Management control in new product development:
Facilitating innovativeness through efficiency

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Benedikt Müller-Stewens

from
Mörschwil (St. Gallen)

Approved on the application of

Prof. Dr. Klaus Möller

and

Prof. Dr. Oliver Gassmann

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St. Gallen, October 24, 2016

The President:

Prof. Dr. Thomas Bieger
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St. Gallen, December 2016

Benedikt Müller-Stewens
Abstract

The continuous development and commercialization of new products is a central determinant of firm performance. Despite its obvious importance, new product development (NPD) activities are characterized by high failure rates. Thus, improving performance by facilitating a firm’s conversion ability from idea to product is at the heart of this dissertation. This cumulative dissertation elaborates, over four articles, how management controls can facilitate firm innovativeness through efficient NPD efforts, i.e. process alignment.

Article 1 advocates for the multidimensional character of NPD performance by reviewing 284 articles. A framework illustrates nine dimensions of performance that support management in assessing NPD holistically. Article 2 groups past approaches that quantify NPD efficiency to performance measurement systems, aggregate absolute metrics, and aggregate relative metrics. It concludes that past research has rarely operationalized efficiency and that available approaches mostly limited their scope to specific dimensions. Exceptions are aggregate relative metrics that have the potential to consider efficiency holistically. Article 3 implements a data envelopment analysis – an aggregate relative measure – in a case study of a chemical firm. The robust implementation shows that efficiency scores might reduce subjectivity in assessing performance, guiding managerial attention and actions to critical project developments. Article 4 tests, in a structural equation model using survey data of 695 research-intensive firms, how management controls can drive NPD efficiency (i.e. process alignment) in order to facilitate innovativeness. Besides the interactive use of controls, the article underlines the beneficial role of diagnostic use of controls, which was frequently considered to be obstructive, although it is shown to facilitate innovativeness through aligned NPD processes. Empirical evidence suggests that both controls and NPD efficiency can enable firm innovativeness and, therefore, can improve conversion ability.

This thesis contributes to prior research in management accounting and innovation management and illustrates a path to improve conversion ability. Firstly, it uncovers the multidimensional success factors of NPD performance that should be reflected by the management control system. Second, it shows how the interactive and diagnostic uses of controls facilitate innovativeness through efficient processes – which can be quantified holistically. Together, this makes holistic NPD efficiency a relevant metric for the management control system, in order to improve conversion ability.
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<th>Description</th>
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<tbody>
<tr>
<td>ABDC</td>
<td>Australian Business Deans Council</td>
</tr>
<tr>
<td>ACMAR</td>
<td>Annual Conference for Management Accounting Research</td>
</tr>
<tr>
<td>AVE</td>
<td>Average variance extracted</td>
</tr>
<tr>
<td>Avg.</td>
<td>Average</td>
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<tr>
<td>BSC</td>
<td>Balanced scorecard</td>
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<tr>
<td>CFI</td>
<td>Comparative fit index</td>
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<tr>
<td>DEA</td>
<td>Data envelopment analysis</td>
</tr>
<tr>
<td>Df</td>
<td>Degrees of freedom</td>
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<tr>
<td>DMU</td>
<td>Decision making unit</td>
</tr>
<tr>
<td>DRS</td>
<td>Decreasing returns to scale</td>
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<tr>
<td>DU</td>
<td>Diagnostic use</td>
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<tr>
<td>Eff.</td>
<td>Efficiency</td>
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<tr>
<td>EFQM</td>
<td>European Foundation for Quality Management</td>
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<tr>
<td>e.g.</td>
<td>Exempli gratia</td>
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<tr>
<td>GFI</td>
<td>Goodness of fit index</td>
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<tr>
<td>i.e.</td>
<td>Id est</td>
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<tr>
<td>IRS</td>
<td>Increasing returns to scale</td>
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<tr>
<td>ISIC</td>
<td>International Standard Industrial Classification of all Economic Activities</td>
</tr>
<tr>
<td>ISPIM</td>
<td>International Society for Professional Innovation Management</td>
</tr>
<tr>
<td>IT</td>
<td>Information technology</td>
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<tr>
<td>IU</td>
<td>Interactive use</td>
</tr>
<tr>
<td>JQ3</td>
<td>VHB-JOURQUAL 3</td>
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<tr>
<td>KPI</td>
<td>Key performance indicator</td>
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<td>MCS</td>
<td>Management control systems</td>
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<tr>
<td>Mio.</td>
<td>Millions</td>
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<tr>
<td>Mn</td>
<td>Mean</td>
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<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>MV</td>
<td>Missing value</td>
</tr>
<tr>
<td>n/a</td>
<td>Not available</td>
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<tr>
<td>NACE</td>
<td>Nomenclature statistique des activités économiques dans la communauté européenne</td>
</tr>
<tr>
<td>NFI</td>
<td>Normed fit index</td>
</tr>
<tr>
<td>No.</td>
<td>Number</td>
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<tr>
<td>NPD</td>
<td>New product development</td>
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<tr>
<td>NPV</td>
<td>Net present value</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>Research and development</td>
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<tr>
<td>RMSEA</td>
<td>Root mean square error of approximation</td>
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<td>SEM</td>
<td>Structural equation model</td>
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<tr>
<td>Sig.</td>
<td>Significance</td>
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<tr>
<td>Std.</td>
<td>Standard</td>
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<tr>
<td>UK</td>
<td>United Kingdom</td>
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<tr>
<td>U.S.</td>
<td>United States</td>
</tr>
<tr>
<td>USD</td>
<td>U.S. Dollars</td>
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<tr>
<td>VHB</td>
<td>Verband der Hochschullehrer für Betriebswirtschaft</td>
</tr>
<tr>
<td>VRS</td>
<td>Variable returns to scale</td>
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<td>vs.</td>
<td>Versus</td>
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1 Introduction

Facilitating innovation through efficient new product development

The continuous development and commercialization of new products is a determinant of competitive advantage and firm performance. Thus, innovating lies at the heart of any firm’s business endeavor. Despite its obvious importance, product development activities are characterized by high failure rates. Merely 14 percent of initial ideas prove commercially successful (Barczak, Griffin, & Kahn, 2009). Thus, a firm’s conversion ability – its capacity to transfer initial ideas to commercialized products – is of utmost importance for firm performance (Chandy, Hopstaken, Narasimhan, & Prabhu, 2006). Despite the stable overall failure rate, Barczak et al. (2009) observe that, since 1982, conversion ability has steadily improved: projects are cancelled earlier in the funnel. This points to higher resource-efficiency. Nonetheless, one in four projects that initiate the formal development process is not commercialized, and only half of these are successfully commercialized (Barczak et al., 2009). Project failure might generally erode through non-appearance of new product launches the firm’s competitive position. Further, owing to high resource endowments during the later development process stages, project failure is also detrimental to a firm’s profitability. Thus, in the following, the focus is on the time from starting a product development project to its market launch. This is referred to as new product development (NPD).

To overcome high failure rates, firms are confronted with a tradeoff challenge. Significant resource endowments for broke-off development projects need to be reimbursed by commercially successful projects, which lowers overall firm profitability. This incentivizes early project break-offs. On the other hand, innovation is risky – the higher the level of innovativeness, the higher the potential for long-term success, but also the higher the chance of failure (Damanpour, 1996; Gatignon, Tushman, Smith, & Anderson, 2002). Early break-offs might block radically innovative projects and might incentivize incrementalism, risking long-term innovation success as well as the firm’s competitive position.¹ This illustrates that innovation is not a “monolithic phenomenon” (Davila, Foster, & Oyon, 2009, p. 284).

¹ Radical and incremental characterize NPD concerning innovation novelty. While radical innovations might change market structures, create new markets, or render existing products obsolete (create new
Portfolios exhibit diverse project characteristics\(^2\) that need to be accounted for by managers’ procedures and routines – the *management control system*\(^3\) – to direct NPD team activities efficiently and effectively: both incremental and radical projects require customized controls in order to account for projects’ various individualities and the firm settings (Bedford, 2015). Owing to the unique characteristics of NPD projects – creative ideas associated with uncertain feasibilities, long development cycles, and context dynamics that rapidly shift market demands – firms are cautious exercising controls from other disciplines in the innovation context (Kerssens-van Drongelen, Nixon, & Pearson, 2000). Firms fear that controls’ rigidity constrains innovativeness. A package of controls (see Bedford & Malmi, 2015) must be flexible enough to take advantage of unexpected opportunities and to circumnavigate sudden threats, but strong enough to keep the strategic direction. Since most projects in mature industrial firms are incremental development projects, this thesis especially addresses firms’ incremental NPD project conversion ability. Thus, the drawn conclusions apply to incrementally innovative NPD projects.

During the creative research phase, the effectiveness of activities and their strategic contributions to the competitive position are the critical performance variables. In contrast, during the subsequent development phase, when the decision to pursue and commercialize an idea have been made – which is the scope of this research project – the primary focus is efficiency in reaching the goals (Chiesa & Frattini, 2007). Thus, in the following, the efficiency of NPD efforts is at the center of interest.

### 1.1 Four articles on efficiency in new product development

This thesis elaborates over four articles (see Table 1), how the use of management controls can drive the overall efficiency of NPD efforts and, thus, can facilitate increased performance. It seeks to improve firm’s conversion ability by enhancing NPD efficiency. **Article 1** advocates the multidimensional character of NPD performance. This should be reflected in assessing project performance, i.e. when quantifying project efficiency. **Article 2** reviews and groups prior approaches to quantifying NPD business paradigm), incremental innovations improve the performance of existing products (within an existing paradigm) (Davila et al., 2009, p. 286).

\(^2\) Distinguishing by extent of novelty is one way of grouping NPD projects. For alternative categorizations (i.e. locus, type, and characteristics of innovation), see Gatignon et al. (2002).

\(^3\) Simons defines a management control system as “the formal, information-based routines and procedures used by managers to maintain or alter patterns in organizational activities” (Simons, 1994, p. 170).
efficiency. Article 3 proves the robustness of a dynamic approach to operationalizing project efficiency holistically, respecting the multidimensionality of NPD. Yet, measuring efficiency is not sufficient to improve efficiency. Thus, Article 4 tests how the use of management controls can drive NPD efficiency (i.e. process alignment) in order to facilitate innovativeness.

In the following, each of the four articles is motivated and the conclusions are drawn in the context of the dissertation. For more detailed elaborations, kindly refer to the full article in question.

