

The Impact of Human Resource Sharing on IT Project Risk

Completed Research Paper

Christian Meier

University of Paderborn,
Warburger Str. 100,
D-33098 Paderborn
Christian.Meier@wiwi.upb.de

Steffen Zimmermann

University of Innsbruck
Universitaetsstr. 15,
A-6020 Innsbruck
Steffen.Zimmermann@uibk.ac.at

Vlad Nicolau

University of Innsbruck
Universitaetsstr. 15,
A-6020 Innsbruck
Vlad.Nicolau@gmail.com

Abstract

The increasing number of sophisticated IT projects and the scarcity of skilled human resources increasingly challenge IT project portfolio managers with the need to do 'more with less'. Consequently, resource sharing among projects provides a widely applied instrument to reduce project costs. However, resource sharing may not only result in cost synergies but also in risk effects. In contrast to cost synergies, these risk effects are rarely considered in business practice and quantification efforts of these risk effects are missing in the literature. Our research is the first to provide a systematic quantitative empirical analysis of the relationships between resource sharing and project risk. We find evidence that projects sharing their human resources are more likely to fall short in their planned scope while being more likely to comply with their planned timeline.

Keywords: Project Portfolio Management, Resource Sharing, Resource Interactions, Project Risk, Empirical Analysis

Introduction

In 2014, companies world-wide have spent 3.8 trillion USD for Information technology (IT), and the investment slope is expected to point further upwards in the years to come (Gartner 2014). At the same time, IT departments face the requirement to spend less money on IT operations and infrastructure, and more on revenue-producing projects¹ in order to facilitate competitive advantage (Thibodeau 2014). As a result, IT managers face an increasing number of challenging and sophisticated IT projects, while urgently required key resources like skilled IT personnel are chronically scarce (CompTIA 2012). Naturally, IT portfolio managers need to do ‘more with less’ and thus, have to efficiently allocate the available resources to the IT projects included in their IT project portfolio. As a managerial instrument to reduce project costs, two or more projects may share some of the required resources (Heinrich et al. 2014). In the corresponding research literature, *resource sharing* typically results in *resource interactions* among the projects. There is a common understanding that these resource interactions occur when the total resource requirements for projects in a given portfolio cannot be represented as the sum of the resource requirements of all of the individual projects (Eilat et al. 2006). It is repeatedly emphasized in the literature that exploiting these resource interactions translates into savings in project portfolio costs (Gear and Cowie 1980; Heinrich et al. 2014; Lee and Kim 2001; Santhanam and Kyparisis 1996). Consequently, a considerable body of knowledge has emerged that provides valuable approaches to minimize project portfolio costs by sharing resources already during project planning².

However, resource sharing³ may not only result in *cost synergies* but also in *risk effects*. For example, a number of projects sharing the same staff member may all be negatively affected if the staff member becomes unavailable (e.g., due to illness). This is in line with Heinrich et al. (2014), who state that unexpected events like, e.g., loss of a resource, or unpredicted peaks of demand for a resource may lead to bottlenecks and capacity overloads with consequences for multiple projects when resources are shared. The authors argue that resource sharing leads to a lower average resource supply, which in turn may increase the probability for the occurrence of the aforementioned bottlenecks and capacity overloads (Heinrich et al. 2014). For human resources these arguments are supported by qualitative insights derived from a case study by Engwall and Jerbrant (2003). The authors find that, when human resources need to be redistributed in highly interdependent project landscapes, it often produces negative effects, e.g., in form of delays, that are propagated to other projects in the portfolio (Engwall and Jerbrant 2003).

Quantification efforts for different degrees of resource sharing and empirical evidence of the risk effects resulting from resource sharing are missing in the literature. We address this research gap by answering the following research question: *How does human resource sharing influence IT project risk?* We provide a first systematic empirical analysis of the relationship between resource sharing and project risk. Due to the high relevance of IT personnel (Engwall and Jerbrant 2003) we focus on sharing of human resources in a first step. Our analysis is based on a real world dataset of 340 human resources that were staffed on 99 IT projects by the IT project portfolio management department of a large production company. We operationalize human resource sharing by defining a specific measure called resource sharing degree (RSD), as described later on in the paper. We operationalize project risks as the observable deviation from the projects planned timeline, budget, and scope. Based on the general idea of Modern Portfolio Theory (Markowitz 1952) and the current body of knowledge on resource interactions, three hypotheses are formulated and tested using Logistic Regression models.

We find first evidence that projects that share a large amount of their human resources with other projects are more likely to fall short in their planned scope. Further, and surprisingly, our results indicate

¹ A project can be defined as “a temporary endeavor undertaken to create a unique product, service or result” (PMI 2015).

² Comprehensive overviews over such approaches can be found, for example, in Chien (2002) in the context of R&D projects, and in Kundisch and Meier (2011a) for IT projects.

³ We understand resource sharing as a managerial instrument to create and/or exploit resource interactions among projects. On an economic level, we refer to *cost synergies* as the cost savings and *risk effects* as the changes in project risk resulting from resource sharing.

that projects that share their human resources are more likely to comply with their initially planned timeline.

The article is structured as follows: In the succeeding section, we discuss the relevant literature for our work. Then, the theoretical background of the paper as well as our research model is presented. In the Dataset section, we provide descriptive statistics and discuss the unique characteristics of our dataset. The description of the main variables for our empirical model is followed by the presentation of the results of the regression analyses. In the penultimate section, limitations of our work as well as implications for research and practice are outlined. Finally, the paper concludes with a short summary of the results.

Related Literature

The investigation of resource interactions among a large number of project candidates and their adequate consideration already during IT project portfolio Selection (PPS) is an important challenge. Resource interactions arise from the shared use of either physical IT infrastructure, software (i.e., applications and services), or labor. A widely accepted definition for resource interactions has been provided by Eilat et al. (2006), who describe that resource interactions may occur when the total resource requirements for projects in a given portfolio cannot be represented as the sum of the resource requirements of all of the individual projects. Due to the multi-faceted nature of project portfolio Management (PPM), several research strands are relevant for our study. The IS, R&D, and OR literature provides us with the methods and frameworks necessary to methodically incorporate resource interactions into PPS. The human resource and IT project management literature strands deliver valuable insights into the managerial aspects of human resource sharing in IT project portfolios. In the following paragraphs, we discuss relevant work from these literature strands.

