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The Role of Sunk Costs in Digitalization – Empirical Evidence from Accounting and Finance

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Completed Research

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Abstract

IT investments are researched in theory and practice from different theoretical perspectives. In accounting and finance, corporate practice in particular shows that large IT investments are either not made or are abandoned during the investment and implementation process. In our view, the economic role of sunk costs has not been given sufficient attention in the literature to date. From a theoretical point of view, the objective or subjective assumption of sunk costs could be a barrier against the adoption of new digital technologies. This paper can partly support this thesis on the basis of empirical data.

Keywords

Digitalization; sunk costs; IT investments; accounting; finance.

Introduction

Digitalization promises to change businesses fundamentally concerning products, processes, and value generation (Hausberg et al. 2019). Digitized data lead to large amounts of information available for analysis with sophisticated analytical methods, i.e business analytics (Chen et al. 2012; Power et al. 2018). Accounting and finance functions are expected to be in the front seat to support managers in such business analytics-based decision-making (Warren et al. 2015).

Albeit, expectations and reality seem to differ. Firms are by far less willing to employ digital tools, change processes and structures than suggested (Elbashir et al. 2013; Bergmann et al. 2020). Even if modern technologies promise benefits for companies and individual users, they are not always adopted in practice or - if they have been adopted by an organization - used by the relevant individuals (Janssen et al. 2020). In the field of information systems, several approaches based on objective explanations and others based more on subjective, affective and conative components have become established.

The diffusion theory (Comin and Hobijn 2010), the theory of planned behaviour (Ajzen 1991) and the theory of reasoned action (Fishbein 1979) belong to the first group. An example of this group is the various technology acceptance models (Davis 1989; Venkatesh et al. 2003). These approaches postulate that users' decisions whether to introduce an individual technology in the company and then ultimately use it in operational work depend on objectifiable criteria such as costs and benefits. Davis has pointed out with "perceived usefulness" that even a supposedly objective variable such as usefulness can contain an intraindividual subjective element.

The second group includes theories and approaches that approach technology adoption via constructs such as trust (Eymann et al. 2008; Hawlitschek et al. 2018) placed in the technology, personality (Buettner 2017; Nacarelli and Gefen 2021; Nam et al. 2019), cognitive workload (Buettner et al. 2013), or technostress (Riedl et al. 2012; Maier et al. 2015).

In contrast to that, we assume that a decision to adopt technology is basically driven by economic considerations and not predominantly dependent on individual psychological motives. A promising theoretical and economic perspective is to view decisions on adopting and implementing business analytics as investment decisions (e.g. Liberatore et al. 2017).

A rational decision-maker compares the expected value of new information technology (IT) such as business analytics and accompanying organizational changes with the value of existing IT. If the existing IT environment is no longer productive or useful under the new IT regime, there will be sunk costs, i.e. the value of existing IT is no longer recoverable. The larger the sunk costs and the more uncertain the value of the new IT, the more reluctant decision-makers are to move to new IT systems. In this sense, high sunk costs can explain the low acceptance of business analytics and digitalization.

This study tests this sunk cost hypothesis with survey-based data from accounting and finance functions in Germany. Based on a sample of n = 952 we perform multiple linear regressions for testing the sunk cost hypothesis.

Our results generally support the sunk cost hypothesis. Firms are less likely to adopt digitalization in finance and accounting if the level of extant IT investments as well as required IT investments is high. The same holds for non-transferable competencies and required new competencies as well as the lack of use cases. Only the budget constraint does not exert a significant influence on average.

The main contribution of our paper is to show that although it might seem irrational from the outside, a lack of investments in digitalization within the finance function of a company might be logically explained by looking at the in-depth mechanisms of perceived sunk costs by financial decision-makers. In short: the decision not to invest in digitalization might be rational in the light of sunk costs.

The paper is structured as follows: the next section discusses the impact of sunk costs and derives hypotheses. Section 3 provides information on measurement, sample and statistical inference, while sections 4 and 5 present descriptive results and the results of hypotheses tests. Section 6 concludes the paper.

Digitalization and sunk costs

Digitalization in accounting and finance functions

While clear terminology is still lacking (Vial 2019; Reis et al. 2020) digitization is often seen as transforming physically stored information into a digital form. In contrast, digitalization encompasses also the effects of digitally stored information, processes and technology on organizations (Brennen and Kreiss 2016; Knudsen 2020). Such effects of digitalization manifest in "(1) digitally supported and linked cross-linked processes, (2) digitally enabled communication, and (3) new ways of value generation based on digital innovations or gained digital data" (Hausberg et al. 2019, 934, p. 934).