Table 1: Overview dissertation project

<table>
<thead>
<tr>
<th>Article 1</th>
<th>Article 2</th>
<th>Article 3</th>
<th>Article 4</th>
</tr>
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<tbody>
<tr>
<td><strong>Title</strong></td>
<td>The efficiency of new product development: Evidence from prior research</td>
<td>Quantifying project efficiency in new product development: Benefits and pitfalls</td>
<td>The role of controls in innovation: An examination of diagnostic use, interactive use, and dynamic tension</td>
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<tr>
<td><strong>Research question</strong></td>
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<tr>
<td>What are drivers of NPD performance that require managerial attention?</td>
<td>How was NPD efficiency operationalized in prior literature?</td>
<td>How can a holistic NPD project efficiency score based on DEA be implemented?</td>
<td>How can controls be used to drive innovativeness through facilitating efficient NPD?</td>
</tr>
<tr>
<td><strong>Reasoning Approach</strong></td>
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<tr>
<td>Inductive</td>
<td>Inductive</td>
<td>Deductive</td>
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</tr>
<tr>
<td>Systematic keyword-based literature review of 284 articles on NPD performance</td>
<td>Evaluative literature review of articles that quantify NPD efficiency</td>
<td>Case study implementing a DEA model for steering purposes in the NPD context</td>
<td>Structural equation model on survey data of 695 North American and European firms</td>
</tr>
<tr>
<td><strong>Result</strong></td>
<td></td>
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<tr>
<td>Framework with 9 clusters that impact NPD performance</td>
<td>3 groups of approaches to quantifying efficiency</td>
<td>Robustness of a DEA model on ongoing NPD projects</td>
<td>Robustness of model that underlines the impacts of controls on innovativeness</td>
</tr>
<tr>
<td><strong>Conclusion concerning dissertation</strong></td>
<td></td>
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</tr>
<tr>
<td>Management control systems should consider the multidimensionality of performance</td>
<td>NPD efficiency research is in its infancy, yet DEA can address the characteristics of innovation</td>
<td>DEA can serve as a tool to direct managerial attention to critical project developments</td>
<td>Interactive and diagnostic use of controls facilitate innovativeness through process alignment (efficiency)</td>
</tr>
<tr>
<td><strong>Contribution</strong></td>
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<tr>
<td>Management controls can facilitate innovativeness through efficient NPD projects</td>
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</table>
1.1.1 Article 1: A review of the multidimensionality of NPD performance

Characteristics of well-proven NPD efforts are central to configure a firm’s processes and structures. Thus, the design and use of a management control system also orientates itself on these well-proven characteristics. Since the 1980s, a large body of literature has evolved that gathered variables that enable successful development activities – so-called success factors. However, research foci quickly specialized very narrowly and dug into selected effects. Thus, past reviews of the literature that systematically collected NPD success factors were insightful, yet dated or selective through a specific research scope (see Montoya-Weiss & Calantone, 1994; Ernst, 2002; Adams, Bessant, & Phelps, 2006). Best practice studies apply a broad perspective to NPD performance, but have ex ante defined variables that they test (e.g. Cooper & Kleinschmidt, 1995; Ragatz, Handfield, & Scannell, 1997; Balbontin, Yazdani, Cooper, & Souder, 1999; Barczak et al., 2009). The result is the absence of a holistic framework to cover the whole range of levers that make NPD activities successful (see Adams et al., 2006). Therefore, we ask: What are the drivers of NPD performance that should be considered in the design and use of management control systems (see Appendix 1, Table 1)? This paper aims to sensitize the management control literature to the multidimensionality of NPD performance, which should be considered when monitoring and steering NPD.

In a systematic literature review of 284 articles, we inductively derive a framework of nine performance drivers and illustrate paths for future research (ranked by decreasing number of articles):

- Management of process characteristics
- Management of inter-firm cooperation
- Knowledge and information generation and management
- Structural steering mechanisms
- Management of teams and team characteristics
- Management of inter-functional cooperation
- Coping with firm-external factors
- Decision-making in processes
- Consideration of strategic and cultural aspects

Generally, the motives collaboration and diversity – either within the NPD team, along the process, or across organizational boundaries – have received increasing attention.
Research has examined how NPD performance can benefit from knowledge heterogeneity and how this can be managed appropriately. This is closely related to the trending topics of knowledge transfer within the NPD team and the firm’s alliance network; both address how a unit’s absorptive capacity can be improved. Further, we identify six topics that, based on the analysis, might be promising for future research on the management control design and use. These cover antecedents to we-ness in diverse NPD teams, increasing speed-to-market through concurrent NPD processes, increasing benefits from inter-functional cooperation, steering the evolution of alliances, managing the fuzzy front-end, and managing NPD costs.

The review contributes to the management control literature by proposing an inductively derived framework of drivers of NPD performance. The inductive approach distinguishes this study from past selective or dated reviews. It organizes current studies in a manner that is useful to derive research questions on emerging yet under-discussed aspects and to map findings. The framework advocates the multidimensional, “non-monolithic” (Davila et al., 2009, p. 284) character of NPD, which should be considered when conceptualizing and analyzing empirical studies in order to ensure homogeneous samples. Researchers need to be aware of potential contingency effects on the control-performance relationship that prior studies might have overlooked (see Haustein, Luther, and Schuster, 2014). Thus, the framework offers hints to paths that might shed light on the (partly) inconclusive effects of control usage on innovation performance. Practitioners can apply this framework as a model to comprehensively assess and control NPD. Thus, managers can consider these facets in order to grow respect for the facilitators of performance and, hence, avoid negative side-effects that management was previously unaware of. Thus, it assists in designing an inclusive management control system.

1.1.2 Article 2: Grouping prior approaches to quantify NPD efficiency

Recent studies find that the efficiency with which resources are transformed into outputs is a facilitator of firm performance (Cruz-Cázares, Bayona-Sáez, & García-Marco, 2013). Efficiency is often touched on in the innovation literature, yet has lacked operationalization⁴. Very few articles discuss efficiency and operationalize it. It becomes clear that the underlying definitions of efficiency vary widely, from limited to financial efficiency (see Werner & Souder, 1997; Hannon, Smits, & Weig, 2015), to

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⁴ Operationalization is the act of measuring a phenomenon that is not immediately measurable (i.e. NPD efficiency). Quantification refers to the mere process of measuring.
holistically covering most involved resources (see Cruz-Cázares et al., 2013). Still, most approaches build on simple input-output linkages, ignoring causalities and the complexity of innovation activities (see Article 1). These gaps aggravate comparability among study results, owing to differing premises. This paper examines how NPD efficiency was operationalized in prior literature (see Appendix 1, Table 2). The literature review seek to create awareness for approaches that holistically operationalize efficiency and to advance research to a similar underlying understanding of efficiency that would minimize ambiguities in the literature.

The paper presents three approaches to operationalization. Besides (1) performance measurement frameworks that hint at selecting specific metrics in order to facilitate efficient NPD activities, there are aggregate metrics that operationalize efficiency and result in a single value. These aggregate metrics are either (2) absolute or (3) relative – considering the relative efficiency of the unit in focus in relation to a peer group. Although the relative metrics, which are all based on the data envelopment analysis (DEA; see Appendix 2), are more holistic in their operationalization, both groups rarely consider the time lag between resource investment and realization of benefit, mix output and outcome indicators5, rely on output estimates in the context of ongoing projects, and do not consider the unit’s strategic focus. Based on the literature, circumventions are illustrated.

This review contributes to the NPD performance measurement literature, since it summarizes prior approaches that operationalize NPD efficiency, and illustrates how a holistic efficiency metric might complement or replace qualitative assessments of efficiency. This metric might serve as a basis to develop empirically proven practices facilitating NPD efficiency. Further, such a metric might support practitioners in establishing, monitoring, and steering their NPD portfolio, or in benchmarking their firm performance with peers based on more objective evidence on efficiency.

1.1.3 Article 3: Quantifying NPD project efficiency and testing its robustness

Interviews with six research-intensive industrial companies revealed that companies struggle to systematically assess NPD project performance (see Müller-Stewens, Wirnsperger, and Möller, 2014). It is transparent how well projects achieve their cost, time, and quality targets. Yet, comparable to prior research (Ittner & Larcker, 1998; Brown and Svenson (1998), in their concept R&D lab, distinguish outputs – the immediate results from the research, as patents and new products – and outcomes – the accomplishments that have value for a firm, as sales or cost savings.
Cardinaels & van Veen-Dirks, 2010), there is unanimous agreement that the challenge is to systematically weigh these performance dimensions to an overall judgment. Instead of assessing systematically, they apply subjective heuristics. Thus, directing firm attention to critical projects is largely reliant on managers’ subjective judgments. Yet, these individual heuristics are subject to potential judgmental biases, meaning that involved managers are not likely to intervene or terminate NPD projects even if objective information hints at commercial failure of NPD projects (Boulding, Morgan, & Staelin, 1993; Schmidt & Calantone, 2002). Thus, there is a distinct need to reduce subjectivity in assessing NPD project performance. A performance measure that quantifies project efficiency, an antecedent to firm performance (Cruz-Cázares et al., 2013), could offer such initial indication. A holistic operationalization of project efficiency could account for the multifacettness of innovation (see Article 1). We ask if a holistic NPD project efficiency score, based on DEA (see Article 2), can be reasonably implemented and which pitfalls it faces (see Appendix 1, Table 3). This paper seeks to reduce subjectivity in directing managerial attention to critical NPD projects, based on a holistic efficiency score.

In a case study with a chemical firm\textsuperscript{6} that runs more than 80 innovation projects concurrently, we develop and implement a DEA-based efficiency metric\textsuperscript{7}, finding robustness. Using the Malmquist productivity index (Färe, Grosskopf, Norris, & Zhang, 1994), we show that the projects’ efficiency changes provide additional insights than a mere static perspective on where to focus managerial attention. From the case study, we derive pitfalls that a promising implementation must address: project base homogeneity; accuracy of the estimated output metrics; consistent data availability at the project level; thoughtful interpretation of the results by experts; promotion of organizational acceptance of the metric.

This research adds to the prior innovation performance measurement literature by suggesting the feasibility of quantifying DEA-based efficiency scores for steering purposes. We test the operationalization of efficiency – a proven antecedent to commercial firm performance (Cruz-Cázares et al., 2013) – concurrently for ongoing rather than ex post for launched projects. This adds to previous laboratory evidence

\textsuperscript{6} We conducted eight interviews and held ten workshops with innovation experts from the company to challenge assumptions and to develop and validate the DEA model. Further, we had full access to portfolio data.

\textsuperscript{7} The DEA model encompasses two input factors (R&D expenses, capital expenditures) and three output factors (cash flow, net present value, success probability).
(Donthu & Unal, 2014), since DEA results might reduce managers’ cognitive biases and might focus managerial attention and actions based on more objective information. In firms with large project portfolios that detach managers from individual projects’ operations, managers should be extra-sensitive so as to identify critical projects to which they should direct their attention.

1.1.4 Article 4: Testing the role of controls in facilitating innovation through NPD efficiency

A quantified efficiency metric (see Article 3) depicts a key performance indicator (KPI), which can be purposefully implemented in a firm context. Controls are subject to frequent debate in innovation research. Since the beginnings of management control research, there has been debate about whether controls are beneficial (Cooper, 1990) or whether they are detrimental (Damanpour, 1991) in innovation contexts. From a polarized initial starting point, positions have converged to more nuanced attitudes that suggest that the same controls can be used differently, for instance interactively and diagnostically (Simons, 1995), and therefore influence innovation outcomes differently (Ylinen & Gullkvist, 2014; Bedford, 2015). Thus, we formally ask how controls can be used to drive innovativeness through facilitating process alignment – an efficient development process (see Appendix 1, Table 4).