Resource interactions arise from the shared use of either physical IT infrastructure, software (i.e., applications and services), or labor. This type of interaction among projects has been analyzed particularly in the context of R&D projects (e.g., by Aaker et al. 1978; DeMaio et al. 1994; Doerner et al. 2006; Eilat et al. 2006; Fox et al. 1984; Gear and Cowie 1980; Stummer and Heidenberger 2003) as well as in the context of IT projects (e.g., by Kundisch and Meier 2011b; Lee and Kim 2001; Santhanam and Kyparisis 1996). The approaches suggested in the IS, R&D and the OR literature strands typically focus on providing useful techniques for modeling resource interactions within mathematical decision models and for solving PPS problems while trying to exploit resource interactions. Important achievements in the area of modeling interactions among more than two projects (e.g., Santhanam and Kyparisis 1996; Stummer and Heidenberger 2003), and solving optimization problems with a single (e.g., Fox et al. 1984; Santhanam and Kyparisis 1996) or multiple objectives (e.g., Doerner et al. 2006; Lee and Kim 2001) have been made by researchers from these fields. Many of these approaches have particularities, from considering resources as hard- and software (e.g., Lee and Kim 2001), materials and facilities (e.g., Aaker and Tyebjee 1978), human resources (e.g., Eilat et al. 2006), or combinations of the aforementioned (e.g., Kundisch and Meier 2011b).

What most of the approaches from these literature strands have in common is that they take “a somewhat methodological perspective on PPM, focusing on algorithms for optimizing portfolios [...]” (Kaiser et al. 2015). Thereby, a discussion of the mechanisms behind resource interactions as well as the potential risks effects associated with exploiting these resource interactions is missing.

In the IS and management literature, few articles can be found which discuss risks and their economic effects associated with human resource utilization in the context of IT projects. Based on a Delphi survey, Schmidt et al. (2001) present a rank-ordered list of risk factors that affect software projects. In the context of human resource staffing, they identify staffing volatility (at some point in the project, losing key human resources) and insufficient availability of human resources as high risk factors for project. Translated to the project portfolio level and to the context of human resource sharing these considerations are in line with Buhl (2012) and the argument that unavailability of a shared resource may negatively affect all sharing projects. In a first qualitative case study Engwall and Jerbrant (2003) analyze the effects of resource allocation on project success. The authors discuss the underlying mechanisms behind the ‘resource allocation syndrome’ and find that, when human resources need to be redistributed due to unplanned events (e.g., sickness) in highly interdependent project landscapes, it often produces negative effects that are propagated to other projects in the portfolio (Engwall and Jerbrant 2003).

The literature on work productivity provides evidence that human resource sharing can have negative effects on the overall productivity of employees. In this context, Diwas (2013) finds that “excessive multitasking can lead to a cognitive bottleneck, and taking on several tasks concurrently may actually decrease productivity”. In line with others, Rubinstein et al. (2001) find that constantly switching between tasks is associated with switching costs for restarting and refocusing, which in turn can lead to a lower effective processing capability. In the context of project portfolio management, projects that heavily rely on team members simultaneously working in a number of projects are likely to be faced with situations in which they have to multi-task more frequently. According to the findings reported in the literature, this potentially leads to decreased work quality compared to projects with a more focused workforce. In this light, Heinrich et al. (2014) argue that misjudgments in the resource requirements and in the estimates of potential cost synergies can lead to resource over-utilization, which in turn is identified by Kappelman et al. (2006) as one of the major risk factors for IT project success.

Heinrich et al. (2014) go further in analyzing resource interactions by focusing on the effects associated with them. The authors define resource interaction effects as the “economic impacts of exploited resource interactions on expected costs and risk” (Heinrich et al. 2014). Based on this understanding, the authors divide interaction effects into *cost interaction effects* and *risk interaction effects*. On an economic level, cost interaction effects are observable as a decrease or increase in the overall resource costs generated by sharing the resources. Risk interaction effects describe the economic effects of risks occurring due to resource sharing. Heinrich et al. (2014) identify that in the literature, resource interactions find frequent discussion in terms of cost interaction effects, while their corresponding risk interaction effects are widely neglected. The authors provide a first conceptual model to discuss both aspects of resource interactions in conjunction. Based on their conceptual model, Heinrich et al. (2014) theorize that exploiting cost interaction effects translate into risk interaction effects as well. The authors also identify internal as well as external risk factors associated with resource sharing. Internal risk factors can be influenced by the project management and include misjudgment of the resource requirements. External risk factors cannot be influenced by project management and include, for example, unplanned unavailability of a human resource due to illness.

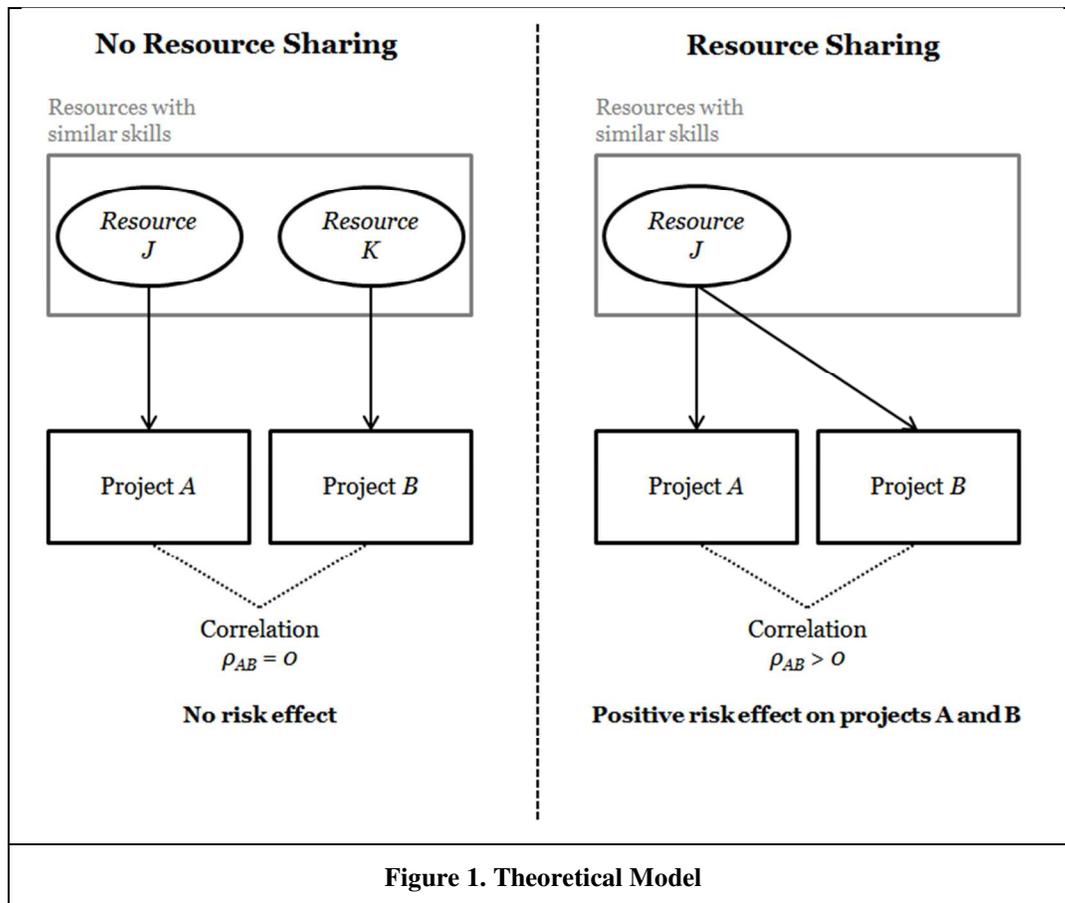
All the above mentioned contributions provide valuable insights for understanding and exploiting the effects of resource sharing in project portfolio environments. These discussions, to date, are based on conceptual models and qualitative studies. However, quantitative empirical studies that investigate the existence and the potential effects of risk interactions due to resource sharing on project portfolios are missing in the literature. Our work aims at filling this research gap by being among the first to quantitatively investigate the relationships between human resource sharing and project risk in a multi-project environment.

