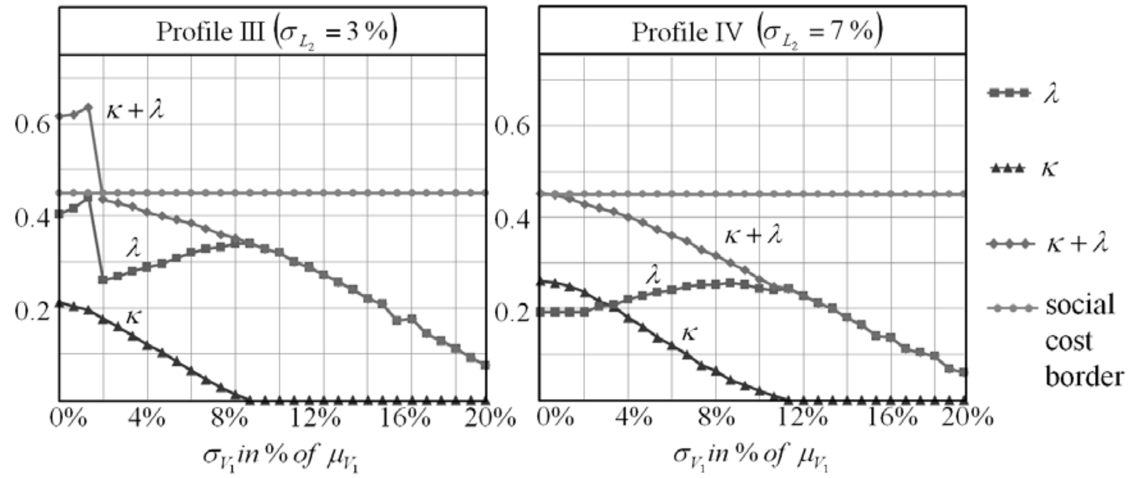

Figure 4. *Profile cuts of Figure 2 (Profiles III and IV)*

In the following, we analyze the influences of the different risk factors and of costs for social effects.

First, the *influences of the risk factors* are analyzed. With growing uncertainty of the effective labor costs at the new site relocation becomes less attractive and is substituted by automation (cp. Profile I). These effects can be observed up to the point where automation becomes too expensive due to increasing process step complexity. After exceeding this point, the automation degree stagnates (cp. Profiles I and II). Therefore, automation can be seen as a substitute for relocation as long as it is not surpassed in attractiveness by retention. Additionally, we can state that automation becomes less attractive with growing uncertainty of the transaction volume. When the automation degree becomes zero, relocation becomes less benefiting, too (cp. Profile III and IV). Regarding both factors together, we can state that in the area of low uncertainty the degree of relocation reacts very sensitive on deviations. These effects, which appear in particular due to uncertainty of the transaction volume (cp. Profile III), are caused by the linear behavior of relocation costs. Thus, in the area of low risk little changes may have enormous effects on the optimal allocation resulting in completely different relocation degrees due to the mutual effects of uncertainties and costs for social effects. Furthermore, uncertainty of the transaction volume causes stronger effects than uncertainty of effective labor costs as both automation and relocation are affected (cp. Profiles III and IV). Though, the results show that automation is still a viable alternative even with volume risk of 7% because it is only - in opposite to relocation - affected by uncertainty of the volume and not by uncertainty of the effective labor costs.

Uncertainty of effective labor costs at the origin site has little effect on the automation degree. With rising uncertainty of the effective labor costs at the low-wage site, automation is still rising slowly (cp. Profiles I and II). In contrast, the relocation degree is affected stronger as relocation directly profits from rising unattractiveness of the origin site due to higher uncertainty of effective labor costs at the origin site. This effect is illustrated in Profiles I and III by the very high relocation degrees in particular in the range of low uncertainty of effective labor costs at low-wage site.