Digitalization affects many aspects and functions in organizations (Kuusisto 2017). Accounting and finance functions are especially relevant for digitalization because they use, transform and provide crucial information for management and other stakeholders (Warren et al. 2015; Chang et al. 2014). Accounting and finance functions are often structured into financial accounting, management accounting, tax preparation and internal auditing as well as monitoring debt and capital structures (Zorn 2004; Chang et al. 2014). The finance function evolved from being a back-office function into an important cornerstone of the value creation of companies (Zorn 2004). Hence, the digitalization of finance functions promises to deliver even more value to a firm (Bhimani and Willcocks 2014). Digitalization in accounting and finance means automation of processes (Harrast 2020) and the use of data analytics methods and instruments (Huerta and Jensen 2017).

There is a lot of enthusiasm for digitalization in general (Mcafee and Brynjolfsson 2017) and accounting and finance in particular (Möller et al. 2020). In contrast to that, the current rate of adoption seems to be rather disappointing. Only around 12% of firms in several OECD countries apply business analytics (Andrews et al. 2018). This is in line with studies of digitalization in finance and accounting (Elbashir et al. 2013; Bergmann et al. 2020) which also show a low adoption rate.

The literature on the adoption of business analytics uses predominantly technology acceptance models to explain the intention to use (Lai et al. 2018) or perceived usefulness of business analytics (Nacarelli and Gefen 2021; Lee et al. 2020). This view neglects a) the fundamental economic cost-benefit decision under uncertainty if firms invest in business analytics and digitalization, and b) the measurement of actual usage, which limits subjective influences in measurement.

Given that, we develop an economic model that views adopting and implementing business analytics as investment decisions (e.g. Liberatore et al. 2017). Since investing in new technology renders existing technology obsolete, sunk costs of existing technology are decision-relevant.

IT investments and sunk costs

The concept of sunk costs has its roots in economics and psychology literature and has somewhat overlapping but also differing meanings. In neoclassical economics sunk costs are costs expensed in the past before a decision on a new investment project is made. Such costs are irrelevant for the decision to invest because they do not change whether one invests or not (Rich and Rose 1995). However, in practice, people seem to include such costs into their decisions leading to what is known as the sunk-cost fallacy (Arkes and Blumer 1985; Roth et al. 2015). A fallacy that is apparent in IT investment decisions also - for example in IT outsourcing (Vetter et al. 2012). But these two notions, the irrelevance of sunk costs for rational decision-making as well as sunk costs as an indicator of biased human decisions, are challenged in the literature.

In the industrial economics literature sunk costs play a significant role in explaining market structure (Sutton 2007). The decision of firms to enter a market depends in this view on some sort of setup costs like purchasing infrastructure needed to produce certain products in a market. In the entry, decision firms assume a certain price level once having entered the market to justify their decision. But after entering the market the price level is no longer directly dependent on the setup costs, which deems them as sunk costs. Higher price competition inside the market will lead to lower post-entry profits, which in turn will refrain firms from entering the market. A market with high setup costs may tend therefore to become an oligopoly (Sutton 2007, 28–29). Sunk costs are then important information in a rational market entry decision.

The relevance of sunk costs applies to rational investment decisions more generally (Chavas 1994; Pindyck 1991). Capital investments are characterized firstly by irreversibility in the sense that capital goods are fixed in their current uses and it is not possible to use them in another way. This is also called asset fixity or asses specificity. Selling or abandoning a capital good no longer in use will result in a salvage value. Sunk costs are defined then as the difference between capital expenditure C and salvage value S. A rational decision-maker will invest in new technology if the net benefit of the new technology, i.e. the value of a new technology net of capital expenditure of this new technology, is larger than the sunk costs linked to the existing and replaced technology. This applies also to capital goods that are not firm-specific like IT equipment and software because other parties see them at least partially as irreversible given that their use can create a “lemon” problem or need costly adaptations and reorganizations (also Pindyck 1991, 1111; Vetter et al. 2012, 186; for empirical results Asplund 2000).