Theoretical Background and Research Model

The goal of this study is to examine the relationships between human resource sharing and project risk in IT project portfolios. The key premises for our research model (see fig. 2) are that firms already naturally include cost synergies resulting from resource sharing into their planning process. To operationalize the risk effects from resource sharing, we first have to establish an understanding of IT project success. In line with the literature (e.g., Morris and Pinto 2007; Standish Group 2013) and the renowned ‘project management triangle’, we consider a project successful, when it delivers its *planned scope* within a *planned timeline* while consuming not more than the *planned budget*. To operationalize risk, we draw from ideas of Modern Portfolio Theory (MPT). MPT owes its origins to a seminal paper by Harry Markowitz from 1952. In the context of financial assets, MPT understands risk as the deviation from the expected returns of the assets. In IT project portfolios, ‘assets’ can be compared to ‘projects’. Ideas from MPT have already been successfully transferred to the IT project portfolio domain in the past. For example, Butler et al. (1999) use MPT to support the selection of security portfolios in the context of software development decisions. Asundi and Kazman (2001) have employed MPT in conjunction with real options theory to support the selection of a portfolio of concurring software investments. Zimmermann et al. (2008) and Zimmermann et al. (2012) applied MPT to develop a decision model for supporting sourcing decisions of software development projects of an IT service provider.

In the context of this paper, we operationalize risk – in a first step – as the unwanted (downside) *deviation from the planned project budgets and timelines*. Further, we observe a project owner-reported

deviation from the planned project scope. Based on the findings in the literature, we argue that resource sharing creates resource interactions among the involved projects. As discussed before, such resource interactions are associated with risks effects (e.g., a shared resource that unexpectedly gets ill may not only endanger project success of one project but of all projects this resource is working for). In MPT, risk effects that result from interactions among assets (in our case IT projects) are measured by correlations. Since resource interactions affect the IT project success of all involved projects in the same direction (e.g. right hand side of Figure 1: project A and B may be delayed if resource J is shared among both projects and unexpectedly drops out), we argue for positive correlations resulting from resource sharing compared to no correlation if resources are not shared (e.g. left hand side of Figure 1: only project A may be delayed if resource J is not shared and drops out unexpectedly).

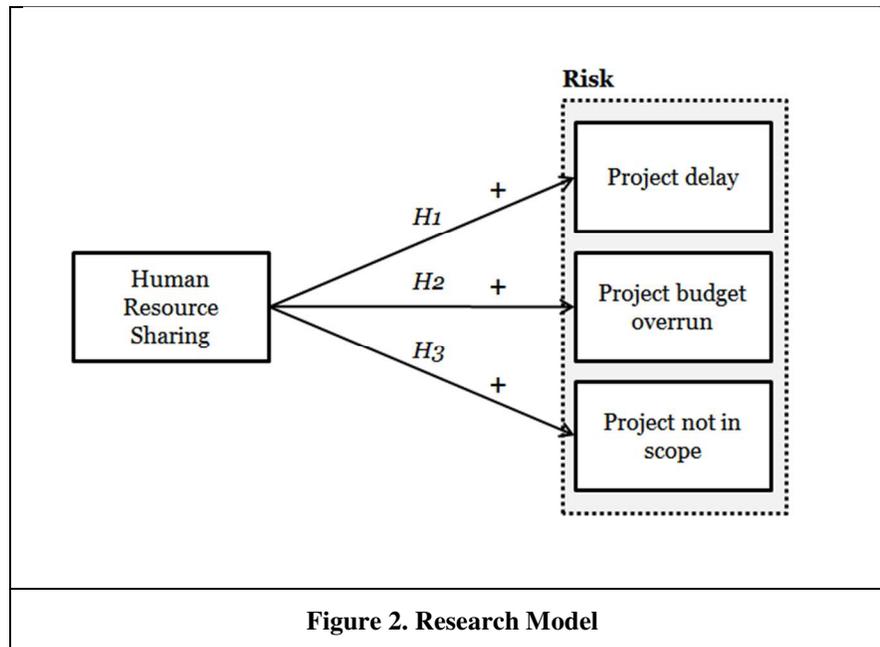


Consequently, we argue that resource sharing leads to positive correlations among the IT projects, which, in turn, increases the risk (positive risk effect) of the involved projects in comparison to the situation without resource sharing (no risk effect). In contrast to cost synergies, which are usually already considered in project planning, the risk effects from resource sharing should be observable in deviations from the planned *project timeline* ($H1$), *project budget* ($H2$), and/or *project scope* ($H3$). Where these risk effects are observable depends on management decisions. For example, if a resource unexpectedly becomes unavailable, management might decide to hire an external replacement and thereby, increase project costs to keep the project on schedule and maintain its scope. Alternatively, management could decide on waiting for the resource to get available again (e.g., in case of illness) at the cost of violating the planned timeline. Another alternative is to stay on budget and on time and to reduce the project scope. This results in a trade-off between the three measures when realizing risk effects. Consequently, it is not sufficient to consider just one risk measure but we have to consider all three measures to get a complete picture of the risk effects from resource sharing. Based on the conceptualized risk effects from resource sharing (cf., Figure 1), we state the following three research hypotheses. The corresponding research model is depicted in Figure 2.

