DISENTANGLING THE RELATIONSHIP BETWEEN THE ADOPTION OF IN-MEMORY COMPUTING AND FIRM PERFORMANCE

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Research in Progress

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Abstract

Recent growth in data volume, variety, and velocity led to an increased demand for high-performance data processing and analytics solutions. In-memory computing (IMC) enables organizations to boost their information processing capacity, and is widely acknowledged to be one of the leading strategic technologies in the field of enterprise systems. The majority of technology vendors now have IMC technologies in their portfolio, and the interest of companies in adopting such solutions in order to benefit from big data is increasing. Although there is first research on the business value of IMC in the form of case studies, there is a lack of large-scale quantitative evidence on the positive effect of such solutions on firm performance. Based on a unique panel data set of IMC adoption information and financial firm performance data for a sample of companies from the Fortune 500 list this study aims at explaining the relationship between the adoption of IMC solutions and firm performance. In this research-in-progress paper we discuss the theoretical background of our work, describe the proposed research design, and develop five hypotheses for later testing. Our work aims at contributing to the research streams on IT business value and business analytics by helping to better understand the nature of the interdependencies between IMC adoption and firm performance.

Keywords: In-memory computing, Business analytics, Business value of IT, Firm performance

1 Motivation

Data management and analysis requirements of enterprises have changed over the past several years. While traditionally analytical applications operated on historical data that has been updated in periodic batch runs (e.g., weekly, monthly), companies now increasingly strive to gain insights from operational data in order to make data-driven decisions in near real-time (Färber et al., 2012; Janiesch et al. 2012; vom Brocke et al., 2014).

A recent technological innovation addressing these new data processing demands is in-memory computing (IMC). The key idea behind IMC is to keep all data and applications in a computer's main memory in order to avoid expensive mechanical hard-drive I/O access (Chaudhuri, Dayal, & Narasayya, 2011), which can result in enormous increases in data processing speed. For example, SAP reports improvements in transaction processing speed by factors up to 100,000 for its in-memory computing appliance HANA (High-performance ANalytic Appliance) (SAP, 2012).

The potential of IMC for setting new performance standards in the area of data management and analytics is recognized by both academics (e.g., vom Brocke et al., 2014; Plattner & Zeier, 2012) and analysts (e.g., Deloitte, 2013; Gartner, 2015). Gartner (2011), for example, identified IMC as one of the top ten strategic technologies in the field of enterprise systems, and estimated that it is likely to be adopted by at least 35% of midsize and large organizations through 2015 (Gartner, 2013). Plattner and Zeier (2011) even state that IMC "marks an inflection point for enterprise applications" (p. xvi) and that it "will lead to fundamentally improved business processes, better decision-making, and new performance standards for enterprise applications" (p. xxxii). And a look at SAP's earnings report shows that sales in SAP HANA exceeded $200 million in 2011, which confirms that companies are willing to invest into IMC (Woods, 2012).

Scientific research on application scenarios for IMC and its business value is scarce, especially in terms of quantitative studies. In fact, anecdotal evidence and case studies indicate that companies are struggling to find valuable use cases for in-memory computing and are asking whether in-memory technologies are "only enabling very specific scenarios, or will […] have a positive impact on the entire IT architecture" (Bärenfänger et al., 2014, p. 1397). Bärenfänger et al. (2014) also point out the importance of analyzing the monetary value contribution of IMC, and Manyika et al. (2011) note that the expertise required to realize its business value seems to not be in place yet. The same applies to the advanced analytics that IMC enables: While LaValle et al. (2013) show that financially successful companies are characterized by high use analytics, they also observe that the main obstacle for advanced analytics adoption is a "lack of understanding how to leverage analytics for business value" (p. 24).

Given the scarcity of empirical research on IMC's business value, we aim at explaining the relationship between its adoption and firm performance by following an econometric approach. In this research-in-progress paper we present our research design and hypotheses development. Our work builds upon a unique multi-year panel data set of IMC adoption information and financial firm performance for a sample of Fortune 500 companies.

The remainder of this research-in-progress paper is structured as follows. First, we present the research background, discussing theoretical and empirical arguments related to the business value of IMC, and challenges of measuring the performance impacts of enterprise systems. Subsequently, we derive our hypotheses on the relationship between IMC adoption and firm performance. We then provide details on our research design, introducing both our unique data set and the econometric specifications for data analysis. We conclude by outlining our next steps and expected contributions.