Uncertainty about future states is a necessary condition for this discussion because without it a firm could find an optimal decision including the non-recoverable cost of investments (Baddeley 2018, 232). The uncertainty about the value of investments is larger for technology that is unknown to a firm than for technology it already uses or which is similar to what it uses (Ulu and Smith 2009; Brynjolfsson et al. 2017).

Besides extant investments and planned investments in a state of uncertainty, a final aspect of such investment decisions relates to budgets or financial resources. The amount of financial resources needed to invest in new technology is crucial for their implementation success (Chwelos et al. 2001) to invest in light of limited resources. More concretely, as budgets are always limited expenditures in past and extant technology, including maintenance and ongoing support, limit the budget available for investing in new technology (McAfee et al. 2010).

Hence, a decision to invest in new IT like business analytics compares then the additional value of new IT net of sunk cost for existing IT (figure 1, panel A). Yet, this decision depends on the degree of uncertainty. While predicting the net benefits of IT, i.e. its discounted value, was and is still difficult (Remenyi et al. 2007), it is more so for new IT like business analytics. Considering a larger degree of uncertainty for new IT compared to existing IT a firm will assign lower discounted values to a new technology which in turn could lead to a negative value net of sunk costs (figure 1, panel B).

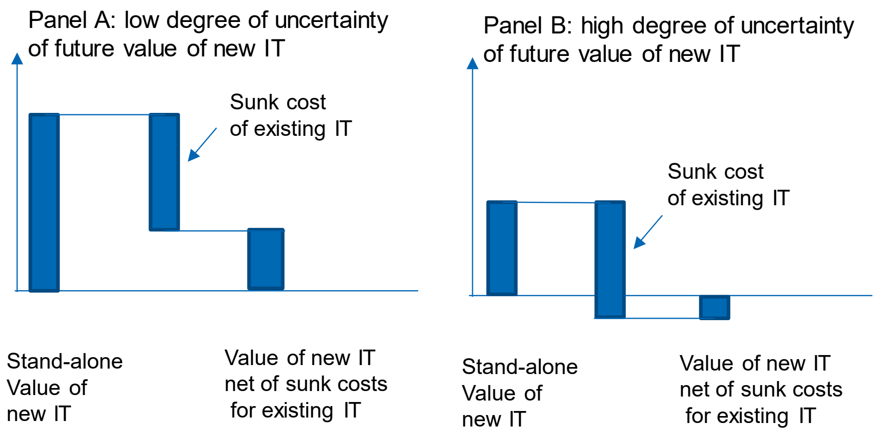

Figure 1. Sunk cost and valuation of new IT (schematic)

It follows that empirical evidence for interpreting sunk cost as a decision bias (Friedman et al. 2007) can be reconciled with bounded rational decision-making which perceives sunk costs as information signals under financial and time constraints (McAfee et al. 2010). Further studies support the role of sunk cost in rational decision making, be it for decisions to invest in R&D (Máñez et al. 2009) or decisions for outsourcing (Bartel et al. 2014).

Given that there is to our best knowledge no study on the impact of sunk costs on the decision to invest in business analytics in accounting and finance, we develop hypotheses to test for sunk costs in the next section.

Hypotheses development

The sunk cost hypothesis states broadly that the amount of investment in the past and the required investments into new technology will impact the investment decision (Chavas 1994).

We can assume that existing investments into information technology deliver some positive value to a firm – without a positive value they wouldn't happen are would be already abandoned. In that sense, and following McAfee et al. 2010, they convey an information signal for future risk and opportunities of further investments and improvements into existing IT. This signal is generally positive in favour of further investments, i.e. the more extant IT investments the more benefits to expect for further investments. Hence, abandoning extant IT would leave a firm with foregone value.

In contrast, the prospects of new IT like business analytics are in general uncertain (Remenyi et al. 2007). It requires changes in competencies, processes and appropriate use-cases (Dang et al. 2017). The higher the required investment is the more reluctant will firms be to invest, as the perceived risk measured in probable or estimated loss will be subjectively higher; also large uncertainty typically leads to higher discount rates and lower expected value of new IT. Applying this argument to investment decisions on digitalization leads to a first hypothesis:

Hypothesis H1: the larger existing and required IT investments the lower the degree of digitalization

Capital investments happen under budget constraints. Given the total amount of budget available for existing and new IT investments, the more budget is spent for existing IT the lesser is available for new investments (McAfee et al. 2010). Hence, the second hypothesis reads:

Hypothesis H2: the lower available budgets for required IT investments the lower the degree of digitalization