Drawing on Simons’ (1995) levers of control framework, in this study, we adopt the concepts of diagnostic and interactive uses of controls to capture two opposing control usage types, and argue that both control uses work together to create dynamic tension and drive product innovativeness through process alignment. We test the conceptual model using structural equation modelling (SEM) on a sample of 695 research-intensive companies from North America and Europe. Our results show that the diagnostic and interactive uses of control are directly associated with innovation rate and product newness. We also find that these relationships are partially mediated by process alignment. Finally, we find that dynamic tension, or the joint use of diagnostic and interactive control uses, is directly associated with both innovation rate and product newness.

This study contributes to the management accounting literature by (1) providing insights into why controls are important for the NPD process by distinguishing between the process architecture designed to guide the process and its effective implementation, which is affected by control use, and by (2) providing more nuanced findings on both innovativeness and the levers of control framework. The results also help to reconcile
previous ambiguities in the literature. In contrast to the largely inconsistent literature, and Henri’s (2006) findings, we show that diagnostic use and dynamic tension generally positively relate to innovativeness (i.e. innovation rate and product newness). Upon further examination, we find that this direct effect of diagnostic use only holds for companies in technologically stable environments. However, diagnostic and interactive uses of controls both impact innovativeness through process alignment in technologically turbulent environments, providing transparent direction in contexts of high uncertainty. Thus, we nuance Henri’s (2006) findings by showing that diagnostic use of control facilitates innovativeness, no matter the extent of technological turbulence. In greater nuance, we underline the importance of aligned development activities, especially in technologically turbulent context conditions. Awareness of these results can enable managers to consciously guide development activities, to ensure goal predictability and short-term flexibility.

1.2 Conclusion and implications

The four articles in this dissertation advance our understanding of performance measurement and management controls in the NPD context. The dissertation elaborates on the facilitative role of NPD efficiency regarding innovativeness and proposes a validated approach to its operationalization that accounts for the multidimensionality of NPD performance. Further, it examines how control usage might enable NPD efficiency (i.e. process alignment). This adds to the management control literature by emphasizing that both enabling controls (interactive controls) and constraining controls (diagnostic controls) have favorable roles in NPD. The findings address a broad audience. Researchers as well as research-intensive firms that maintain a large portfolio of mostly incremental NPD projects will benefit from the insights.

1.2.1 Theoretical implications

NPD efforts are characterized by high failure rates (Barczak et al., 2009). Thus, this dissertation seeks to improve firms’ conversion ability – from idea to product – through the conscious use of management controls and efficient NPD processes (Chandy et al., 2006). This has a substantial impact on firm performance.

Success factors of NPD practices have seen increasing interest from many disciplines, including marketing, engineering, management accounting, operations management, and innovation management. This has led to a specialization of research streams that are increasingly detached from one another. Despite multiple reviews and best practice studies, the literature lacks an inductive review of the available evidence on beneficial NPD
practices without constraining the focus ex ante (see Adams et al., 2006; Haustein et al., 2014). Article 1 provides such an inductive framework. It assists management control research in identifying potential contingency variables that nuance previously inconsistent findings on the control-innovation relationship. More importantly, the systematic review advocates the multidimensionality of NPD performance and derives trending topics and paths for future research. Although it is agreed that resource-efficient NPD processes are critical for firm success (Adams et al., 2006; Chiesa & Frattini, 2007; Cruz-Cázares et al., 2013), the review in Article 2 underlines that its operationalization is still in its infancy in practice and academia – especially when accounting for the multidimensionality of NPD performance, as elaborated in Article 1. Yet, it groups prior approaches and depicts how multidimensionality could be considered (i.e. an aggregate relative metric based on DEA) and derives how operational challenges might be circumvented. In Article 3, we demonstrate, applying a DEA-based approach, that the efficiency of ongoing NPD projects can be reasonably operationalized holistically. This enables one to examine, for instance, antecedents to efficient projects. Such development could make results more robust and comparable, than if each study applies an individual operationalization either via scale assessments or via unidimensional frequently financial performance variables. Further, such holistic operationalization could consider tradeoffs among performance dimensions that might otherwise be overlooked (see Swink, Talluri, & Pandejpong, 2006).

After having elaborated on the performance measurement implications of Articles 1 to 3, we examine the antecedent roles of management controls to NPD efficiency and innovativeness. Article 4 suggests that the management control system can facilitate innovativeness through process alignment, a motive of an efficient NPD process. We find that both interactive and diagnostic use of controls impact innovativeness through process alignment, the role of which is especially underlined in technologically turbulent environments. This nuances prior findings (Bedford, 2015; Henri, 2006; Ylinen & Gullkvist, 2014) and emphasizes the role of process efficiency (i.e. process alignment). Uncertain settings – for instance technologically turbulent environments – require aligned NPD processes that work in the direction of a firm’s strategic goals. While the role of the development process in the control-innovation relationship is considered a major issue, it has received little attention (Rijsdijk & van den Ende, 2011).

1.2.2 Practical implications

The research also offers insights to practitioners. First, the dissertation sensitizes firms for the multidimensional character of NPD performance by proposing a framework with
nine critical components of NPD performance (Article 1). This has effects on a firm’s performance measurement, which should assess NPD activities more holistically. Second, we propose shifting focus when assessing NPD project performance from mainly financial metrics that are subjectively weighted to a holistic efficiency metric that guides managerial attention and action (Article 2). The performance drivers (Article 1) are exemplary aspects that could be contained in a holistic DEA-based efficiency metric of which the robustness is validated (Article 3). This broadens the perspective, because it considers tradeoffs among performance-relevant characteristics that otherwise remain ambiguous. Such an efficiency metric might complement the current KPI set and might be involved in performance management practice. The research underlines that efficiency is not the premise of each NPD project, but it is necessarily the overarching goal at the portfolio level. Thus, managers can individually interpret the scores and can determine reactions to critical developments. Still, the metric allows for systematic assessments and reduces managers’ subjectivity in assessing NPD project performance. Yet, a metric, just by being measured, does not change behavior or increase efficiency. It must be used appropriately in the firm’s management control system.

Therefore, in Article 4, we examine how the use of management controls can drive efficient NPD processes. We formally test the roles of the seemingly opposing interactive and diagnostic use of controls and find that both drive process alignment, a motive of an efficient NPD process, which itself facilitates innovativeness (i.e. innovation rate and product newness). Diagnostic use monitors outcomes in order to ensure predictable goal achievement (Simons, 1995). In contrast, interactive use incentivizes the regular involvement of superiors during decision activities in order to stimulate search and learning (Simons, 1995). Especially the positive influence of diagnostic use is accentuated, since this was formerly understood as being obstructive in innovation contexts (Song & Montoya-Weiss, 1998; Henri, 2006). We also underline the importance of efficient implementation (not only the architecture) of the development process, which entails that the requirements of the development process are transparent to the NPD team and that the team understands these requirements and perceives the process as having a defined structure.

This dissertation assists research-intensive firms to design and use their management control system to track and steer their NPD projects more holistically, by applying an efficiency mindset, which improves conversion ability and therefore improves innovativeness and firm performance.
1.3 Appendix

1.3.1 Appendix 1: Article overview

1.3.1.1 Table 1: Overview article 1

<table>
<thead>
<tr>
<th>Title</th>
<th>Performance in new product development: A comprehensive framework, current trends, and research directions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Authors</td>
<td>Benedikt Müller-Stewens, Klaus Möller</td>
</tr>
<tr>
<td>Abstract</td>
<td>New product development (NPD) is critical for a firm’s competitive advantage. Since the early 1980s, NPD research has steadily increased and has defined successful practices. However, owing to this research field’s fragmented character, there is still ambiguity about what successful NPD looks like. Evidence on the management control-performance relationship is inconclusive and calls for comprehensive analyses. There is still no holistic framework covering promising practices and structures. Drawing on a body of 284 article publications, we inductively develop a framework with nine clusters that, together, make up NPD performance (ranked by decreasing number of articles): management of process characteristics, management of inter-firm cooperation, knowledge generation and management, structural steering mechanisms, management of teams and team characteristics, management of inter-functional cooperation, coping with firm-external factors, decision-making in the NPD process, and consideration of strategic and cultural aspects. We populate each cluster with variables that are proposed to drive performance and derive trends and paths for future research. The review makes two contributions: it pools a diverse field of research in a single framework, proposing and illustrating elements that compose NPD performance in order to classify current studies and locate future research questions. Furthermore, it provides a tool against which firms can evaluate their own NPD.</td>
</tr>
<tr>
<td>Keywords</td>
<td>New product development, NPD, Systematic review</td>
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| Status | • ACA-UNISG Working Paper Series  
• Under review at the Journal of Management Control. Preparing for submission of 3rd revised version. |
### Introduction

1.3.1.2 Table 2: Overview article 2

<table>
<thead>
<tr>
<th>Title</th>
<th>The efficiency of new product development: Evidence from prior research</th>
</tr>
</thead>
<tbody>
<tr>
<td>Author</td>
<td>Benedikt Müller-Stewens</td>
</tr>
<tr>
<td>Abstract</td>
<td>The efficiency of new product development (NPD) activities is of increasing interest, because it constitutes an antecedent to firm commercial performance. Especially NPD activities in incrementally innovative settings that face intensive competition are exposed to efficiency pressure. Currently, research relies on discussed rather than empirically proven relationships. Although efficiency is often touched on, its operationalization is rare and diverse. To further advance the field from qualitative efficiency assessments to quantitative evidence, a review of the literature that operationalizes NPD efficiency is necessary. Derived from the literature, the author clusters the articles into three approaches: (1) performance measurement systems facilitate efficient NPD processes through a proposed menu of metrics, (2) aggregate absolute metrics contrast spent inputs and received outputs, and (3) aggregate relative metrics contrast individual productivity with that of peers. Aggregate relative metrics apply data envelopment analysis. The classification of past research highlights the advantages of holistic operationalization of NPD efficiency, which can be reflected in aggregate relative metrics, and proposes ways to overcome common challenges. This contributes to research as well as to practice by sensitizing for approaches that might serve as a basis for future empirical research projects or that might be transformed into monitoring or steering tools.</td>
</tr>
<tr>
<td>Keywords</td>
<td>New product development; efficiency; review; data envelopment analysis</td>
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</table>
| Status | • ACA-UNISG Working Paper Series  
• Preparing for submission to *R&D Management* |
Introduction

1.3.1.3 Table 3: Overview article 3

### Article 3

<table>
<thead>
<tr>
<th><strong>Title</strong></th>
<th>Quantifying Project Efficiency in New Product Development: Benefits and Pitfalls</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Authors</strong></td>
<td>Benedikt Müller-Stewens, Klaus Möller</td>
</tr>
<tr>
<td><strong>Abstract</strong></td>
<td>New product development (NPD) is a major determinant of a company’s competitive advantage. However, weighting the relative importance of multiple performance dimensions, e.g. time, costs, and quality, aggravates systematical assessments of ongoing NPD projects. Relying on decision heuristics to direct attention and action to critical projects, portfolio managers give space to subjectivity. Prior research finds that these decisions might be subject to cognitive bias that impedes early reactions on critical project developments. This hinders successful projects particularly in large portfolio contexts where managers are more detached from the individual project’s operations and rely on standardized procedures. We aim at reducing the subjective leeway in weighting metrics by testing an efficiency-based approach that systematically directs managerial attention to critical projects. The case study of a chemical company with more than 80 (incremental) innovation projects per year demonstrates that the Data Envelopment Analysis (DEA) can be reasonably implemented in a product development context supplementing existing metrics. Common robustness tests support applicability. Using the Malmquist productivity index, we show that a dynamic perspective on the projects’ efficiency changes provides additional insights to a mere static perspective on where to focus managerial attention. Derived from the case study, a promising implementation is required to address pitfalls: homogeneity of the project base; accuracy of the estimated output metrics; consistent data availability on project-level; thoughtful interpretation of the results by experts; promotion of organizational acceptance of the metric. This research adds to prior innovation-performance measurement literature by being the first study that proves feasibility of quantifying DEA-based efficiency scores for steering purposes. We test the operationalization of a concurrent rather than lagged indicator of project efficiency – a proven antecedent to commercial firm performance. This adds to previous laboratory evidence, as DEA results might facilitate reducing managers’ cognitive bias and focusing managerial attention and action based on more objectified information.</td>
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**Keywords** | New product development; efficiency; case study; data envelopment analysis; Malmquist productivity index |