Costs for social effects generally weaken the attractiveness of relocation and automation. While – even high – costs for social effects are accepted when there is no or only low uncertainty (cp. Profiles I and III), increasing uncertainty fosters the effects of these costs since cost reduction potential of relocation and automation becomes uncertain and the costs for social effects also support this trend (cp. Profiles II and IV). In general, we can state that avoiding costs for social effects, for instance by moderate automation and relocation, is a preferable option as the sum of the optimal allocation λ and κ is running on or nearby the *social cost border* (cp. Profiles I and II).

Summarizing, we can state that with growing uncertainty of the transaction volume keeping the work at the high wage and less risky site is the preferred alternative of the decision maker. Second, if the volume can be predicted very precisely, relocation – even with willingness to pay costs for social effects – is a realistic option. Thus, accepting these costs may be necessary to obtain a risk/return efficient allocation. However, the decision maker should have complete information or should at least be able to estimate parameters with the required precision. Yet, with increasing risk, taking costs for social effects should be avoided. Third, automation is an interesting alternative bearing cost reduction potential, if the uncertainty of the transaction volume is not too high. Here, the decision maker should first choose process steps that are easy and inexpensive to automate.

4 CONCLUSION

Though relocating and automating business processes bear much economic potential, there are only few quantitative decision support models. In particular, there is a lack of research considering both alternatives in an integrated approach. Thus, in this paper we propose a risk/return based approach to calculate optimal degrees of relocation and automation for individual business processes considering the specific cost structures and risk profiles. In comparison to prior research, this approach comes up with several enhancements: First, we simultaneously consider relocation and automation. Second, such decisions also have effects on the original site since jobs may be abolished. Hence, we consider such social effects by quantifying negative outcomes of disestablishing jobs. Finally, we analyze the influence of uncertainty. Applying the model, the results provide a recommendation for automation or site selection for business process steps. Employing data of a business process of a major FSP, the applicability of this approach is illustrated.

In practice, sourcing and automation decisions for business processes gain more and more importance. With the presented model, we can support such decisions and provide evidence for several facts. First, automation becomes unattractive, if information of the future transaction volume is incomplete. But, automation is a viable alternative, if the effective labor costs cannot be predicted precisely. Second, relocating process steps is affected negatively both by uncertainty of transaction volume and uncertainty of effective labor costs. Third, taking costs for social effects is only sensible, if the decision maker has sufficient information. This is an interesting finding since it suggests that social effects should be assessed carefully. Finally, not considering uncertainties may lead to false decisions.

Furthermore, there is still extension potential. First, we assumed that human workmanship causes variable costs whereas automation causes fixed costs and modeled the relocation alternative as cost center. However, there are still other cost types due to other possible contracting types or charging structures such as fixed price payments or internal profit centers. These types could be considered as well. Second, we assumed infinitely divisible processes. However, in reality processes may not always be cut as proposed by the model. Still, most processes consist of several steps and can nearly be allocated as optimized. Thus, feasible discrete allocations may lie near the theoretical optimum, also delivering a good economic solution. Third, especially regarding the automation considering outsourcing possibilities such as on-demand solutions would be another way for extension as the costs could be variable in this case. However, this implies that a process step is offered by external vendors as required. Summarizing, the analysis of the proposed model for supporting sourcing and automation decisions not only revealed interesting insights, it can also form the foundation for further research.

References

Agrawal, V., Farrell, D. and Remes, J.K. (2003). Offshoring and beyond. McKinsey Quarterly, Special Edition, 24-35.

Alpar, P. (1992). Automation of Banking Functions and Its Managerial Implications. IEEE Transactions on Engineering Management, 39 (4), 378-385.

Arrow, K.J. (1971). The Theory of Risk Aversion. Arrow, K.J. (Ed.): Essays in the Theory of Risk-Bearing, 90-120.

A.T. Kearney (2007). Offshoring for Long-Term Advantage.

Bainbridge, L. (1983). Ironies of automation. Automatica, 19 (6), 775-780.