Hypothesis H1: Human resource sharing is positively related to project delay

Hypothesis H2: Human resource sharing is positively related to project budget overrun

Hypothesis H3: Human resource sharing is positively related to not finishing the project in scope.



Dataset

The dataset used within this paper contains cross-sectional resource and project data from a large production company engaged in worldwide activities and based in Austria. With approximately 20,000 employees and over 2,200 stores worldwide, the company earns more than 2 billion Euro revenues per year. To manage their complex IT landscape, the company operates a large IT department. In a period between 2009 and 2013, the IT department completed over 300 IT projects, e.g., comprising infrastructure, software development, IT organization, ERP, software evaluation, and software upgrade/rollout projects. The project durations ranged from 3 months to 2 ½ years, with half of the projects taking between 6 and 12 months. Our dataset comprises a randomly drawn sample of 99 projects and 340 resources that were staffed on these projects. The 99 projects in the sample are distributed to the following project categories: Infrastructure (9%), software development (39%), ERP projects (5%), software evaluation (13%), IT organization (13%), and software upgrade/rollout (21%).

The companies' multi-project management environment is standardized and managed by an IT portfolio management department. The projects are centrally monitored in a software tool. A project manager is responsible for planning and coordinating a respective project. For each project, the dataset comprises information about planned and realized start and end dates, planned and realized budgets, and the projects priority. Further, the projects are evaluated by the project owners on whether they were adequately executed and whether they reached the initially planned scope on a four point ordinal scale ranging from 'minus minus' to 'plus plus'.

In addition to the project related information, the dataset comprises monthly data about the realized working times (in person days) for each employee involved in the projects. For all resources in the sample, there is information about their position in the projects (project manager or team member). The sample exhibited various missing data entries. Table 1 and Table 2 provide descriptive statistics for the dataset. The number of complete observations for each set of information is depicted by the numbers in column 2 of Table 1. For the *employed resources per project*, the total number of observations indicate that for all 99 projects in the sample, information about the employed human resources is available.

	Total # of Obs.	Mean	Std. Deviation	Min	Max
Resources in Sample	340				
Projects in Sample	99				
Planned Budget (in €)	81	72.525,78	172.542,25	6.500,00	1.440.000,00
Realized Budget (in €)	74	71.176,52	160.377,41	2.373,00	1.212.000,00
Planned duration (Calendar Days)	75	269,81	151,10	90,00	1.005,00
Realized duration (Calendar Days)	75	330,10	202,99	30,40	972,80
Employed Resources per project	99	12,13	15,49	1,00	128,00

	Characteristic	Frequency	Percent
Priority	Must	5	0,05
	High	3	0,03
	Normal	91	0,92
	Total	99	1
Project execution	Minus Minus	2	0,03
	Minus	6	0,08
	Plus	47	0,61
	Plus Plus	21	0,28
	Total	76	1
Project Scope	Minus Minus	1	0,01
	Minus	6	0,08
	Plus	22	0,29
	Plus Plus	47	0,62
	Total	76	1
Project Timeline	Stopped	2	0,03
	Late	45	0,64
	In time	21	0,30
	Early	2	0,03
	Total	70	1
Project Budget	Over budget	25	0,35
	In budget	1	0,02
	Under budget	45	0,63
	Total	71	1

The descriptive statistics exhibit some interesting characteristics of the sample. By comparing the mean of the planned and realized budget, it becomes apparent that the planned budget is, in average, larger than the realized budget. More specific, approximately 65% of the projects in the sample have not exceeded their planned budget, which somewhat contrasts the typical tenor of project failure reports (e.g., by Standish Group 2013). However, reviewing the project timeline data from the sample reveals that almost the same percentage of projects (67%) violates their planned timeline, while only a small number of projects stay behind their intended scope. These observations encourage the aforementioned argument that there is interplay between the three measures and that risk effects are observable in different measures, depending on management decisions. In our sample, management seems to steer the trade-off between the three IT project success measures strongly towards the scope of the projects, while timeline adherence seems to be of least importance. This is also supported by inquiries with the company providing the dataset.

Main Variables

Independent Variable: Resource Sharing Degree

The independent variable in our analysis is the resource sharing degree $RSD_j \in [0,1[$ for each project j . It measures among how many projects the human resources that work for project j are shared. If all the resources employed in a particular project j are exclusively used in that project, then $RSD_j = 0$. RSD_j attains its maximum value in a situation, where all available resources are working for all projects and each resources' working time is evenly distributed among all projects. In such a case, with an increasing number of resources, RSD_j converges to 1. The resource sharing degree for each project is calculated by

$$RSD_j = 1 - \sum_i s_{ij} \cdot c_{ij} \quad (1)$$

where s_{ij} measures the number of days a resource i spent on project j in relation to the total working time of a resource i (see Table 3 for an illustrative example). The parameter c_{ij} measures the number of days that a resource i spent on project j in relation to the total working time spent on project j by all resources (see Table 4 for an illustrative example).

	Project 1		Project 2		Total Resource Working Time (Days)
	Absolute	Relative (s_{i1})	Absolute	Relative (s_{i2})	
Resource 1	500	0,57	380	0,43	880
Resource 2	200	0,25	600	0,75	800
Resource 3	150	0,30	350	0,70	500

	Resource 1		Resource 2		Resource 3		Total Project Working Time (Days)
	Absolute	Relative (c_{1j})	Absolute	Relative (c_{2j})	Absolute	Relative (c_{3j})	
Project 1	500	0,59	200	0,24	150	0,18	850
Project 2	380	0,29	600	0,45	350	0,26	1330

After calculating c_{ij} of each resource i to a project j , c_{ij} is multiplied with s_{ij} of the corresponding resource (see columns 2-4 in Table 5) and then added up for each project (column 5 in Table 5). Then, the resulting measure is subtracted from 1 resulting in an intuitively interpretable measure that increases with an increasing amount of resource sharing (see rounded values in column 6 of Table 5).

Table 5. Illustrative Example (continued) – RSD					
	Resource 1	Resource 2	Resource 3	Sum	RSD _j
Project 1	0,3342	0,0588	0,0529	0,4460	0,55
Project 2	0,1234	0,3383	0,1842	0,6459	0,35

Calculating the RSD this way provides a very intuitive and reasonable measure. Due to the available data, it comes with simplifying assumptions. A resource that works evenly distributed among a number of projects might exhibit a higher degree of multitasking than a resource that is working with a large portion of its work share in a main project, and with smaller time shares in a number of other projects. This may result in a skewness of the work share distribution for each resource that is considered only in a basic form within the RSD. Further, the three success measures for each project are only assessed at one point in time, when the project is finished. A more precise RSD could be calculated, if information about budget consumption, timeline adherence and achieved milestones could be made available on a monthly level, as aggregation of the resources monthly employment data comes with a loss of accuracy in measuring resource sharing.