**Status** | • ACA-UNISG Working Paper Series  
• Conference contribution at:  
  • International Society for Professional Innovation Management (ISPIM) Annual Conference 2016  
• Preparing for submission to the Journal of Product Innovation Management |
1.3.1.4 Table 4: Overview article 4

<table>
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<tr>
<th>Title</th>
<th>The Role of Controls in Innovation: An Examination of Diagnostic Use, Interactive Use, and Dynamic Tension</th>
</tr>
</thead>
<tbody>
<tr>
<td>Authors</td>
<td>Benedikt Müller-Stewens, Sally K. Widener, Jan-Christoph Steinmann, Klaus Möller</td>
</tr>
<tr>
<td>Abstract</td>
<td>The purpose of this paper is to empirically investigate the relationship between different uses of control systems, the alignment of the product development process, and innovativeness in terms of product newness and innovation rate. The paper builds on the levers of control framework by Simons (1995) and suggests that, in addition to the individual uses of controls, using controls jointly can result in dynamic tension that enhances innovativeness. Using data from a survey of 695 R&amp;D professionals from North America and Europe, this study uses structural equation modelling to examine whether diagnostic use, interactive use, and dynamic tension (the joint use) are positively related to innovativeness through process alignment. The results show that process alignment is a strong predictor of innovativeness, which is driven by interactive and diagnostic uses. Exploratory analysis emphasizes the role of process alignment in technologically turbulent environments. The results show that dynamic tension is positively associated with product newness and innovation rate, but the relationship is not mediated by process alignment.</td>
</tr>
<tr>
<td>Keywords</td>
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• Conference contributions at:  
  • Annual Conference for Management Accounting Research (ACMAR) Doctoral Colloquium 2015  
  • International Society for Professional Innovation Management (ISPIM) Annual Conference 2015  
  • Annual Conference for Management Accounting Research (ACMAR) 2016  
• Under review at Management Accounting Research |
1.3.2 Appendix 2: The data envelopment analysis

The development of performance measurement from a mere financial focus to a more holistic focus that considers indicators from a variety of dimensions required that established tools be adapted. Whereas prior tools – for instance the DuPont Model (Fischer, Möller, & Schultze, 2015) – did not allow for non-financial indicators, more recent tools reflect the proposed multidimensionality – for instance, the balanced scorecard (Kaplan & Norton, 1996). However, most of these frameworks do not aggregate the individual KPIs to a single number. Yet, depending on the circumstances, such overarching aggregate indicator might be beneficial, for instance in the case of a large number of objects observed. DEA provides such an aggregate indicator (Charnes, Cooper, & Rhodes, 1978).

1.3.2.1 Underlying efficiency concept

The basis of the technical efficiency term, which DEA is based on, derives from the 1906 work of Pareto on welfare economics, in which he states that social policy could only be justified if it made some persons better off without making others worse off (see Pareto, 2014). This avoids weighting one’s gains with others’ losses. This concept was carried over into production economics by Koopmans (1951), who notes that an input-output transformation is efficient if and only if none of the inputs or outputs can be improved without worsening at least one input or output. Because in social science applications the ideal input-output transformation level is not known, Farrell (1957) emphasizes the available evidence from peers. This relative efficiency concept is a basis for DEA examinations.

1.3.2.2 Functionality

The observed objects are labeled decision making units (DMU). These are considered to be black boxes, meaning no detailed knowledge is necessary about the processes and value flows within the units. Efficiency is measured with criteria that are clustered to inputs (criteria that are to be minimized) and outputs (criteria that are to be maximized), which together characterize the DMU. The basis for the calculation is the quotient of output and input – the productivity (see Figure 1). The more productive a certain unit is, the more output it can generate from a given amount of input.8 Because there are no optimal values in the practice of social science, a judgment always requires comparison.

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8 The input-oriented approach minimizes inputs while holding outputs constant. The output-oriented perspective maximizes outputs while holding inputs constant.
with other units. Dividing a DMU’s productivity \( (x) \) by the most productive DMU, the best practice \((bp)\), equals the efficiency of the unit focus.\(^9\)

\[
\text{Productivity} = \frac{\text{Output}}{\text{Input}}
\]

\[
\text{Efficiency}_x = \frac{\text{Output}_x}{\text{Input}_x} / \frac{\text{Output}_{bp}}{\text{Input}_{bp}}
\]

Thus, productivity is an inherent part of efficiency, which adds assessment to the concept of productivity (Fried, Lovell, & Schmidt, 1993).

*Figure 1: The basic logic behind productivities and efficiencies*

The more output per input can be generated, the higher a DMU’s efficiency. The slope of the curve determines the productivity.

In contrast to the simple one-input, one-output model, DEA considers multiple input and output indicators with differing units\(^{10}\) in a single model. Each input and output indicator is linked to a factor weight that add up to 1 for inputs and 1 for outputs. Yet, the weights are not determined manually, but by linear maximization. This means that

---

\(^9\) The monotony criterion forces efficiencies to never increase if inputs increase or outputs decrease (Scheel, 2000).

\(^{10}\) When dividing the productivity of the DMU in focus by best practice productivity, the indicators’ units are deleted. Thus, DEA can handle multiple units in the same model.
a DMU’s factor weights of are optimized in relation to the other DMUs in the reference set.

Formally written, DEA is a non-parametric method that calculates relative efficiency scores \((E)\) following the linear maximization of a ratio of weighted \((u)\) outputs \((y)\) to weighted \((v)\) inputs \((x)\). It is subject to the condition that the weights are determined by the data on all DMUs \((j)\) in the reference set (Charnes et al., 1978, p. 431):

\[
\text{max } E_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}
\]

Subject to:

\[
\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1;
\]

\(j = 1, \ldots, n\)

\(u_r, v_i \geq 0\)

\(r = 1, \ldots, s\)

\(i = 1, \ldots, m\)

This optimization is individually conducted for each DMU and results in an efficiency frontier that is defined by the DMUs with the largest relative ratios. These units are 100 percent efficient and represent the benchmarks for the inefficient units that are ‘enveloped’ by the efficiency frontier. A unit’s distance to the frontier represents the deviation from 100 percent efficiency (see Figure 2).\(^{11}\)

\(^{11}\) The convexity assumption requires that all weighted combinations of indicators are able to be realized.
Figure 2: The data envelopment analysis

The figure illustrates a model with two inputs and one output with constant returns to scale.
1.3.2.3 Further developments

Since its original publication in 1978, DEA became a widely accepted and applied approach with more than 4,500 articles using it until 2013 (for systematic reviews of the literature, see Emrouznejad, Parker, & Tavares, 2008; Liu, Lu, Lu, & Lin, 2013). Besides applications, DEA also experienced methodological further developments (see Georgi, 2015, p. 71). In the following, we outline the developments that are touched on in the dissertation project.

Super-efficiency

DEA is sensitive to outliers. Thus, so-called super-efficiency further differentiates among units on the efficiency frontier, which originally all have 100 percent as the assigned score. It follows the same logic as the original DEA approach, but the unit in question is excluded from the reference set, which results in previously efficient units obtaining scores equal or above 100 percent (see Figure 3; Andersen & Petersen, 1993). This super-efficiency measure was widely utilized for evaluating sensitivities due to outliers.

Figure 3: Super-efficiency

Exemplary illustration of the super-efficiency calculation of DMU Z. It was excluded from the reference set, which is why it lies outside the reference set and has an assigned score of above 100 percent.
Returns to scale

The original DEA model assumed constant returns to scale. However, there might be special effects (e.g. synergies) that deter such proportional relationships. Thus, approaches developed to account for different kinds of variable returns to scale (see Figure 4). While constant returns to scale are the strongest structural assumption, variable returns to scale are the weakest, which fit the observed data the best. Studies often compare results of constant and variable return to scale models in order to isolate size effects (Scheel, 2000).

Figure 4: Returns to scale

The figure illustrates four scale variability types. The more variability is modeled, the more DMUs are efficient. (adapted from Scheel, 2000, p. 42)

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12 The constant returns to scale model is often referred to as CCR – an abbreviation of the founding authors, Charnes, Cooper, and Rhodes (Charnes et al., 1978). Comparably, the variable returns to scale model is referred to as BCC – Banker, Charnes, and Cooper (Banker, Charnes, & Cooper, 1984).
**Malmquist productivity index**

Comparing efficiencies of different dates requires additional thought, owing to the relativity of the efficiency score. Not only the DMU in question might change its input and output values, but also the DMUs in the reference set, which might shift the efficiency frontier. This might affect the efficiency score, even if the DMU in focus has not changed. The Malmquist productivity index is an approach to address these concerns (see Figure 5; Färe et al., 1994).

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**Figure 5: Malmquist productivity index**

The index is composed of an efficiency change component and a technology change component, the product of which equals the Malmquist productivity index. The efficiency change is calculated as the ratio of the annual efficiency scores relative to their respective technology. A value below unity reflects an efficiency decline:

\[
\frac{0X_{2016}}{0b} / \frac{0X_{2015}}{0c}
\]

In contrast to the efficiency change that compares two isolated dates, the technology change component accounts for overall changes in productivity, meaning that it operationalizes the efficiency frontier shift between two dates, i.e. 2015 and 2016. A value above unity reflects a technological improvement:
Technological change = \sqrt{\frac{0b}{0a} \times \frac{0d}{0c}}

The generally applicable formula of the Malmquist productivity index \((M)\) for a DMU \((0)\) with inputs \((x)\), outputs \((y)\), and a technology \((d)\) between the dates \((t)\) and \((t + 1)\) reads (Färe et al., 1994, p. 71):

\[ M_0 = Efficiency \ change \times Technological \ change \]

\[ M_0 = \frac{d_{t+1}^d(y_{t+1}, x_{t+1})}{d_t^d(y_t, x_t)} \times \left( \frac{d_{t}^d(y_{t+1}, x_{t+1})}{d_{t+1}^d(y_{t+1}, x_{t+1})} \times \frac{d_{0}^d(y_t, x_t)}{d_{0+1}^d(y_t, x_t)} \right)^{1/2} \]
1.4 References


**Introduction**


Performance in new product development:
A comprehensive framework, current trends, and research directions

Benedikt Müller-Stewens
Klaus Möller
2.1 Abstract

New product development (NPD) is critical for a firm’s competitive advantage. Since the early 1980s, NPD research has steadily increased and has defined successful practices. However, owing to this research field’s fragmented character, there is still ambiguity about what successful NPD looks like. Evidence on the management control-performance relationship is inconclusive and calls for comprehensive analyses. There is still no holistic framework covering promising practices and structures. Drawing on a body of 284 article publications, we inductively develop a framework with nine clusters that, together, make up NPD performance (ranked by decreasing number of articles): management of process characteristics, management of inter-firm cooperation, knowledge generation and management, structural steering mechanisms, management of teams and team characteristics, management of inter-functional cooperation, coping with firm-external factors, decision-making in the NPD process, and consideration of strategic and cultural aspects. We populate each cluster with variables that are proposed to drive performance and derive trends and paths for future research. The review makes two contributions: it pools a diverse field of research in a single framework, proposing and illustrating elements that compose NPD performance in order to classify current studies and locate future research questions. Furthermore, it provides a tool against which firms can evaluate their own NPD.