Implementing and using digital tools and process changes requires competencies often different from existing ones (To and Ngai 2006). Resources invested in incumbent staff training and competencies might be not adequate for future digitalization which requires different knowledge and experience and contribute to sunk costs. The next hypothesis is then:

Hypothesis H3: the more competence changes are needed the lower the degree of digitalization

Finally, the literature on capital investments in general (Pindyck 1991) as well as on sunk costs (Chavas 1994) stresses the important role of uncertainty in decision-making. Given the degree of novelty of digitalization to most firms, this novelty creates uncertainty of how to use and successfully implement digital tools like business analytics or machine learning (van Ark 2016; Brynjolfsson et al. 2017). The lack of use-cases might then hinder digitalization as noted in the next hypothesis:

Hypothesis H4: the fewer possible use-cases are known, the lower the degree of digitalization

While digitalization affects all accounting and finance functions, it may be doing so to different degrees. Financial accounting focuses on reporting stakeholder-relevant information (Armstrong et al. 2010) and hence is predominantly backwards-looking. This implies that financial accountants use fewer business analytic tools but more automated processes to organize their reporting tasks more efficiently (Kokina et al. 2021). Management accounting, on the other hand, is forward-looking and focuses on forecasts, planning and variance analyses which naturally has more possible uses for business analytics (Rikhardsson and Yigitbasioglu 2018). Tax accounting and internal auditing might sit in-between as some of their tasks are more reporting and analyzing past data and some are more analytical (Bhimani 2021). It follows that we differentiate in our study between these three accounting and finance functions to understand similarities and differences between them.

Measurement, data and inference

Variables

The dependent variable is the degree of digitalization. Our measurement model for digitalization focuses on the key components of digitalization in accounting and finance (Elbashir et al. 2013; Keimer et al. 2018; Bergmann et al. 2020), i.e. actual use of certain instruments and technologies, the automation of processes as well as the application of business analytics. In total 12 items were combined with exploratory factor analysis. The internal reliability measured with Cronbach's alpha is 0.761 which is deemed adequate (Kline 2016, 93).

Several independent variables form the basis for the hypotheses tests. Table 1 summarizes the variables used for testing hypotheses H1 to H4.

Hypothesis	Variable	meaning	measurement	scale	transformation
H1	zInvest	Extant and required investments	Index of two items	Ordinal scale 1 … 6	z score
H2	zCompetence	Existing competencies of staff (amount, suitability for digitalization); amount of required competencies of staff for digitalization	Index of three items	Ordinal scale 1 … 6	z score
H3	zBudget	budget available for digitalization	One item (reversed)	Ordinal scale 1 … 6	z score
H4	zUse_case	Clear use-cases exist for digitalization	One item (reversed)	Ordinal scale 1 … 6	z score

Table 1. Overview on independent variables

We use company size as an additional control variable given that size is an important contingency factor in accounting and finance (Chenhall 2003) as well as information technology usage (Zolas et al. December 2020). Size is measured in classes and then standardized as a z-score for analyses.

Data and inference

We developed a questionnaire, improved it through pre-tests and provided it as an online survey in collaboration with an association of accounting and finance professionals in February and March 2020. This association sent it to around 8,000 email accounts of their members as well as participants in past seminars. The usable sample size is n = 952.

Given the metric nature of the dependent and independent variables we test the hypothesis with a linear model of the form:

Digitalization = zInvest + zCompetence + zBudget + zUse_case + zSize

Reporting of results include estimated effects with 95% confidence intervals and p-values (Cumming 2014). As discussed at the end of section 2.3, we differentiate into three subsets of our sample, financial accounting, management accounting, and tax and internal auditing, and estimate regressions for the total sample as well as per subset.

Descriptive Results

In the total usable sample of n = 952, 51.6 % of respondents are male, 48.4 % female. The median age is in the range of 31 to 40 years old. Nearly all respondents have vocational educations and professional degrees, mostly as financial accountants (63.7 %), less so as management accountants (6.6%). Only 6.2 of respondents have no vocational education or professional qualification. Academic qualifications apply to one-third of the respondents, with bachelor degrees (20.9%) more often than master degrees (11.9%). The work experience in finance and accounting range from zero to more than 35 years with a median in the range of 10 to 14 years.

While the total sample consists of n = 952 cases, 420 or 44.1% work in financial accounting, 137 or 14.4% work in management accounting and 262 (27.5%) work in tax and internal auditing. The rest are functions (like general management and the like 14%) and are not separately analyzed in this paper.