Dependent Variables

Based on our research hypotheses $H1$, $H2$, and $H3$, we define three dependent variables of interest for our analyses. In line with the Standish Group (2013), we consider IT project success as delivering the projects' *planned scope* within a *planned timeline* while consuming not more than the *planned budget*. To test our research hypotheses, we use binary indicator variables and employ logistic regression models.

Project Delay ($H1$)

To test hypothesis $H1$, we define a binary indicator variable **Delay_Dummy** for each project. This variable indicates if the corresponding projects' realized closure date exceeds the initially planned closure date. We use a binary delay flag provided with the dataset for each project. Theoretically, calculating the delay dummy solely based on the closure dates could result in a situation where a project with a *duration* that was *shorter* than planned, but for some reason, finished at a later date than planned, would be marked as late. Due to numerous missing values in the dataset we were unable to derive a sufficiently high number of observations to calculate the delay based on the planned and realized project *durations* rather than the projects *closure dates*. However, by careful investigation of the dataset, we could not find a single situation where the Delay_Dummy calculated based on the closure dates have varied from the ones calculated based on the duration. Therefore, we assume that calculating the delay dummy based on the closure date and based on project duration both yield similar results. **Delay_Dummy** attains the value '1', if the projects realized closure date is later than the planned closure date and '0' otherwise.

Project Budget Overrun ($H2$)

To measure if planned budget deviates from the realized budget ($H2$), we define a binary indicator variable **Over_Budget_Dummy**. **Over_Budget_Dummy** is derived by a budget status flag provided with the dataset. The dummy attains the value '1', if the projects realized budget exceeds the planned budget. If it stays in or under budget, the dummy is '0'.

Project not in Scope ($H3$)

As our third variable we define the binary variable **In_Scope_Dummy**. Our dataset allows us to observe a project owner-reported assessment of the IT project success. In the dataset at hand, the project owner is the instance that commissions and pays for the project. After the conduction of a project, the project owner evaluates the success as well as the execution quality of the project on a four-point ordinal scale. Inquiries with the company showed that IT project success is almost exclusively determined by

maintaining the intended project scope. Therefore, we use IT project success as a proxy for achieving a projects' planned scope, as scope itself is not documented in the dataset. As the success measure provided by the project owner is subjective in comparison to the objective measures for project timeline and budget, with our dataset we cannot adequately control for any biases in the subjective success evaluation. However, we assume that potential biases appear randomly across all of the projects' evaluations and thus, the measure is usable as approximation to measure the achievement of project scope. The ordinal scaled evaluations by the project owners are translated into the binary variable **In_Scope_Dummy** by interpreting projects that have been evaluated with "plus" or "plus plus" as a project having at least achieved its planned scope and evaluations of "minus" or "minus minus" as underachievement of the planned scope.

Control Variables

Our dataset allows us to control for several other aspects that might influence the dependent variables of interest. With the variable **Persons_Involved**, we control for the staff size of the projects. In the dataset at hand, projects are classified by the company into *must*, *high*, and *normal* priority projects. The variable **Priority_Dummy** controls for the effect of projects with different priorities. As another feature of our dataset, we are able to observe the subjective evaluation of a projects execution. The project owner reports a measure comparable to IT project success, to evaluate the overall execution quality of the projects. We define the **variable Positive_Execution_Dummy** to control for owner-reported execution quality. The literature on project management provides evidence that managerial experience is an important factor for overall IT project success. To control for different levels of managerial experience, we introduce the variable **Manager_Tenure**. *Manager_Tenure* represents the number of projects an assigned project manager in our dataset has managed so during the observational period. While this variable is not an exact representative of the overall manager experience (including management experience outside of our observational period), it is the best approximation possible to calculate for our dataset. In addition, we control for the project types with the control variable **Project_Type**. The company distinguishes between not chargeable projects (*Project_Type* = 0) and business projects (*Project_Type* = 1). Not chargeable projects are projects that are not owned by a business unit (for example, an internal project of the IT department), while business projects are projects that are owned by and chargeable to a certain business unit. The definition of all the variables can be found in Table 6.

Table 6. Definition of Variables	
Name of Variable	Definition
<i>RSD</i>	Continuous variable [0,1] that indicates to which degree a corresponding project makes use of shared resources
<i>Delay_Dummy</i>	Binary dummy variable that indicates if a project exceeded its planned timeline
<i>Over_Budget_Dummy</i>	Binary dummy variable that indicates if a project exceeded its planned budget
<i>In_Scope_Dummy</i>	Binary dummy variable that indicates if a project has achieved its planned scope
<i>Persons_Involved</i>	Number of human resources that have been working on a particular project
<i>Priority_Dummy</i>	Dummy variable that indicates, if the project is a high priority project (including 'must' projects)
<i>Positive_Execution_Dummy</i>	Binary dummy variable that indicates if the execution quality of a project was evaluated positively by the project owner
<i>Manager_Tenure</i>	Continuous variable that indicates the project managers involvement as project manager for other projects during the observational period
<i>Project_Type</i>	Binary dummy variable that indicates if the project is a business project.

Empirical Model

The dataset for our study is cross-sectional and the dependent variables are binary indicators measuring whether a project was delayed (Delay_Dummy), exceeded its planned budget (Over_Budget_Dummy), or achieved its planned scope (In_Scope_Dummy). Accordingly, we use logistic regression models to examine the correlation between RSD and the likelihood of a project being over budget, over time, or in scope.⁴ A positive correlation between the RSD and the Delay_Dummy would provide support for our hypothesis *H1*, a positive correlation between RSD and the Over_Budget_Dummy would provide support for our hypothesis *H2*, and a negative correlation between RSD and the In_Scope_Dummy would provide support for our hypothesis *H3*. We further add the control variables presented in the preceding subsection. Thus, we consider the following main model in latent variable form (Wooldridge 2010):

$$Y^*_i = \alpha + \beta_1 RSD_i + \zeta X_i + \varepsilon_i \quad (2)$$

$$Y_i = 1 [Y^*_i > 0],$$

where the subscript represents project *i*, X_i is a vector of project-level control variables, and ε_i is the random error term.