Acknowledgement

We thank Florian Müller for his strong support during data collection.
2.2 Introduction

One determinant of gaining and sustaining competitive advantage is a firm’s ability to develop and launch successful new products. Nonetheless, the large majority of initiated new product development (NPD) projects fail (Barczak et al. 2009). Thus, successful NPD is of utmost interest for research and practice. For the past roughly 40 years, research on promising NPD practices has gained increasing attention. It suggests that innovation is not a random nor spontaneous output, but results from processes that must be managed.

This has attracted the attention of the management control literature. Although controls were traditionally perceived as detrimental to product development through their inherent rigor (see Damanpour 1991), recent evidence indicates that controls are a “key element of dynamic organizations rather than a peripheral, even negative element” (Davila et al. 2009, p. 300). Thus, controls play a central role in facilitating successful NPD. Management control systems (MCS) can be defined as the “formal, information-based routines and procedures managers use to maintain or alter patterns in organizational activities” (Simons 1995, p. 5). Yet, to direct organizational behavior, management needs a clear picture of what is beneficial and what is detrimental for firm performance. Prior management control research frequently focuses on the influence of different control practices on (innovation) performance, and rarely considers varying firm specificities (see the review by Haustein et al. 2014). Comparably, performance measurement literature has mainly considered – if at all – technological and market uncertainty’s influence on the choice of adequate performance indicators (e.g. Pappas and Remer 1985; Kerssens-van Drongelen et al. 2000). Yet, NPD is a complex process – not a monolithic phenomenon – that should also be evaluated as such (Davila et al. 2009; Tidd and Bessant 2009). For instance, NPD practices might differ with concerning: various processes that coexist and work in parallel; expertise that might stem from varying functions within a firm, or from alliance partners outside the firm that requires a firm’s absorptive capacity; customers or suppliers that might be involved to varying extents in the NPD process. To facilitate the efficacy and efficiency of NPD activities, a firm must respond to its specifics via tailored MCS design and procedures. Similarly, past research claims that MCS should be examined comprehensively rather

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13 We define new product development (NPD) as the process that starts with a conceptualized idea and closes with the market launch of novel or updated goods (see Neely et al. 1995). We delineate NPD from research projects that involve basic research activities that eventually provide input to subsequent NPD (see Chiesa and Frattini 2007).
than limited to single paths with inconsistent results (Ferreira and Otely 2009). Thus, management control necessitates a framework that advocates the multifacetteds of NPD in order to nuance prior generalistic findings on the control-performance relationship and to customize MCS configurations accordingly.

Many facets of NPD have been illuminated by conceptual and empirical studies from multiple disciplines, including marketing, engineering, management accounting, as well as operations and technology management. Further, studies have applied numerous study designs and methodological variations. While digging deeper in their various literature foci, it became increasingly challenging to draft a comprehensive understanding of the antecedents of NPD performance. Past reviews of the literature that systematically collected NPD success factors were insightful yet selective through a specific research scope or have dated (see Montoya-Weiss and Calantone 1994; Ernst 2002; van der Panne et al. 2003; Adams et al. 2006). A review of MCS design contingencies in innovation companies overlooks as yet unexplored paths in the MCS literature that the innovation literature might hint to (see Haustein et al. 2014). Best practice studies apply a broad perspective on NPD performance, but have ex ante defined variables they test, and are therefore constrained in scope (see Cooper and Kleinschmidt 1995; Ragatz et al. 1997; Balbontin et al. 1999; Sun and Wing 2005; Barczak et al. 2009). The result has been the “absence of a holistic framework covering the range of activities required to turn ideas into useful and marketable products” (Adams et al. 2006, p. 21). This accentuates the need for a framework that illustrates the critical activities that facilitate NPD performance in order to nuance findings on MCS design and usage.

We formally ask what the drivers of NPD performance are that should be considered in the design and use of management control systems? We address this gap by systematically reviewing the literature on NPD performance gathered through a keyword-based approach and inductively conceptualizing a comprehensive framework of NPD performance drivers. We also illustrate trending topics and provide suggestions for further research on NPD performance.

From a systematic review of 284 articles, we inductively derive a nine-cluster framework that distinguishes a firm’s external and internal perspectives that can further be split into a cooperation, expertise, and process group. It reveals that NPD process characteristics and the management of inter-firm cooperation are among the clusters experiencing most attention. More generally, the motive of collaboration and diversity – either within the NPD team, along the process, or across organizational boundaries –
has received increasing attention. Research has focused on how NPD performance can benefit from knowledge heterogeneity and how this can be managed appropriately. This relates closely to the trending topic of knowledge transfer within the NPD team and the alliance network that examines how a unit’s absorptive capacity can be improved. Further, we identify six topics that might be promising for future research. These cover antecedents to feelings of familiarity in NPD teams, conditions for beneficial concurrent NPD processes, inter-functional integration of NPD processes, the evolution of alliances, managing the fuzzy front-end, and managing NPD costs.

Our review contributes to the management control literature by responding to the call for comprehensive assessments of phenomena (Adams et al. 2006; Ferreira and Otley 2009). We propose an inductively derived framework of NPD performance drivers. This sets itself apart from prior reviews through its inductive character and the illustration of interrelationships among the clusters. The framework advocates the multidimensional character of NPD, which should be considered when conceptualizing and analyzing empirical studies in order to ensure homogeneous samples. Researchers should be cautious of potential contingency effects on the control-performance relationship that prior literature might have overlooked. Thus, the framework offers hints to paths that might shed light on previously inconclusive effects. Practitioners can apply the framework as a model to comprehensively assess and control NPD. Thus, managers can address these diverse facets and can therefore avoid negative side-effects that managers were previously unaware of. In short, the framework assists one to design an inclusive yet customized MCS.

The paper is structured as follows: first, we develop the research framework and present the descriptive results of the bibliometric study; second, we classify the publications and develop a framework; third, we describe the nine clusters in detail; fourth, we derive trends and directions for further research from the analysis.

2.3 Methodology

In the following, we will describe the data collection and data analysis process in order to ensure replicability and a shared understanding of the approach (vom Brocke et al. 2009). The basis for the inductive analysis is a systematic review based on a structured search process with pre-defined keywords of the research domain in order to limit bias and random errors (Cook et al. 1997).
2.3.1 Data collection

We conducted a systematic review following the suggestion that the methodological rigor of reviews should be strengthened (Tranfield et al. 2003). The systematic review’s strength lies in exploring structural patterns within published documents and in minimizing researcher bias through objective measures. Additionally, evolutions within a research field can be objectively illustrated. We follow the methodological approach developed by Tranfield et al. (2003):

- Development of clear and precise aims and objectives
- Pre-planned methods
- Transparent search of all potentially relevant articles
- Use of explicit, reproducible criteria in the selection of articles for review
- Appraisal of the quality of the research and the strength of the findings
- Synthesis of individual studies using an explicit analytic framework
- Balanced, impartial, and comprehensible presentation of the results.

We chose the Web of Science database administered by Thomson Reuters as the publications’ source, since it covers a large and multidisciplinary collection of bibliographic and full-text content. We defined the search request according to NPD performance-related topics and filtered explicitly for journal publications (exclusion of for instance books and conference proceedings), since journal articles have the highest impact on a research field (Furrer et al. 2008). The primary filter criterion required the publication’s title to cover new product development or NPD. The secondary filter criterion required the titles to also contain performance-related and NPD-related attributes: project, process, performance, success, efficiency, effectiveness, productivity, or evaluation.14 The search, in January 2016, resulted in 675 article publications. We limited the search for terms included solely in the articles’ title, because these articles focus on NPD performance issues, rather than if the search algorithm also screened articles’ abstracts15 that could select articles incidentally because the keywords turned up in different sentences independent from each other. These would need to be excluded manually in a separate filtering step. Thus, we avoided

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14 The search algorithm reads: (“NPD” OR “New Product Development”) AND (Project* OR Process* OR Performance OR Success OR Efficiency OR Effectiveness OR Productivity OR Evaluati*). The asterisk in the search algorithm allows for flexible endings.

15 Screening publications’ abstracts for the defined search algorithm generated 6,830 hits.
a subjective step but concurrently risk missing relevant articles with non-conforming titles. Yet, notwithstanding the large sample size, we argue that structural patterns become clear.

To filter for article relevance and quality, we applied two influential journal rankings: the Australian Business Deans Council Journal Quality List of 2013 (ABDC ranking) and the VHB-JOURQUAL 3 ranking of 2015 (JQ3 ranking).16 We applied both as complements to account for geographic specifications. We limited the search to articles published in scientific journals that are ranked either between A* and B (56% of ranked journals; ABDC ranking) or between A+ and B respectively (48% of ranked journals; JQ3 ranking) to ensure scientific relevance of the examined research. We considered articles that conformed to either or to both ranking filters. Roughly two-thirds of the articles were selected through both rankings, while one-third was selected in one ranking and, in the other ranking, it was either not ranked or received a lower score. This reduced the sample of relevant publications to 303. In contrast to previous reviews (see Haustein et al. 2014), we did not filter for journals of a specific discipline, for instance management accounting, in order to avoid a pre-selection bias. We wanted to inclusively uncover antecedents to performance. Some of these antecedents might have not been mentioned in a management control context before.

Contrary to other studies that applied systematic reviews (Tranfield et al. 2003), we did not filter for a specific timeframe. Such restriction to the sample could distort the conclusion of the research question, since we would not regard research that might complement the NPD performance understanding solely due to publication date. Further, we did not limit the analysis to empirical studies. We considered all papers that could be clearly allocated to a single cluster, independent of their methodological approach.17 In case of conceptual papers and literature reviews, we argue that although there were no hypotheses tested, propositions and discussions hint at antecedents to NPD performance that might complement our framework.

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16 The *ABDC ranking* comprises 2,767 journals that are divided into four categories of quality (A*, A, B, and C) based on qualitative and quantitative assessments.

The *JQ3 ranking* considers 889 journals, which are evaluated on multiple dimensions by the association’s members that are academic business researchers. The highest reputed journals are ranked A+ and decrease via A, B, C, to D.