Regarding characteristics of the firms the respondents work for, 70.8% of firms are corporations, 17.4% private companies. The size of the firms is measured as categories of the number of employees. 61.8% are smaller or up to 250 employees which classifies them as SMEs. The median is in the range of 101 to 150 employees. The firms of the respondents cover a wide range of industries. The three most mentioned ones are manufacturing (23.4%), services (14.4%) and retail (9.0%).

Table 2 depicts Pearson correlation coefficients of all variables. It is apparent that digitalization correlates negatively with all independent variables and positively with firm size. This let us suspect that the following regressions will probably support our hypotheses.

Pearson correlations		Digitalization	zInvest	zCompetence	zBudget	zUse_case	firm size
Digitalization	r	1	-0.267	-0.348	-0.231	-0.317	0.236
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000
	N	952	952	952	952	952	952
zInvest	r		1	0.464	0.341	0.342	-0.063
	Sig. (2-tailed)			0.000	0.000	0.000	0.051
	N		952	952	952	952	952
zCompetence	r			1	0.431	0.613	-0.036
	Sig. (2-tailed)				0.000	0.000	0.272
	N			952	952	952	952
zBudget	r				1	0.507	-0.068
	Sig. (2-tailed)					0.000	0.036
	N				952	952	952
zUse_case	r					1	-0.051
	Sig. (2-tailed)						0.116
	N					952	952
firm size	r						1
	Sig. (2-tailed)						
	N						952

Table 2. Correlations of dependent, independent and control variable

Hypotheses tests

As noted, we estimate regressions for all data and regressions for each of three functions. The regression results are printed in table 3 and visualized as estimates with their 95% confidence intervals in figure 2. Model fit statistics indicate a good model fit, F-tests for the models are all statistically significant with $p < 0.001$ while adjusted R^2 is 0.243. The variance inflation factors for coefficients are between 1.01 and 1.88 which does not indicate problems of multicollinearity between variables in the regressions.

Overall, the sign and magnitude of estimates for independent variables support the postulated hypotheses except for H3, the impact of budgets on digitalization. The latter does not affect digitalization in a significant way. Regarding the subsets for finance and accounting functions, noteworthy differences exist for management accounting. The effect of competence is much stronger for management accounting while the non-existence of use-cases is on average about zero, meaning that in management accounting functions the need for different competencies is strongly discouraging digitalization while how to apply digital tools and processes are not seen as a problem.

The control variable firm size is generally positively linked to digitalization, i.e. smaller firms are less adopting digitalization and larger firms are adopting more. A further look into possible interactions between firm size and other independent variables reveals only for the management accounting function a result different from the general impact of firm size. Figure 3 shows that the lack of use-cases apparently hinders small firms from implementing digitalization while larger firms are not affected.

	All data	Financial accounting	Management accounting	Tax & internal audit
(Intercept)	0.000	-0.110 *	0.309 ***	-0.101
	[-0.057, 0.057]	[-0.195, -0.024]	[0.162, 0.455]	[-0.208, 0.006]
zInvest	-0.107 **	-0.131 **	-0.156	-0.082
	[-0.173, -0.041]	[-0.224, -0.037]	[-0.323, 0.011]	[-0.201, 0.037]
zCompetence	-0.197 ***	-0.186 ***	-0.333 ***	-0.136 *
	[-0.274, -0.119]	[-0.296, -0.076]	[-0.526, -0.139]	[-0.268, -0.003]
zBudget	-0.026	-0.053	-0.020	-0.009
	[-0.094, 0.042]	[-0.156, 0.050]	[-0.187, 0.146]	[-0.125, 0.107]
zUse_case	-0.136 ***	-0.137 *	0.009	-0.156 *
	[-0.213, -0.059]	[-0.247, -0.026]	[-0.193, 0.211]	[-0.286, -0.025]
zSize	0.213 ***	0.121 **	0.196 **	0.294 ***
	[0.156, 0.270]	[0.037, 0.205]	[0.062, 0.330]	[0.178, 0.410]
N	952	420	137	262
R2	0.196	0.199	0.271	0.213

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 3. Regression results reporting effects and 95% confidence intervals