Main Results

Table 7. Main Results			
Dependent Variables	Delay_Dummy	Over_Budget_Dummy	In_Scope_Dummy
RSD	-0.0282**	-0.00308	-0.0332*
	(0.0121)	(0.0119)	(0.0189)
Persons_Involved	0.0400	0.0116	0.0309
	(0.0259)	(0.0203)	(0.0617)
Priority_Dummy	1.848	1.968**	-1.565
	-1.385	(0.884)	-2.045
Positive_Execution_Dummy	1.886***	1.072	5.869***
	(0.621)	(0.689)	(0.879)
Manager_Tenure	-0.527***	-0.202	-0.106
	(0.172)	(0.231)	(0.246)
Project_Type	0.772	-0.249	-1.051
	(0.729)	(0.631)	(0.853)
Constant	0.111	-1.421	0.0950
	(0.996)	-1.169	-1.727
N	93	93	93
Log pseudolikelihood	-49.31	-47.15	-19.66
(Pseudo) R ²	0.23	0.13	0.64

⁴ We get qualitatively the same results if we estimate probit models or linear probability models.

Table 7 shows the estimation results of our model for the three dependent variables *Delay_Dummy*, *Over_Budget_Dummy*, and *In_Scope_Dummy*.

Project Delay (H1)

The second column of Table 7 shows the results of the logistic regression for *Delay_Dummy* as the dependent variable. The estimated coefficient of -0.0282 (s.e. = 0.0121) on RSD indicates that there is a significant negative correlation between the RSD and the likelihood that a project exceeds its planned timeline. The sign of the coefficient indicates that – in contrast to our hypothesis *H1* – a higher resource sharing degree is related to a lower likelihood of violating the planned project timeline. However, since we estimate a logistic regression model, the coefficient on this variable cannot be simply interpreted as the change in the mean of the dependent variable for a one unit (percent) increase in RSD, with all other predictors remaining constant. Rather, they need to be interpreted as the natural logarithm of the factor by which the predicted odds of $Y_i = 1$ change, given a one percent increase in RSD, and holding all other predictor variables at a fixed value. Therefore, we first have to calculate the odds ratio, which is equal to the exponent of the coefficient of the respective variable to provide a meaningful interpretation of our result.⁵

Calculating the odds ratio for RSD gives us $\exp(-0.0282) = 0.972$. This value can be interpreted as follows: Increasing the RSD for a project by 1% is associated with a decrease of 2.8% in the odds that the project will be late (keeping all other predictors at a fixed value). With respect to our hypothesis *H1*, this is a surprising result. There could be numerous plausible explanations for the observed relationship. For example, if a project is in danger of being late, the management might react by reallocating resources from other projects to the project at risk, or by reducing the scope or increasing the budget of the corresponding project to keep the project on schedule. Unfortunately, our dataset does not provide the necessary data to confirm or rule out different explanations for this observation sufficiently. Consequently, hypothesis *H1* has to be rejected.

The control variables *Positive_Execution_Dummy* (coefficient = 1.886, s.e. = 0.621) and *Manager_Tenure* (coefficient = -0.527, s.e. = 0.172) both show a highly significant (1% confidence level) correlation to *Late_Dummy*. Increasing *Positive_Execution_Dummy* from zero to one results in the increase of the odds ratio for a project to exceed the planned timeframe by 559% (holding all other predictors at a fixed value). A possible explanation for this relationship may be found in the descriptive statistics of the dataset. The share of projects that have been evaluated as being executed positively ('plus', or 'plus plus') in our dataset is 90%. Thereby, the observed relationship could be distorted by the distribution of the variables realization in the dataset. In a confirmatory model with two dummy variables (one for 'plus' and one for 'plus plus'), the coefficient of the 'plus plus' dummy decreases substantially in contrast to *Positive_Execution_Dummy*, and it is only significant on a 10% confidence level, while the results for RSD and *Manager_Tenure* remain basically unchanged.

The identified correlation between *Manager_Tenure* and *Late_Dummy* shows a positive sign. Increasing the number of projects managed by the project manager by 1 is related to a 41% decrease in a projects odds ratio of being late. This finding is rather intuitive and may be explained by the improved management skills and foresight associated with increasing management experience. Besides the discussed ones, no other variables of our model show a significant and economically meaningful correlation to *Late_Dummy*.

Project Budget Overrun (H2)

The third column of Table 7 shows an estimated coefficient of -0.00308 (s.e. = 0.0119) on RSD indicating that there is no significant correlation between the RSD and the likelihood that a project exceeds its planned budget. Based on the current data, hypothesis *H2* has to be rejected.

⁵ The odds are defined as $\frac{P(Y_{ij}=1)}{(1-P(Y_{ij}=1))}$.

In the third column of Table 7, the positive coefficient of *Priority_Dummy* indicates that high priority projects are more prone to budget overspending, which is somewhat counterintuitive. A possible explanation for this might be that high priority projects are more likely to receive additional budgets when they are required. Unfortunately, our dataset provides no insights into management decision of single projects and we are not able to determine, for example, if projects get re-prioritized to a higher level, if they run out of budget, or if they get additional budgets more easily than normal priority projects. No other variables of our model show a significant and economically meaningful correlation to the two budget-related variables of interest in our models.

Project not in Scope (H3)

The fourth column of Table 7 shows the results of the logistic regression for *In_Scope_Dummy* as the dependent variable. The estimated coefficient of -0.0332 (s.e. =0.0189) on *RSD* indicates that there is a significant (confidence level of 5%) negative correlation between the *RSD* and the likelihood that a project is perceived as successful by the project owner. An increase of 1% in *RSD* is associated with a 3.4% decrease in the odds that a project will be classified as successful. These findings support hypothesis *H3* that a higher *RSD* results in a reduced project scope.

Further, we observe a strongly significant (1% confidence level) positive correlation between *Positive_Execution_Dummy* and *In_Scope_Dummy* (coefficient = 5.869, s.e. = 0.879). If the execution of the project has been evaluated positively ('plus' or 'plus plus') the odds ratio for a project for *In_Scope_Dummy* increases by $\exp(5.869) = 254\%$. This is not surprising, because a well-executed project should be more likely to be successful than a 'badly' conducted project. However, while technically, *Positive_Execution_Dummy* seems to be a good predictor for IT project success, its practical use for predicting IT project success is somewhat diminished, because (at least in our dataset) both measures are evaluated only *after* the project has been finished. Resource sharing, in contrast, typically takes place during the projects are conducted, and thus, can be measured already when the project is running. Therefore, it is highly unlikely that the scope-assessment is *causing* the relationship rather than the resource sharing itself. However, we only are able to observe correlations between *RSD* and *In_Scope_Dummy*. Therefore, while the findings supporting hypothesis *H3*, we cannot safely assume that *RSD* is the (only) driving mechanism behind this relationship. In future research, the causal relationships between human resource sharing and IT project success have to be investigated.