17 For instance, we allocated a conceptual paper that develops a model on personality’s role in NPD teams (see Reilly et al. 2002) to the *management of teams and team characteristics*. In contrast, a best practice study on general drivers of success in NPD could not be allocated clearly (see Barczak et al. 2009). Thus, we excluded the latter from analysis.
Adjusting the sample for editorials (3), book reviews (3), wrongly filtered\textsuperscript{18} articles (3), and a retracted article (1), we came up with 293 articles. Nine of these publications could not be classified\textsuperscript{19}, since they covered a meta-perspective that is not related to a single content-driven cluster, for instance the development of general NPD success factors. Thus, the descriptive analysis and the classification were based on a final sample of 284 articles.

It becomes clear that few of the filtered articles stem from accounting journals, for instance, *Accounting, Organizations and Society* (see Gopalakrishnan et al. 2015). Yet, there are articles on management controls in multidisciplinary journals, for instance, the *Journal of Product Innovation Management* (see Bonner et al. 2002; Green and Welsh 2003; Salomo et al. 2007; Schmidt et al. 2009; Rijsdijk and van den Ende 2011). One reason might be that accounting article titles often refer to the more general *innovation* rather than *new product development*, which was considered in the algorithm.\textsuperscript{20} We defined the algorithm systematically. While this cannot avoid specific missing publications, it circumvents systematic bias.

### 2.3.2 Data analysis

Many review articles and meta-analyses recommend limiting and structuring of one’s information presentation (Tranfield et al. 2003). To classify the articles, we evaluated each publication regarding the focus area of the research question. Our aim is to systematically identify NPD performance drivers investigated by prior studies and to classify them into a comprehensive framework using an inductive approach. Thus, we chose to not apply a theoretical framework as template, because that would have guided the classification and its emphases ex ante. In contrast, we manually defined a keyword that described the examined core phenomenon of each publication, for instance, *customer involvement in NPD, supplier involvement in NPD, open innovation*, or *relational governance in collaboration* (see Appendix 1). If there were multiple publications with a similar focus, these were linked. This resulted in 135 standalone keywords. In a second step, we formed more aggregate groups of these 135 classifications. We clustered related focus areas, which resulted in nine groups of

\textsuperscript{18} Two articles referred to identically named journals that were not considered in the ranking. One article was included twice in the output with very similar labelling.

\textsuperscript{19} Excluded owing to a meta-perspective that could not be allocated to a single cluster: Barczak et al. (2009); Cooper (1983); Ernst (2002); Kandemir et al. (2006); Lester (1998); Page (1993); Rao (1997); Storey and Easingwood (1993); Wind and Mahajan (1988).

\textsuperscript{20} For examples of management control studies with *innovation* in the title, see Davila et al. (2009); Bisbe and Malagueño (2009, 2015); Haustein et al. (2014); Bedford (2015).
articles; for instance, the *management of inter-firm cooperation* for the abovementioned keywords. Each publication is part of solely one cluster, to carve out emerging and saturated research fields. If articles integrated multiple aspects, for instance a main effect and a moderating effect, we classified them according to their main research contributions. In short, we argue that a certain research focus reflects a pillar of a more aggregated performance cluster.

The clustering procedure was exposed to some subjectivity in judgment. However, we limited qualitative tolerance by applying the four-eye principle in defining the keywords and by discussing inconclusive cases.

### 2.4 Success factors of new product development

#### 2.4.1 Descriptive results

Descriptive analysis shows that the research interests in the field of NPD performance have their origin in the early 1980s, with the number of annual publications increasing the current roughly 25 publications a year (see Figure 6). Concurrently, the reader must be aware that the general number of publications has also risen, which explains that we cannot make a statement on the development of the relative share of publications dedicated to NPD.

*Figure 6: Number of NPD-related publications by year (total = 284)*

When checking the origin of the publications, measured by the first author’s department domestic country, we found that North America and Europe together made up for 78.5% of the publications (see Figure 7). North America is largely dominated by the United States (87.6% of North America’s publications), while in Europe, the United Kingdom
(UK; 26.2% of Europe’s publications) and the Netherlands (17.5% of Europe’s publications) made up to almost half of Europe’s publications.

Figure 7: Number of publications by first author’s department domestic country with split of Europe (total = 284)

The relevant articles were published in 64 journals. On average, each journal has published 4.4 articles, yet the standard deviation is high (s = 8.9). Further, the five journals with the most articles published roughly half of the total publications (48.2%; see Figure 8). Especially surprising is that the *Journal of Product Innovation Management*, which is ranked A* by the ABDC ranking and A by the JQ3 ranking, and therefore reflects a highly competitive environment, published 23.2% of all articles. The presence in highly ranked journals highlights the scientific rigor of the focal issue in the innovation literature.

Figure 8: Top five journals with the most publications by number (total = 284)
The systematic grouping procedure of comparable research foci among the 135 first-level classifications resulted in nine clusters (see Table 2).

<table>
<thead>
<tr>
<th>Name of cluster</th>
<th>Number of articles</th>
<th>% of total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Management of process characteristics</td>
<td>53</td>
<td>18.7%</td>
</tr>
<tr>
<td>Management of inter-firm cooperation</td>
<td>48</td>
<td>16.9%</td>
</tr>
<tr>
<td>Knowledge generation and management</td>
<td>36</td>
<td>12.7%</td>
</tr>
<tr>
<td>Structural steering mechanisms</td>
<td>36</td>
<td>12.7%</td>
</tr>
<tr>
<td>Management of teams and team characteristics</td>
<td>30</td>
<td>10.6%</td>
</tr>
<tr>
<td>Management of inter-functional cooperation</td>
<td>26</td>
<td>9.1%</td>
</tr>
<tr>
<td>Decision-making in the NPD process</td>
<td>22</td>
<td>7.7%</td>
</tr>
<tr>
<td>Coping with firm-external factors</td>
<td>21</td>
<td>7.4%</td>
</tr>
<tr>
<td>Consideration of strategic and cultural aspects</td>
<td>12</td>
<td>4.2%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>284</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

2.4.2 The NPD performance framework

Nine clusters depict an integrated perspective on NPD success drivers. To illustrate the interrelationships, we developed a framework that structures these clusters (see Figure 9). Such structured illustration sets this framework apart from previous reviews that define loosely coupled elements without linkages (see Montoya-Weiss and Calantone 1994; Ernst 2002; Haustein et al. 2014). The most prominent difference is the orientation of the research focus. Some clusters focus on company-external contingencies of the NPD process, and some on phenomena within a firm. We define firm-external as the practices and structures that mainly address the interaction with actors from outside the firm or that address phenomena that are contingent on the firm’s context. These clusters are: management of inter-firm cooperation, coping with firm-external factors, and consideration of strategic and cultural aspects.

We complementarily suggest that firm-internal clusters contain all practices and structures that are primarily limited by the firm’s boundaries. This can be further disaggregated to the objects of interest: cooperation, expertise, and process. Cooperation within the firm comprises the management of NPD teams and team characteristics and the management of inter-functional cooperation. These two clusters have cooperation at their center – within the NPD team, or between functions. Expertise covers articles that primarily address the phenomena of learning and knowledge...
application: knowledge generation and management and decision-making in the NPD process. Lastly, process addresses articles that focus primarily on topics directly associated with the NPD process and its management: the management of process characteristics and structural steering mechanisms. It became clear that certain phenomena might be located at the interface between clusters. We derived the clusters from the most prevalent phenomenon concerning the overarching research contributions.

We observed that the management of process characteristics (53 publications) and inter-firm cooperation (48 publications) experienced extraordinary attention in relation to the seven other clusters. Research on firm-internal phenomena, cooperation (56 publications), expertise (58 publications), and process-specific issues (89 publications), make up for 71.5%, while external issues covered 28.5% of the total research. This means that most articles focused on firm-internal aspects. Lastly, 36.6% of all publications discussed issues regarding the overall topic collaboration.
Figure 9: Illustration of clusters driving NPD performance, with the number of publications in brackets (total = 284)

Cooperation:
- Management of teams and team characteristics (30)
- Management of inter-functional cooperation (26)

Process:
- Management of process characteristics (53)
- Structural steering mechanisms (36)

Expertise:
- Knowledge generation and management (36)
- Decision-making in the NPD process (22)

Coping with firm-external factors (21)

Consideration of strategic and cultural aspects (12)
2.4.3 *Drivers of NPD performance*

We will now describe the individual clusters regarding their content.

2.4.3.1 *Firm-internal – Cooperation: Management of teams and team characteristics*

Thirty articles covered NPD team-related issues: NPD team configuration, trust and familiarity in NPD teams, individual characteristics, and team behavioral effects.

*NPD team configuration.* Functional diversity (Keller 2001; Genç and di Benedetto 2015) and knowledge heterogeneity (Tsai et al. 2014) within a stable (Akgün and Lynn 2002) NPD team improves goal adherence and shortens development cycles. However, functional diversity diminishes team cohesiveness. Yet, cohesiveness facilitates successful NPD (Sivasubramaniam et al. 2012). The net effect of functional diversity on NPD performance via increased goal adherence but decreased team cohesiveness is inconclusive (see Section 2.5). Team cohesiveness is related to trust and familiarity within NPD teams.

*Trust and familiarity in NPD teams.* Research maintains that trust and familiarity among NPD team members facilitate performance via goal commitment and knowledge-sharing (Haon et al. 2009; Dayan 2010; Markham and Lee 2014). High-trust settings protect team members’ minority opinions and, in cases of complex decisions, expertise may come from one person (Markham and Lee 2014). Thus, this setting might facilitate the sharing of sensitive information. Since such family-like settings might also have dysfunctional effects, managers must treat these with care.

*Individual characteristics.* It seems vital to foster team member and team leader characteristics that facilitate learning and information-sharing, because both anteced NPD performance. Team members’ social competence facilitates learning and product performance (Mu et al. 2011), while their knowledge of multiple functions (e.g. marketing and technological knowledge) drives product innovativeness through information-sharing (Park et al. 2009; Liu et al. 2015). Further, McDonough (1993) notes that work experience within the company increases development speed. These characteristics are assumed to be universal, although research proposes that personality traits differ in contexts of low and high innovativeness (Reilly et al. 2002). For instance,

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21 Fan et al. (2009) evaluated approaches to operationalize collaboration satisfaction, which is related to cohesiveness.

22 Procedural justice, distributive justice, and transformational leadership are antecedents to trust (Dayan et al. 2009).
the ability to intuitively process information is beneficial only in radical settings (de Visser et al. 2014).

Research emphasizes team leader openness in turbulent environments, which encourages new ideas and teamwork (Aronson et al. 2006, 2008). Others generally highlight the importance of a democratic (Sarin and McDermott 2003) or a transformational leadership style (Sun and Shang 2014), which foster team learning and team climate. Contrary to this evidence, Strang (2011) argues for the transactional leadership style in NPD teams. These inconclusive effects of leadership style on performance hint to as yet unknown contingency factors. One factor might be innovativeness level, which has barely been addressed.