2 Research Background

2.1 The Business Value of In-Memory Computing

Academic literature on the business value of analytics, and the impact of IMC in particular, is scarce. Nonetheless, our research can be informed by at least three streams of literature.

The first stream of literature is theoretical. As summarized by Brynjolfsson et al. (2011), it builds on arguments stemming from information theory (Blackwell, 1953) and the information-processing view of the firm (Galbraith, 1974). One of their key arguments suggests that the availability of information that is more fine-grained, less noisy, better distributed and available in greater volumes increases its usage in decision making and, in turn, triggers higher firm performance. So, at least in theory analytics-enabling technologies like IMC, which aim at improving the information processing capacity of an organization, should contribute to increased firm performance.

The second stream of literature consists of case studies that explicitly look at the use and impact of IMC (e.g., Piller and Hagedorn, 2011, 2012; Wessel et al., 2013; vom Brocke et al., 2014; Bärenfänger et al., 2014). For example, based on an in-depth study of potential IMC application scenarios at a global tool manufacturer vom Brocke et al. (2014) propose a framework of business value generation through in-memory technology. Their framework combines technological characteristics of IMC (e.g., in-memory data storage and processing), first-order effects (e.g., latency time reduction), second-order effects (e.g., advanced business analytics), and the resulting business value effects (productivity increase). Similarly, Bärenfänger et al. (2014) conducted a multiple-case study and derived a process model of business value creation through IMC, comprising the following elements: (1) implementation drivers (e.g., insufficient performance of current IT solutions), (2) technological enablers (e.g., fast processing of large data volumes), (3) realization conditions (e.g., adaptation of operational business processes), (4) business benefits (e.g., deeper and faster insights into data), and (5) contribution to strategic goals (e.g., data-driven decision making). The authors conclude that the „technical advantages of in-memory computing can lead to business value in various applications across industries, albeit not always in a measurable monetary way“ (Bärenfänger et al., 2014, p.1403).

The third stream of literature consists of quantitative studies focusing on the connection between the adoption of analytics in general and firm performance. Over the last years several large-scale surveys have been conducted in this field, often in collaboration between industry and academia. For example, a study by IBM (LaValle et al., 2011, 2013) found that top-performing organizations use analytics five times more often than lower performers do. Another survey conducted by Brynjolfsson et al. (2011) in conjunction with McKinsey and Company investigated the relationship between decision making based on data and business analytics (called "data driven decision making" or DDD) and firm performance. They showed "that firms that adopt DDD have output and productivity that is 5-6% higher than what would be expected given their other investments and information technology usage" (p. 1).

In total, we can summarize that there are theoretical and empirical arguments for the positive effect of general analytical information systems on firm performance. Yet, the thesis that in-memory computing leads to the positive effect on firm performance requires further investigation. Examining in-memory computing in relation to various industries, business processes, and use cases as well as various performance indicators is required in order to explain and assess IMC business value, and determine the most promising areas of IMC adoption in organizations.

2.2 Measuring the Performance Impact of Enterprise Systems

The problem of quantifying the financial impact of IT on firm performance has been widely discussed in the literature over the decades (Bakos, 1987, Brynjofsson & Hitt, 1996; Bharadwaj et al., 1999; Brynjofsson & Hitt, 2000; McAfee, 2002; Brynjofsson & Hitt, 2003; Melville, Kraemer & Gurbaxani, 2004; Ranganathan & Brown, 2006; Hendricks, Singhal & Stratman, 2007; Aral & Weill, 2007; Tambe & Hitt, 2012). In general, quantitative studies on IT adoption and firm performance face one common dilemma in their quest to show the business value of IT: Do companies become successful because of adopting IT, or do successful companies adopt IT?

Various methods (e.g., lagged variables, instrumental variables) have been proposed to address this issue of causality. A promising approach proposed by Aral, Brynjolfsson & Wu (2006) is based on the availability of detailed information about the IT adoption process. While most studies measure IT adoption as a single event, Aral et al. (2006) suggest distinguishing between license purchase events and go-live events (in the context of enterprise systems there are typically one or two years passing between these two events). This allows for measuring the performance effects of license purchases and go-lives separately. In addition, Aral et al. (2006) examine the impact of specific IT applications separately. In particular, they distinguished between the impact of Enterprise Resource Planning (ERP), Customer Relationships Management (CRM), and Supply Chain Management (SCM) systems. Based on this differentiation between license purchase and go-live as well as between different types of enterprise systems the authors suggest a framework of five possible causal relationships between IT and firm performance:

1. **No relationship**: If there is neither a positive relationship between enterprise system license purchases and firm performance, nor between go-live events and firm performance, it can be assumed that the adoption of enterprise systems has no measurable financial impact on firm performance.
2. **Performance-led IT investment**: If there is a positive relationship between enterprise system license purchases and firm performance, and no relationship between system go-lives and firm performance, it can be assumed that financially successful companies invest in enterprise systems.
3. **IT-driven performance**: If there is a positive relationship between enterprise system go-live events and firm performance, and no relationship between license purchases and firm performance, it can be assumed that the use of enterprise systems has a positive impact on firm performance.
4. **Classic simultaneity**: If there is a both a positive relationship between enterprise system license purchases and firm performance, and between go-live events and firm performance, no further insights into the direction of the causality between enterprise system adoption and firm performance can be gained.
5. **Virtuous cycle**: If there is (a) no relationship between the purchase of ERP systems and firm performance, and (b) a positive relationship between the go-live of ERP systems and firm performance, and (c) a positive relationship between the purchase of SCM/CRM systems and firm performance, and (d) a positive relationship between the go-live of SCM/CRM systems and firm performance (beyond the performance gains from ERP), it can be assumed that the initial investments in ERP drive performance gains, encouraging further investments in complementary enterprise systems (CRM, SCM), which in turn further improve firm performance.

The above described five possible causal interpretations of the relationship between the adoption of enterprise systems and firm performance will build the foundation for our empirical investigation of the impact of IMC on firm performance, as will be outlined in the following section.

3 Hypothesis Development

Discussing the general value of information in management, Brynjolfsson et al. (2011), building on the seminal theoretical works of Blackwell (1953) and Galbraith (1974), summarize that "technologies that enable greater collection of information, or facilitate more efficient distribution of information within an organization should lower costs and improve performance" (p. 7), and also find first empirical evidence for a positive effect of analytical information systems on firm performance. IMC and the analytics it enables can without doubt be regarded as such information processing technologies. As Bärenfänger et al. (2014) argue, IMC supports „data-depending processes in ways impossible in the past" (p. 1397) through (1) faster data processing, (2) more flexible data access, (3) more up-to-date data, (4) less aggregates and deeper drill-downs, (5) simpler data models, and the (6) convergence of OLAP and OLTP. Hence, we hypothesize:

H1: Companies adopting in-memory computing experience greater performance than those that do not.

The notion of "information intensity", that is, the degree to which a company's products, services and operations depend on the information collected and processed (Lee, 2008), has been discussed by several researchers, such as, Zhu (1999) and Bhatt & Stump (2001). Thong (1999) argued that businesses in more information-intensive industries have higher information-processing needs and are more likely to adopt information systems than those in less information-intensive industries. Lee (2008) has analyzed numerous IT investment studies and found that studies relying on samples from high information-intensive industries (e.g., financial services, insurance, retail, healthcare) found positive effects of IT investments, or at least mixed results, as opposed to studies in low information-intensive industries (e.g., construction, specific manufacturing industries). Finally, in the context of IMC, Bärenfänger et al. (2014) derived a list of critical success factors of IMC implementation. Among other factors they mentioned IMC adoption in a business process where "time is a direct cost driver" and "the value of data processing velocity is high". Hence, we hypothesize:

H2: Firms from high information-intensive industries that adopt in-memory computing experience greater performance than adopters from low information-intensive industries.

Various surveys on business analytics and its underlying technologies (e.g., big data) emphasize the value of analytics for customer-facing business processes. For example, a study by Schroeck et al. (2012) found that customer-centric outcomes are the number one functional objective for big data analytics, with almost half of respondents ranking it as their top priority. Likewise, a recent survey by BARC (Bange et al., 2015) showed that marketing and sales are the areas in which companies use big data analytics the most, and also plan the most investments. Focusing on IMC, Acker et al. (2011) emphasize the value of IMC for customer relationship management, suggesting customer-related application scenarios for various industries (e.g. in telecommunications: value-add services, subscriber database consolidation, fraud management). Their study argues that the real-time business process support provided by IMC for operations, customer relationship management, and business intelligence introduces a new level of customer experience. And Booz & Company (2011) predicts that the shift towards in-memory technology will be driven by business-side demand for real-time customer and operational information. Hence, we hypothesize:

H3: Companies that adopt in-memory computing to support customer-facing business processes experience greater performance than those that adopt it to support non customer-facing business processes.