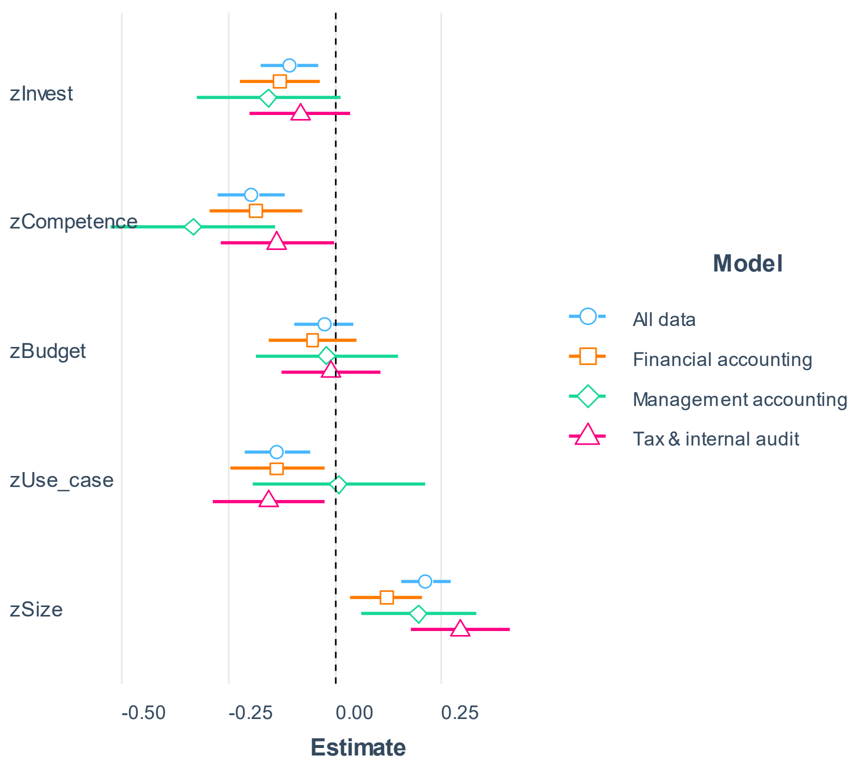

Figure 2. Comparing model estimates with 95% confidence intervals

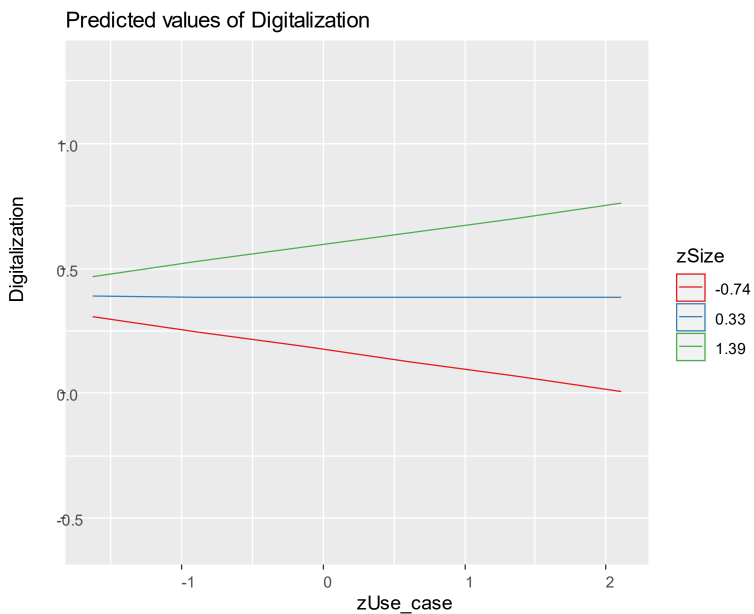

Figure 3. Interaction firm size and use cases for management accounting function

Discussion

Sunk costs are a factor to be considered in rational decision-making on investments in general as well as in information technology. This study hypothesized that sunk costs may also hinder firms in adopting digitalization. This is especially relevant given the low adoption rate of digitalization in practice and the still debated causes for that situation in research and practice.

The results support in general the role of sunk costs in digitalization with the example of finance and accounting functions with some exceptions. The extant amount of investments as well as the level of additional investments needed lower the degree of digitalization. The same holds for existing competencies that could not be brought to use in digitalization as well as competencies needed for future digital tools and processes. Also, the lack of possible use-cases hinders the adoption of digitalization. The hypothesized negative effect of budget constraints was not supported by the results. The results between three different finance and accounting functions are the same except for management accounting. There, the problem of competencies is stronger felt in management accounting functions while the lack of use cases seems to be not that problematic on average.