Bloch, M. and Spang, S. (2003). Reaping the benefits of business-process outsourcing. McKinsey on IT, 1-9.
Brockner, J. (1988). The effects of work layoffs on survivors: Research, theory, and practice. Research in Organizational Behavior, 10 (1), 213-256.
Criscuolo, C. and Leaver, M. (2005). Offshore Outsourcing and Productivity. Presented at OECD conference on Globalisation of Production.
Dutta, A. and Roy, R. (2005). Offshore Outsourcing: A Dynamic Causal Model of Counteracting Forces. Journal of Management Information Systems, 22 (2), 15-35.
Everest Research Institute. (2005). Global Outsourcing Annual Report.
Farrell, D. (2005). Offshoring: Value Creation through Economic Change. Journal of Management Studies, 42 (3), 675-683.
Freund, R.J. (1956). The Introduction of Risk into a Programming Model. Econometrica, 24 (3), 253-263.
Gartner Research (2007). Gartner on Outsourcing 2007-2008: Business Process Outsourcing.
Gartner Research (2008a). Four Steps to BPO Success.
Gartner Research (2008b). BPO Imperatives for Success.
Gebauer, J. and Scharl, A. (1999). Between Flexibility and Automation: An Evaluation of Web Technology from a Business Process Perspective. Journal of Computer-Mediated Communication, 5 (2).
Lacity, M.C. and Willcocks, L. (2000). Global Information Technology Outsourcing: In Search of Business Advantage. 1st edition. John Wiley & Sons, Inc. New York, NY, USA.
Lankford, W.M. and Parsa, F. (1999). Outsourcing: a primer. Management Decision, 37 (4), 310-316.
Lee, P.M. (1997). A comparative analysis of layoff announcements and stock price reactions in the United States and Japan. Strategic Management Journal, 18 (11), 879-894.
Levina, N. and Su, N. (2008). Global Multisourcing Strategy: The Emergence of a Supplier Portfolio in Services Offshoring. Decision Sciences, 39 (3), 541-570.
Levy, D.L. (2005). Offshoring in the New Global Political Economy. Journal of Management Studies, 42 (3), 685-693.
neoIT (2006). Offshore Insights - Market Report Series, 4 (4).
Nikolaidou, M., Anagnostopoulos, D. and Tsalgatidou, A. (2001). Business process modelling and automation in the banking sector: A case study. International Journal of Simulation Systems, Science & Technology, 2 (2), 65-76.
Quélin, B. and Duhamel, F. (2003). Bringing Together Strategic Outsourcing and Corporate Strategy: Outsourcing Motives and Risks. European Management Journal, 21 (5), 647-661.
Rouse, A.C. and Corbitt, B. (2004). IT-supported business process outsourcing (BPO): The good, the bad and the ugly. 8th Pacific-Asia Conference on Information Systems (PACIS), Shanghai, China.
Sheridan, T.B. and Parasuraman, R. (2000). Human Versus Automation in Responding to Failures: An Expected-Value Analysis. Human Factors, 42 (3), 403-407.
Stohr, E.A. and Zhao, J.L. (1997). A technology adaptation model for business process automation. In Proceedings of the 30th Hawaii International Conference on System Sciences, 4, 405-414.
Vestring, T., Rouse, T. and Reinert, U. (2005). Hedge your offshoring bets. MIT Sloan Management Review, 46 (3), 27-29.
Wei, Z., Macwan, A.P. and Wieringa, P.A. (1998). A quantitative measure for degree of automation and its relation to system performance. Human Factors, 40 (2), 277-295.
Winkler, J., Dibbern, J. and Heinzl, A. (2006). Success in Offshoring of Application Development-Does Culture Matter? In Proceedings of the 14th European Conference on Information Systems (ECIS) (Ljunberg, J. and Andersson, M. (Ed.)), Göteborg, Sweden, l640-1650.
Yang, D.H., Kim, S., Nam, C. and Min, J.W. (2007). Developing a decision model for business process outsourcing. Computers and Operations Research, 34 (12), 3769-3778.
Zimmermann, S., Katzmarzik, A. and Kundisch, D. (2008). IT Sourcing Portfolio Management for IT Services Providers – A Risk/Cost Perspective. Forthcoming: In Proceedings of 29th International Conference on Information Systems (ICIS).