With regards to the business process benefits of IMC Bärenfänger et al. (2014) distinguish between transactional use cases and analytical use cases. While transactional IMC use cases primarily aim at time savings (e.g., reduced lead times of business processes), the goal of analytical IMC use cases is to gain deeper business insights (e.g., extracting new and useful knowledge about customers from historical transaction data). This differentiation is in line with the organizational ambidexterity theory that distinguishes between *exploiting* existing capabilities and *exploring* new opportunities (March, 1991). In the IMC context exploiting would mean running the same business processes, but faster; while exploring would mean enabling completely new business processes, or even business models. It has been argued that "refining exploitation more rapidly than exploration" (March, 1991, p. 71) is likely to be effective in the short run, but self-destructive in the long run. Hence, we hypothesize:

H4: Companies that adopt in-memory computing to implement analytical use cases experience greater performance than those that adopt it to implement transactional use cases.

Provided that IMC adoption is associated with greater performance, we suggest that its effect on firm performance is best explained by the "virtuous cycle" effect, as described in Section 2.2. Specifically, we assume that a *positive relationship between go-live of an initial IMC solution and firm performance* encourages companies to invest more into IMC, indicated by a *positive relationship between firm performance and purchase of further IMC solutions*, which, in turn, will trigger further performance gains, indicated by a *positive relationship between go-live of follow-up solutions and firm performance*. This theoretical argument is supported by the findings from Bärenfänger et al. (2014), who found in their multiple-case study that gaining experience with big data is an important strategic objective of adopting IMC solutions. In addition, vom Brocke et al. (2014) emphasize that value creation through IMC is restricted by the capabilities of the overall socio-technical structures and processes of an organization and its IT landscape, and that a single project is unlikely to deliver sustainable business value. And Seddon et al. (2012) found empirical evidence that the pursuit of multiple ongoing business analytics projects is an important antecedent of deriving greater benefits from business analytics. Hence, we hypothesize:

H5: For companies adopting multiple in-memory solutions, the firm performance effects of in-memory computing are best described by the "virtuous cycle" interpretation.

4 Research Method

4.1 Data

Following the approach of Aral et al. (2006), we collected detailed information on IMC purchase and go-live events of more than 200 companies in the time frame from 2009 to 2015. In particular, our data set comprises information about Fortune 500 companies that during this time period have concluded license agreements for IMC solutions with one of the largest vendors. The data set, which has been retrieved from the vendor's project database, includes the name of the company, the year of the purchase, the year of the go-live, and the so-called use case. The use case describes the functional (e.g., customer relationship management, supply chain management, financial reporting) and technical (e.g., database, data warehouse, cloud solution, business application) scope of the purchased IMC solution. In total there were more than 100 use cases, which we grouped into four functional categories (inbound, operations, outbound, and support), utilizing the framework suggested by Dehning et al. (2007), two broad technical categories (database-tier, e.g. database management system, data warehouse, versus application-tier, e.g. sales pipeline analysis, smart meter analytics), and two general information processing goals (transactional processing versus analytical processing). The distinctions between these categories will be used to investigate hypothesis H3 ("customer-facing business processes"), H4 ("exploitation vs. exploration"), and hypothesis H5 ("virtuous cycle"). Regarding the virtuous cycle hypothesis, we assume that database-tier IMC solutions play the role of ERP systems, initially triggering the virtuous cycle, and that application-tier IMC solutions are follow-up investments, which will generate additional firm performance gains (comparable to CRM and SCM systems in the original formulation of the virtuous cycle hypothesis).

For each firm from our list of IMC adopters we queried the CRSP/Compustat Merged Database to retrieve their industry classification and financial performance data for the years from 2009 to 2015. As some companies from our list of IMC adopters are not publicly traded on U.S. stock exchanges, we had to remove a small number of cases from our panel data. Subsequently, we constructed the same financial performance measures that have been used in prior research on the performance effects of IT adoption (Table 1).