The study results support an economic perspective on digitalization which sees it as a problem of investment decisions. While the upfront costs of additional investments are often more tangible the possible future value of digitalization is behind a veil of ignorance. In such a situation it is reasonable not to invest or to wait for additional information. The road to digitalization is only taken by firms if they see reasonable additional value net of sunk costs of existing investments in IT. According to our results, the level of investments, competencies and existing use-cases play a significant role in this decision. The seemingly reluctance to invest is then not an unwillingness to realize the great potentials of digitalization but the outcome of a rational decision process.

Sunk costs explain the reluctance of adoption as an outcome of a decision process of rational actors weighing cost and benefits under uncertainty. In so doing, its explanation is based on economic principles that should apply to a vast array of situations (see also Besanko et al. 2015) and that lie behind many cases that seems at first glance very different and with sometimes conflicting evidence. Zolas et.al. (December 2020), for example, provide large scale evidence from US firms that small and young firms, as well as large and old firms, adopt more advanced information technologies. From a sunk cost perspective young and small firms invested less in IT in the past, experiencing low sunk costs while older and larger firms have more resources at their disposal that allows them to invest in new IT despite large investments in the past. Another case is the higher rate of adoption of robotic process automation (RPA) compared to machine learning (Pramod 2021; van der Aalst et al. 2018). Since RPA is a technology that is employed complementary to existing technology it does not render the latter obsolete which leads to low sunk costs. In contrast, machine learning applications are not a "from-the-shelve" solution. They require substantial efforts to implement and possible applications are not self-evident while on the other hand offering substantial and disruptive changes in business processes and models (Agrawal et al. 2018). Therefore machine learning comes with large sunk costs.

Yet, the sunk cost explanation of adoption and investment decisions of technology does not incorporate or consider differences of traits, preferences and perceptions of individuals like in technology acceptance models (Venkatesh et al. 2003) and other psychological approaches (e.g. Nam et al. 2019). Instead, it builds on relations of basic economic variables and decisions. It is an open question which of these approaches delivers a larger explanatory power. While a direct comparison of various approaches could answer that question, we lack studies and evidence for that. Looking at other research areas where economic and psychological explanations are offered is the question of what determines firm performance: managerial idiosyncracies or economic variables? Evidence shows consistently that the economic context, like the industry within a firm operates, explains the majority of variance of firm performance. Individual managers and their peculiarities explain only a small part of it (Henderson et al. 2012; McGahan and Porter 2002).

The sunk cost theory offers also practical implications. In light of uncertainty and large sunk costs, it is rational for firms to wait for use-cases and "best practices" that show sufficient opportunities for reaping the benefits of new technology. This creates a time lag between the availability of new technology like business analytics and widespread adoption which was visible in the past also (Brynjolfsson et al. 2017; Brynjolfsson and Hitt 2000) and which sometimes lead to hype-cycles in practice (Dedehayir and Steinert 2016).

Several limitations are worth mentioning. First, given that there is no agreed-upon and tested scale for digitalization in accounting and finance functions, we employed a self-developed measurement scale. A need for scale-development (e.g. Rossiter 2002) in this research area is apparent; it could base future empirical work on more solid ground as in other areas where tested measurement scales are available, like for example management accounting (Schäffer 2007).

Second, while our research aimed at sunk costs in decisions to adopt technology, we measured the degree of adoption, and in that sense, the outcome of decisions and not the decisions themselves. To understand what information goes into such decisions and which considerations and methods are employed, field studies might be a more suitable method to understand actual decision processes.

Third, considering the future application of yet-to-adopt technologies additional cost categories might shed light on determining the ex-ante value of new technologies. Such cost categories are under the caption of switching costs which include for some scholars also sunk costs (Dang et al. 2017). Switching costs encompass costs for learning a new system, cost for implementing the system, and costs due to reduced performance at the beginning of using a new system. Future research on adopting digital tools and change in processes could focus on such additional cost categories and their impact on adopting digitalization.

Still, the paper contributes to the literature on digitalization with an economic explanation for adoption decisions. A lack of investments in digitalization within the finance function of a company might be logically explained by looking at the in-depth mechanisms of perceived sunk costs by financial decision-makers. In short: the decision not to invest in digitalization might be rational in the light of sunk costs.

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