**Behavioral effects.** In contrast to individual characteristics, behavior can be actively influenced. Research proposes that structural autonomy and team decision empowerment improve performance (Badir et al. 2012; Chen et al. 2015). The given space facilitates team improvisation and reflexivity, which both allow one to flexibly align goals with environmental circumstances (Dayan and Basarir 2010; Magni et al. 2013). Further, Chen (2015) finds that a proactive (responsive) market orientation drives radical (incremental) innovation performance. The effect can be further strengthened by process-based (outcome-based) reward structures. Further, in contexts of management support, perceived stress (i.e. team crisis and anxiety) positively impacts on speed-to-market (Akgün et al. 2007a). Stressors encourage teams to pay attention to a threat. Lastly, some studies find a positive effect of telework (Coenen and Kok 2014) or co-location (Lakemond and Berggren 2006) on NPD performance by enabling knowledge-sharing, cross-functional cooperation, and inter-organizational involvement. In short, evidence underlines the importance of management support, which can turn stress into a strategic tool to improve performance, while – at the same time – team autonomy and decision authority drive performance. Combining these two findings requires autonomous teams to perceive management support in order to allow stressors to drive performance.

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23 Tighe (1998) developed a framework to gain managerial approval for NPD projects in autonomous settings: defining the project, impacts on the organization, and effects on the organization’s financials.

24 Market orientation is dichotomized as responsive and proactive. A responsive market orientation serves current customer needs, while a proactive market orientation discovers and satisfies latent and emerging customer needs. (Chen 2015, p. 36)

25 Process-based rewards are tied to procedures, behaviors, or other means of achieving desired outcomes. Outcomes-based rewards are tied to the actual results. (Chen 2015, p. 39)
2.4.3.2 Firm-internal – Cooperation: Management of inter-functional cooperation

Twenty-six articles focus on the cooperation between different firm functions during NPD. Organizations’ cross-functionally spread tacit knowledge drives the need for inter-functional cooperation (Subramaniam et al. 1998). Most articles cover the cooperation between R&D and marketing.

R&D-marketing integration. This is almost unequivocally found to drive NPD performance (see Ernst et al. 2010). Gemser and Leenders (2011) find that, in settings of high technological and market risk, intense cooperation is worthwhile – yet, teams’ openness to external information might outweigh the net effect of cooperating. Thus, future research might examine settings in which the benefits of cooperating exceeds the costs of coordination.

Research posits that the extent of beneficial cross-functional integration depends on the development stage (Olson et al. 2001). Cross-functional integration increases as projects proceed and, contrary to other collaborations, R&D-marketing integration is highest and most beneficial during early process stages, especially during the design stage (see Hise et al. 1990; Ernst et al. 2010).

Further, the literature has gathered success factors of the R&D-marketing cooperation: formalized interaction between the functions (Song et al. 1996), information system capability of the involved parties (Bendoly et al. 2012), actively learning from prior projects (Sherman et al. 2005), organizational climate (Cordón-Pozo et al. 2006; Fain et al. 2011), bi-directional communication that leads to trust between the involved departments (Massey and Kyriazis 2007; Kyriazis et al. 2012), and informal social systems (i.e. managerial guanxi; Perks et al. 2009).26 Moenaert and Souder (1990) develop a causal model of what a good cooperation between marketing and R&D might look like, based on three central constructs: task specification, structural design, and climate orientation.

Alternative functional integration. In contrast to R&D-marketing integration, facilitative contingencies of these alternate integrations have not been studied in any depth. It is subject to assumptions, if the identified success factors can be transferred to other inter-functional collaborations. The research focus is on examining the differing extents of integration concerning the project stages. Considering marketing-manufacturing integration, greater integration drives NPD speed in each development stage, especially

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26 For eight propositions of good R&D-Marketing cooperation, see Souder (1988).
Article I

the design stage (see also Song and Swink 2009; Kong et al. 2015). R&D-finance integration is especially beneficial in early project stages of low-innovation projects, while marketing-finance integration positively impacts NPD performance in late project stages (Hempelmann and Engelen 2015). More generally, Gomes et al. (2003) find that integration in early project stages of highly innovative projects drives product quality, while, in later stages, it drives speed-to-market. Lastly, Roper et al. (2015) find that the design department has maintained its beneficial role on NPD performance (see also Sosa et al. 2015).

Multiple articles have examined structural mechanisms for how cross-functional interaction might be effectively coordinated: through standards, procedures, plans, milestones that formalize dialogue (Nihtilä 1999), cross-functional teams that intensify information exchange and learning (Nihtilä 1999), successive simulation games that motivate dialogue (Smeds et al. 2003), web-based applications that structure information exchange (Hameri and Nihtilä 1997), and the team autonomy level that motivates teams and induces flexibility (Gerwin and Moffat 1997). In firms with formalized NPD processes, interactions have a transactional bias, while in contexts of flexible NPD processes, interactions have social objectives (Felekoglu et al. 2013).

2.4.3.3 Firm-internal – Expertise: Knowledge generation and management

Thirty-six articles examine the importance of intangible assets, knowledge generation, and knowledge transfer.

The importance of intangible assets. Research emphasizes intangible assets such as (market) information, learning capability, and expertise as sources of competitive advantage concerning NPD (Taylor and Lowe 1997; Lewis 2001; Hultink et al. 2011; Ignatius et al. 2012). This calls for systematic knowledge management (Ramesh and Tiwana 1999). However, most firms still struggle to collect and disseminate information. These firms frequently ignore non-quantitative data forms of information and ignore the full information use spectrum throughout the process (Zahay et al. 2004). Specifically, information dependency within NPD processes – the “link between NPD activities in consecutive stages”, for instance an NPD activity plan – might lead to process inflexibility, which hinders successful process implementation, and might lead to a bias towards financial decision criteria in contrast to customer and market decision criteria (Jespersen 2012, p. 259). Knowledge management might reduce stage-to-stage information dependency and might broaden the spectrum of considered sources of information.
Knowledge generation. Knowledge generation and team learning are linked to continuous improvement (Caffyn 1997; Caffyn and Grantham 2003). Learning drives new product success and speed through information acquisition, distribution, interpretation, and implementation (Akgün et al. 2006; Acur et al. 2010). Yet, under which conditions learning results in product success is the subject of discussion (see Schulze and Hoegl 2006; Liu et al. 2005; Li et al. 2010; Chu et al. 2011; Chen et al. 2012). For instance, in contexts of high task complexity (i.e. in environmental dynamism), learning’s effect on success is stronger through applying gathered unlearning and improvising competences (Akgün et al. 2005). Generally, studies identify a tradeoff between maximizing business performance in the short term and increasing knowledge capital (Ahn et al. 2006). Yet, both are necessary for long-term firm performance. Research identifies pitfalls that hinder learning: people avoid ambiguity and prefer easily understood solutions, people focus on own goals and foster compartmentalized thinking, and people maintain the status quo and maintain inertia (Adams et al. 1998).

Facilitative factors of learning address these pitfalls: knowledge-oriented human resource configuration (i.e. cooperative work design, recording of work-related experiences, compensation systems tied to collective achievements, training, and staffing personnel; Chiang and Shih 2011), team stability, team member familiarity, interpersonal trust (Akgün et al. 2007b; Hsu and Fang 2009), and a supportive organizational climate to change (Thwaites 1992).27 Learning is also a prominent topic in the management control literature that has examined MCS characteristics that facilitate learning (Kloot 1997; Ditillo 2004; Chenhall 2005). Although these studies did not explicitly address the NPD context, evidence stems from comparable knowledge-intensive settings.

Knowledge transfer. Successful knowledge transfer28 depends on actors’ absorptive capacity (Newey and Verreynne 2011; Tavani et al. 2013; Wang and Li-Ying 2014). Generally, implicit knowledge is less easily transferable than explicit knowledge (Schoenherr et al. 2014). Thus, common challenges associated with knowledge transfer are: a lack of explicit definition and prioritization of information in the NPD process, a

27  For conceptual frameworks of antecedents and outcomes of knowledge acquisition, see Murray and Chao (2005); for organizational learning, see Bartezzaghi et al. (1997), Ruy and Alliprandini (2008), and Akbar and Tzokas (2013).

28  For knowledge transfer models in NPD teams, see Frank and Ribeiro (2014); among actors in the firm, see Jepsen (2013); across firm boundaries, see Corallo et al. (2012).
lack of tools to support transfer in heterogeneous environments, and the dissemination of information to process users (Bradfield and Gao 2007). Further, in cross-company settings, buyers’ learning intent drives knowledge transfer, but concurrently acts as an incentive for suppliers to protect their knowledge (Lawson and Potter 2012).

2.4.3.4 Firm-internal – Expertise: Decision-making in the NPD process

Twenty-two articles cover topics relating to decision-making in the NPD process, with a focus on decision support and project termination decisions.

Decision support. Decisions in NPD are mostly based on weighing up tradeoffs among the development schedule, development costs, and product performance (Gupta et al. 1992; van Oorschot et al. 2011). However, decisions are not always made on a level field and are subject to biased perceptions. Risk perception is higher when the project’s synergy with the firm’s current business is lower (Cooper 1981). In the case of project delays, teams do not realize that projects are in trouble and repeatedly fall into decision traps, reducing the likelihood of success (van Oorschot et al. 2013). In such cases, team intuition29 might warrant product success (Dayan and Elbanna 2011). Yet, good decisions are crucial for NPD success. Thus, studies have developed and tested numerous decision support tools to objectify and formalize the procedure.30

Project termination decision. Formal termination decision processes (i.e. decision criteria and decision committees) positively influence decision quality (Schmidt et al. 2001; Lechler and Thomas 2015). Yet, executive advocacy, performance judgments, and threshold effects might counteract these governance components (Green et al. 2003). Further, managers are more reluctant to terminate highly innovative projects (Schmidt and Calantone 1998). Thus, firms are eager to reduce cognitive effects through the use of systematic decision-making tools.

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29 Team intuition depends on past team member experience, transactive memory systems (knowledge possessed by each member and awareness of who knows what), team empowerment, decision importance, and decision motives (opportunity or crisis) (Dayan and Elbanna 2011).

30 A selection of decision-making support tools are: narrowing down alternatives by applying multiple-criteria decision-making techniques as the analytic hierarchy process (Ayag 2005a, 2005b; Akomode 1999), developing a structuring matrix, for instance uncertainty vs. R&D option value (Lint and Pennings 2001), risk-scenario decision tool (Marmier et al. 2013), applying neural network decision support (Thieme et al. 2000), monetary quantification of differences among alternatives (Wouters et al. 2009), process model for resource scheduling and allocation (Abrantes and Figueiredo 2015), sensitizing for role of internal politics (Jones and Stevens 1999), operationalization to reduce escalation of commitment (Donthu and Unal 2014), grouping actors in collaborative decisions (Jaber et al. 2015), applying portfolio thinking (Kester et al. 2014), and integrative model of the NPD decision process (Calantone and di Benedetto 1988).
2.4.3.5 Firm-internal – Process: Management of process characteristics

Fifty-three articles seek to understand increasing speed-to-market, launching concurrent NPD process, and the characteristics of a high-quality NPD process.