Ratio	Definition	Interpretation
Labor productivity	Sales/number of employees	High ration indicates more productivity per employee
Return on assets	Pretax income/assets	High ratio indicates efficient operation of firm without regard to its financial structure
Inventory turnover	Cost of goods sold/inventory	High ratio indicates more efficient inventory management
Return on equity	Pretax income/equity	High ratio indicates higher returns accruing to the common shareholders
Profit margin	Pretax income/sales	High ratio indicates high profit generated by sales
Asset utilization	Sales/assets	High ratio indicates high level of sales generated by total assets
Collection efficiency	Sales/accounts receivable	High ratio indicates effective management of customer payment
Leverage	Debt/equity	The higher the ratio, the more leveraged the firm

Table 1. Definitions and Interpretations of Financial Performance Measures (Aral et al., 2006; Hitt et al., 2002).

4.2 Econometric Methods

We plan to analyze our panel data set applying two commonly used econometric approaches.

First, we replicate the approach of Hitt et al. (2002) and Aral et al. (2006) in order to ensure the comparability of our results with their findings. We will use the following general specification of a pooled regression model to examine the relationship between IMC and various measures of financial performance:

(1) $$\log(\text{Performance Numerator}_{fy}) = \beta_{fy0} + \beta_{fy1} \log(\text{Performance Denominator}_{fy}) + \beta_{fy2}\,\text{Purchase}_{fy} + \beta_{fy3}\,\text{Go-Live}_{fy} + \beta_{fy4}\,\text{Controls}_{fy} + \varepsilon_{fy},$$

where *f* and *y* indicate the firm and year of an observation. *Performance Numerator* and *Performance Denominator* represent the elements of the financial performance ratios, as defined in Table 1. *Purchase* represents dummy variables indicating whether a company has purchased IMC licenses, *Go-Live* represents dummy variables indicating whether a company has performed a go-live of an IMC solution, and *Controls* represents a set of control variables. For some analyses multiple Purchase and Go-Live variables will be used in order to separately model the purchases and go-lives of IMC solutions of various functional and technical scopes, and to distinguish between the purchase and go-live of an initial IMC solution and follow-up solutions. In order to isolate economy-wide shocks and other potential reasons for performance variations between companies we apply a set of control variables, namely: year, industry (2-digit SIC level), industry capital intensity, company size (based on annual firm revenue), advertising expenditure per employee (Mithas et al., 2012).

Second, in addition to the above pooled model we plan to estimate panel data models that account for the panel structure of our data set, that is, the fact that we have both cross-sectional (multiple firms) and longitudinal (multiple years for each firm) data. In particular, it is planned to use random-effects, fixed-effects, and mixed models to estimate the effects of IMC on firm performance (Wooldridge, 2012).

5 Outlook

This research-in-progress aims at contributing to our understanding of the business value of IMC by quantifying its effect on firm performance by applying standard econometric methods. Furthermore, we aim at disentangling the interdependences between IMC adoption and business value by building on a causal framework explaining the effect of IT on firm performance, which was first outlined by Aral et al. (2006). By analyzing a unique data set we can contribute to research on the business value of IMC, uncovering the nature of IMC adoption effects for various industries, business processes, and use cases. Investigating this will shed light on the mediating factors of the relationship between IMC adoption and firm performance gains (for a more detailed discussion see, e.g., Sharma et al. (2014)). From a practitioner perspective these results will allow to analyze potential IMC investments and determine whether they will be effective in a certain business case.

As with all econometric studies, our research design is not without limitations. For example, while differentiating between purchase and go-live events allows us to make detailed claims about causality, we also have to acknowledge that in our data set there are far more purchase events than go-live events. Most IMC solutions were purchased and implemented after 2012, and a great portion of these projects is still ongoing. This can undermine the statistical power of our analysis. We should also keep in mind that our findings can be undermined by the fact that some companies might have implemented IMC solutions from other vendors than the one we are focusing on in this research. Likewise, some companies might have implemented technological alternatives to IMC, such as Apache Hadoop.

In future research, we plan to include IMC solutions from other vendors into our analysis and to compare the business value of IMC solutions with the value of alternative big data analytics technologies. We also intend to complement our econometric approach with case studies about the companies showing outstanding results in our sample in order to gain deeper insights into the process of deriving business value from IMC solutions and the key mediating factors. Finally, future research could explore first- and second-order effects of IMC adoption in-depth, focusing on both financial and non-financial indicators, to better support companies in their technology adoption decisions. Sharma et al. (2014) suggest, for example, that factors such as decision-making processes, organizational capabilities, and governance structures play moderating roles on the path from adopting business analytics solutions to superior organizational performance.

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