Discussion

Limitations

There are several limitations that have to be considered when interpreting the results of this study. First of all, due to the characteristics of our dataset we can only report correlations for the observed variables. Thus, we cannot conclusively show that resource sharing is the driving mechanism behind the identified relationships. In future research, the causal relationships between human resource sharing and IT project risk have to be further investigated. Therefore, we aim to collect the following additional data from the data sources of our cooperating company: First, we collect data of additional projects to confirm our conclusions with respect to hypothesis 1 and 3, and to further analyze if we can draw some important conclusions with respect to hypothesis 2. Second, we collect data about the chronological order of the correlated observations 'manager tenure' and 'project delay'. With these chronological data, we will be able to investigate potential causal relationships in future work between the number of managed projects during a certain period of time, and project delay. Third, we found that increasing the *RSD* for a project by 1% is associated with a decrease of 2.8% in the odds that the project will be late. There could be numerous plausible explanations for the observed relationship which we are unable to confirm or rule out with our current data set. Thus, we collect project management data of the respective projects (e.g., staffing decisions over the projects runtime). Based on these data, we aim to investigate whether the observed correlation is merely a managerial answer to projects that are already in danger of being delayed, or if resource sharing is the cause for project delay. Fourth, we collect monthly data about the progress of the three project success measures instead of only observing them at the beginning and the end of a project. Based on these data, we will be able to monthly analyze the effect of resource sharing on project risk

instead of only at the end of the planning period. Complementing our approach, we aim to design field experiments to isolate the causal effects of resource sharing on project risk.

The use of cardinal variables and linear regression models could provide interesting information to further quantify the budgets and timeline deviations. While our dataset does not offer a sufficiently large number of observations on the corresponding data entries to get significant results in linear regression models, the results of confirmatory linear regression analyses provide qualitatively the same results as the logit models. In future research, the strength of the effects could be further quantified by using linear regression models or more elaborate multi-variate regression models on a richer and more comprehensive dataset.

We calculate the RSD as an aggregated measure for each project. While our approach to calculate the RSD provides a very intuitive and reasonable measure, due to the available data, it comes with some necessary simplifications. A resource that works evenly distributed among a number of projects might exhibit a higher degree of multitasking than a resource that is working with a large portion of its work share in a main project, and with smaller time shares in a number of other projects. While this relationship is already incorporated into our RSD in a basic form, in future work, this skewness of the work share distribution for each resource could be considered within the RSD calculation more elaborately. Further, the RSD measure could be extended by considering the sharing degree of a resource in relation to the average sharing degree of other resources to obtain a more complete picture.

In addition, we currently assume a linear relationship between resource sharing and its effects on the performance measures. It is not unlikely that this relationship rather follows a U-shape. More specifically, the effect of resource sharing might be beneficial (e.g., due to improved utilization of slack times) up to a certain point. Then, at some point, the potential negative effects of resource sharing (e.g., due to increasingly switching between a high number of projects) might overtake. This might as well be an interesting lane for future research.

Due to the lack of information in the dataset, the potential effects of sharing on the *resources themselves* cannot be observed directly. As seen, e.g., in Zika-Viktorsson et al. (2006), project overworking may have negative effects on the resources' productivity and is associated with impaired performance, high levels of psychological stress reactions, and decreased individual competence development. In contrast, the literature on work productivity (e.g., Diwas 2013) provides evidence that multitasking resulting from resource sharing also may lead to positive effects (e.g., improved utilization of slack times, cross project learning). Due to our research setting, we are not able to separate the positive and negative effects and quantify them accordingly. The separation of these potentially concurring effects could provide a highly interesting lane for future research. Furthermore, in our analyses we assume that on average, every resource reacts similar with regards to working for more or less projects. In reality, this may not be entirely true as people behave differently with regards to work amounts.

Finally, the results of this study are derived from analyzing IT projects. While we think that the results might – at least partially – be applicable to non-IT projects, the investigation of the generalizability of our findings to other project types is subject to future work.

Implications for Research and Practice

Despite these limitations, our study yields valuable insights to researchers and practitioners from the field alike. For researches, our work provides a valuable starting point to further investigate the effects of exploiting resource interactions on IT project success. The developed RSD measure can be adopted and improved by researchers and its quality as a predictor for IT project success should be tested on different real world datasets. The dataset at hand does not allow checking back qualitatively, if the hypothesized risks due to resource sharing simply did not arise in our sample. Therefore, we encourage researchers to engage in the endeavor of investigating these effects empirically on primary data specifically gathered for this purpose.

The findings of our study constitute the basis for a well-informed managerial decision making by being among the first to provide empirical evidence for the risk effects of human resource sharing in IT project portfolios. For practitioners, our findings indicate that cost synergies derived by human resource sharing – while being a valuable and widely practiced managerial tool – potentially come along with risk effects that should be taken into consideration when planning and conducting IT Portfolios, as unconsidered risk

effects due to resource sharing potentially can compromise IT project success. Our findings can sensitize portfolio planners for these risk effects and thereby improve the incorporation of resource interactions into their portfolio decisions. Potential bottlenecks may be identified before their negative effects have to be realized and the procurement strategies for the corresponding resources may be improved at an early planning stage to reduce the risk of resource shortage during portfolio implementation. Further, adequate capacity buffers could already be incorporated during resource allocation planning.

Conclusion

The exploitation of resource interactions among human resources is a topic of high relevance in IT project portfolio management. On an economic level, exploiting resource interactions by sharing resources among two or more IT projects may translate into cost synergies and thereby in reduced portfolio costs (Gear and Cowie 1980, Lee and Kim 2001, Santhanam and Kyparisis 1996, Heinrich et al. 2014). However, no empirical research on the risk effects from resource sharing can be found in the literature so far. This paper attempts to fill this gap. Based on evidence from various streams of literature, we derive three hypotheses about the interrelationship between human resource sharing and project risk. We argue that Human resource sharing is positively related to project delay (*H1*), positively related to project budget overrun (*H2*), and positively related to not finishing the project in scope (*H3*). Using a data set of 99 IT projects, our analysis provides first evidence to support hypothesis *H3*. More specifically, a 1% higher degree of human resource sharing is associated with a decrease of 3.4% in the odds that the initially planned project scope will be achieved (as evaluated by the owner). Somewhat counterintuitively, our results indicate that projects that share their human resources are more likely to comply with their initially planned timeline, not supporting hypothesis (*H1*). In our data set we were not able to find statistically significant findings for hypothesis *H2*. With these findings, we partially confirm findings from Standish Group (2013), who state that increases in experienced and training of project management professionals can be tied directly to increases in success rates. In this regard, by observing one of our control variables, we find evidence that with increasing project manager experience the likelihood that a project can hold its initially planned timeline increases as well.

Acknowledgments

We thank the Austrian Science Fund (FWF): P 23567-G11 for funding this research.

References

- Aaker, D. A., Tyebjee. T. T. 1978. "A Model for the Selection of Interdependent R&D Projects", IEEE Transactions on Engineering Management (25:2), pp. 30-36.
- Asundi, J., and Kazman, R. 2001. "A Foundation for the Economic Analysis of Software Architectures", Proceedings of the 3rd Workshop on Economics-Driven Software Engineering Research (EDSER-3), Toronto, Canada.
- Buhl, H. U. 2012. "The Contribution of Business and Information Systems Engineering to the Early Recognition and Avoidance of "Black Swans" in IT Projects", Business & Information Systems Engineering (4:2), pp. 55-59.
- Butler, S., Chalasani, P., Jha, S., Raz, O., and Shaw, M. 1999. "The Potential of Portfolio Analysis in Guiding Software Decisions", Proceedings of the 1st Workshop on Economics-Driven Software Engineering Research (EDSER-1), Los Angeles, California.
- Chien, C. F. 2002. "A portfolio-evaluation framework for selecting R&D projects", R&D Management (32:4), pp. 359-368.
- De Maio, A., Verganti, R., and Corso, M. 1994. "A multi-project management framework for new product development", European Journal of Operational Research (78:2), pp. 178-191.
- Diwas, S. K. C. 2013. "Does Multitasking Improve Performance? Evidence from the Emergency Department", Manufacturing & Service Operations Management (16:2), pp. 168-183.
- Doerner, K. F., Gutjahr, W.J., Hartl, R. F., Strauss, C., and Stummer, C. 2006. "Pareto ant colony optimization with ILP preprocessing in multiobjective project portfolio selection", European Journal of Operational Research (171:3), pp. 830-841.
- Eilat, H., Golany, B., and Shtub, A. 2006. "Constructing and evaluating balanced portfolios of R&D projects with interactions: A DEA based methodology", European Journal of Operational Research (172:3), pp. 1018-1039.
- Engwall, M., and Jerbrant, A. 2003. "The resource allocation syndrome: the prime challenge of multi-project management?", International Journal of Project Management (21:6), pp. 403-409.
- Fox, G. E., Baker, N. R., and Bryant, J. L. 1984. "Economic models for R and D project selection in the presence of project interactions", Management Science (30:7), pp. 890-902.
- Gartner 2014. "Gartner Says Worldwide IT Spending on Pace to Grow 3.2 Percent in 2014", online article <http://www.gartner.com/newsroom/id/2698017> (Accessed: 15.04.2015)
- Gear, T. E., and Cowie, G. C. 1980. "A note on modeling project interdependence in research and development", Decision Science (11:4), pp. 738-748.
- Heinrich, B., Kundisch, D., and Zimmermann, S. 2014. "Analyzing Cost and Risk Interaction Effects in IT Project Portfolios", BIT: Banking and Information Technology (15.2/2014), pp. 8-20.
- Kaiser, M. G., El Arbi, F., and Ahlemann, F. 2015. "Successful project portfolio management beyond project selection techniques: Understanding the role of structural alignment", International Journal of Project Management (33:1), pp. 126-139.
- Kappelman, L. A., McKeeman, R., and Zhang, L. 2006. "Early Warning Signs of it Project Failure: The Dominant Dozen", Information Systems Management (23:4), pp. 31-36.
- CompTIA 2012. "Business Operations Impacted by Widening IT Skills Gap, New CompTIA Study Reveals", study published online <http://www.prnewswire.com/news-releases/business-operations-impacted-by-widening-it-skills-gap-new-comptia-study-reveals-142304645.html> (Accessed: 23.04.2015)
- Kundisch, D., Meier, C., 2011a. "IT/IS Project Portfolio Selection in the Presence of Project Interactions - Review and Synthesis of the Literature", Wirtschaftsinformatik Proceedings, Zürich.
- Kundisch, D., Meier, C., 2011b. "A new Perspective on Resource Interactions in IT/IS Project Portfolio Selection", Proceedings of the European Conference on Information Systems, Helsinki.
- Lee, J. W., and Kim, S. H. 2001. "An integrated approach for interdependent information system project selection", International Journal of Project Management (19:2), pp. 111-118.
- Markowitz, H. 1952. "Portfolio Selection", The Journal of Finance (7:1), pp. 77-91.
- Morris, P., and Pinto, J. K. 2007. "The Wiley Guide to Project, Program, and Portfolio Management", Hoboken, NJ: John Wiley & Sons
- PMI (2015): "What is a project?", online article <http://www.pmi.org/About-Us/About-Us-What-is-Project-Management.aspx> (Accessed:07.09.2015)

- Rubinstein, J. S., Meyer, D. E., Evans, J. E. 2001. "Executive control of cognitive processes in task switching", *Journal of Experimental Psychology: Human Perception and Performance* (27:4), pp. 763-797.
- Santhanam, R., and Kyparisis, G. J. 1996. "A decision model for interdependent information system project selection", *European Journal of Operational Research* (89:2), pp. 380-399.
- Schmidt, R., Lyytinen, K., Keil, M., and Cule, P. 2001. "Identifying software project risks: an international Delphi study", *Journal of management information systems* (17:4), pp. 5-36.
- Standish Group International (2013). "The Chaos Manifesto 2013 – Think Big, Act Small", online article <http://versionone.com/assets/img/files/ChaosManifesto2013.pdf> (Accessed: 23.04.2015).
- Stummer, C., and Heidenberger, K. 2003. "Interactive R&D portfolio analysis with project interdependencies and time profiles of multiple objectives", *IEEE Transactions in Engineering and Management* (50:2), pp. 175-183.
- Thibodeau, P. 2014. "Dissatisfaction with IT grows: Business wants more from IT - and as it does, it becomes more critical", online article <http://www.computerworld.com/article/2489140/it-management/dissatisfaction-with-it-grows.html> (Accessed: 23.04.2015)
- Wooldridge, J. M. 2010. "Introductory Econometrics – A Modern Approach", South-Western College Publishing, USA.
- Zika-Viktorsson, A., Sundström, P., and Engwall, M. 2006. "Project overload: an exploratory study of work and management in multi-project settings", *International Journal of Project Management* (24:5), pp. 385-394.
- Zimmermann, S., Katzmarzik, A., and Kundisch, D. 2008. "IT Sourcing Portfolio Management for IT Services Providers – A Risk/Cost Perspective", 29th International Conference on Information Systems (ICIS), Paris, France.
- 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), pp. 24-45.