Antecedents and outcomes of speed-to-market. Development speed is of central interest to firms, because it pushes NPD performance yet also increases project difficulty (Swink 2003). Thus, research has gathered factors that accelerate development speed. While speed is a dependent variable in multiple studies, these papers focus on increasing NPD speed. Anteceding variables are effective project scheduling (Cohen et al. 1996), a formal NPD strategy, a climate for innovation, the use of cross-functional teams (Parry et al. 2009), product modularity (Chryssochoidis and Wong 2000; Danese and Filippini 2010), the definition of product requirements, technological feasibility, senior management support, sufficient resource allocation, strong project management (Owens 2007), and simulation-based process optimization (Bassett et al. 2004).

Concurrency in NPD. An aspect that is attracting increasing attention is the shift from sequential development to concurrent NPD activities, since these are thought to shorten time-to-market for new products and to increase efficiencies. However, there is mixed empirical evidence for the correlation between concurrency and NPD performance. Few propose an overall positive effect of process concurrency on reduced time-to-market (Prašnikar and Škerlj 2006; Jayaram and Malhotra 2010). Generally, increasing concurrency results in a tradeoff between development time and effort. Thus, increasing concurrency seems beneficial in low uncertainty and detrimental in high uncertainty (Bhuiyan et al. 2004). In contrast, Ahmad et al. (2013) found no evidence of any positive effect of concurrency on NPD performance; in line with Bhuiyan et al. (2004), they propose a negative effect in projects with high uncertainty.

31 Speed-to-market facilitates NPD project success (Jayaram and Narasimhan 2007; Ranjbar 2013), product profitability (McNally et al. 2011), and timeliness of product roll-out (Chryssochoidis and Wong 2000).
32 For case studies of accelerated NPD processes, see Karagozoglu and Brown (1993) and Bernasco et al. (1999).
33 Further antecedents to speed-to-market were referred to in other clusters: work experience within the company (McDonough, 1993), perceived stress in combination with management support (Akgün et al. 2007a), technological competence (Acur et al. 2010), telework (Coenen and Kok 2014), and co-location (Lakemond and Berggren 2006).
34 For research modeling concurrent NPD processes, see Haque and Pawar (2001), Juan et al. (2009), Wang and Lin (2009), and Koyuncu and Erol (2015).
These largely inconclusive findings call for further research on how process concurrency can be beneficially implemented. Research proposes that one reacts on tradeoffs by reducing complexity and standardizing, for instance, platform strategies (Swink et al. 2006). Platform strategies have been shown to reduce delays and budget overshoots (Pasche et al. 2011). In case, performance tradeoffs can be operationalized and controlled by a comprehensive efficiency score, for instance, data envelopment analysis (Swink et al. 2006). Sahay and Riley (2003) suggest distinguishing between compatibility and customer interface standards.

**NPD process design.** Multiple articles focus on NPD process design characteristics and their (scientific) assessment.35 Others have gathered overarching success factors of NPD processes.36 Yet others have developed contingency factors that influence process design. One of these is extent of product innovativeness (Rochford and Rudelius 1997; Harmancioglu et al. 2007).37 Research maintains that NPD processes should reflect the specific project characteristics and the business context (MacCormack et al. 2012). This could mean that for projects that are new to the world, it is promising to use extensive NPD processes rather than shortcuts that might be recommendable in product modification projects (see Rochford and Rudelius 1997).38 Yet, the structures of NPD processes for incremental and radical innovative projects are often alike (de Visser et al. 2010). This gap between practice and research requires further sensitizing. How can

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35 For NPD process models and their assessment, see: a sphenomorph model for complex settings (Barclay et al. 1995); core characteristics of NPD process (Calantone et al. 1995); NPD process for financial services (Edgett 1996); fractal model of the NPD process (Spivey et al. 1997); revamping a NPD process (McDonough and Barczak 1999); NPD process with focus on design and manufacturing (Bajaj et al. 2004); an NPD process in the toy industry (Sun and Wing 2005); cognitive maps to analyze processes (Carbonara and Scozzi 2006); the technology acquisition process (Cáñez et al. 2007); agile NPD process design (Fekri et al. 2009); fuzzy linear programming to maximize customer satisfaction (Chen and Ko 2010); NPD proficiency (Sandvik et al. 2011).

36 A selection of success factors encompasses formalized planning and coordination (Malhotra et al. 1996); the project evaluation process; the existence of new product managers (Reidenbach and Moak 1986); strategic market focus within the NPD process (Balbontin et al. 1999); resource and skills availability (Huang et al. 2002); a lead user process to generate ideas (Lilien et al. 2002); actor networks during idea generation (Simon and Tellier 2011); a value proposition process to assess ideas (Hughes and Chafin 1996); customer support process during product design (Goffin 1998); compatibility and customer interface standards (Sahay and Riley 2003); proficiency in idea development, market opportunity analysis, technological development, product testing, and commercialization (Song and Perry 1997). For NPD process best practice studies, see Barclay (1992a, 1992b).

37 Other contingency factors are industry competitiveness, cycle time, senior management involvement, process formality, customer inputs, cross-functional integration (Harmancioglu et al. 2007), degree of centralization, and experience in new product development (Varela and Benito 2005).

38 For a description of a promising NPD process for discontinuous innovations, see Veryzer (1998).
different process designs be managed without having the additional complexity of coordination exceed the additional benefits of the customized processes?

2.4.3.6 Firm-internal – Process: Structural steering mechanisms

Thirty-six articles focus on the design and use of monitoring and steering tools in the NPD process. NPD performance measurement is mainly used to ensure the coherence and relevance of portfolios, to re-orient projects before failure, to decide on corrective actions, to support the launch decision, to enhance motivation, and to facilitate decision-making (Godener and Söderquist 2004). Process management drives NPD performance (Salomo et al. 2007).

Designing steering tools. First, a high tool\textsuperscript{39} usage level supports the attainment of competitive objectives in NPD (Maylor 2001). Second, promising performance management systems that explicitly address NPD context specificities are developed.\textsuperscript{40} Third, information technology (IT) tools in NPD maintain their positive performance impacts (Durmuşoğlu and Barczak 2011; Balaji et al. 2011). The internet enhances information availability and usage, helps one to better understand and target the market, helps to generate new ideas, increases business analysis speed, facilitates collaboration, and improves NPD efficiency and effectiveness (Ozer 2003; Büyüközkan et al. 2007; Peng et al. 2014).

Using steering tools. It is a common notion in research that project management steering tools might inhibit innovation via their rigid output control – upper management enforcing goal achievement (Bonner et al. 2002; Pons 2008). In contrast, frequent dialogue between hierarchical levels (McDonough and Kinnunen 1984) and team member involvement in setting operational controls drive performance. Thus, besides design, the implementation and use of the tools are key (Bessant and Francis 1997). For instance, managers evaluate incremental projects more proficiently and use more

\textsuperscript{39} A selection of tools, methods, and techniques covers: output controls, non-technical outside assistance (LaBahn and Krapfel 1996), target costing (Afonso et al. 2008), portfolio assessment tied to program profitability and impact (Cooper and Kleinschmidt 1995), a Lagrangian decomposition heuristic (Varma et al. 2007), predictive models (Watkins 1984), risk management practices (Oehmen et al. 2014), design for excellence, failure mode and effects analysis, conjoint analysis (Yeh et al. 2010), focus groups, partnering customers and lead users, prototyping for highly innovative projects, and cross-functional development teams (Tidd and Bodley 2002). For compilations of management tools for NPD projects, see Maylor (2001, p. 95) and González and Palacios (2002, p. 263).

\textsuperscript{40} A selection of performance management systems covers: total cost analysis (Chen et al. 2006), dynamic multi-project management (de Maio et al. 1994), Six Sigma quality improvement (Jou et al. 2010), governance stage-gate controls (Baker and Bourne 2014), a risk management framework (Mu et al. 2009), and procedural guidelines to a performance management system (Rogers et al. 2005).
(technical) criteria than for radical projects, which are evaluated mainly financially (Schmidt et al. 2009; Durmuşoğlu et al. 2013). Comparably, “technical feasibility, intuition and market potential are stressed in the early-screening gates of the NPD process, a focus on product performance, quality, and staying within the development budget are considered of paramount importance after the product has been developed. During and after commercialization, customer acceptance and satisfaction and unit sales are primary considerations” (Hart et al. 2003, p. 22; see also Tzokas et al. 2004). This shows that the same tools can be used differently, and the emphasis can be determined individually. This notion is prominent in management control studies that propose a balance between enabling and constraining control usages (e.g. Simons 1995; Rijsdijk and van den Ende 2011; Bedford 2015). Such balance supplements traditional project management that proposes mainly constraining uses (i.e. output controls) and addresses innovation managers’ concerns (Pons 2008).

**Individual incentives.** Employee incentive schemes influence a firm’s profitability (Natter et al. 2001). However, research warns of unfair individual rewards and punishments (Faure 2009). Dysfunctional behavior can be reduced via profit-sharing contracts and component-level target costing (Mihm 2010). In this light, firms should be aware that the company-internal and external perceptions of project performance might differ significantly (Sicotte et al. 2004).

2.4.3.7 **Firm-external: Management of inter-firm cooperation**

Forty-eight articles cover aspects of cooperation with parties from outside the firm, mainly suppliers and customers.

**Customer involvement.** Research doubts collaboration’s generally positive impact on NPD success. For instance, customer collaboration: while Chien and Chen (2010; see also Souder et al. 1998; Lin and Huang 2013) find a generally positive effect on performance, Tranekjer and Søndergaard (2013) find decreasing project costs, and Knudsen (2007) even a detrimental effect, because customers might be unable to conceptualize ideas behind their own experiences. Further, through customer power (Stock 2014), potential risks include loss of expertise, dependence on customers, and limitation to incremental innovation (see Song et al. 2013). Thus, Song et al. (2013) developed a risk evaluation approach for customer cooperation under uncertainty.

**Antecedents and outcomes of collaboration.** Jassawalla and Sashittal (1998) hold that structural integration does not equal fruitful collaboration (see also Chen and Lin 2011).
Thus, the literature has gathered factors that facilitate promising collaborations. This is called network capability (Mu 2014; Yu et al. 2014) or collaborative competence (Mishra and Shah 2009). Based on the collaborative settings, classification patterns developed. The presence of various factors that facilitate successful cooperation suggests uncovering archetypes of collaborative configurations. Present classifications are thin.

Few articles explicitly address open innovation, as the purposive inflows and outflows of knowledge to accelerate internal innovation (Chesbrough 2006). Success factors seem comparable to general facilitators of cooperation (see footnote 41; Pullen et al. 2012). Grönlund et al. (2010) propose an open innovation process to benefit from opening up the NPD process to external parties. Although elements of open innovation occur in other studies of cooperation, it is surprising that such trending topic in practice has seen little research attention, given the potential scope.

**Evolution of alliances.** Alliances can preserve the core competences of licensing companies (Takayama et al. 2002). Alliances mostly evolve stepwise from outsourcing relationships (Marion et al. 2015). The extent of inter-organizational learning required to develop an NPD project is contingent on the extent of innovation (i.e. radical vs. incremental) and the development mode (i.e. modular vs. integrated) – both determine the strength of the ties between partners (Badir and O’Connor 2015). Prior business ties contribute indirectly to collaboration satisfaction (Bstieler and Hemmert 2015).

**Supplier involvement.** Supplier involvement is mutually beneficial (Yeniyurt et al. 2014) to both buyers (Petersen et al. 2005; Song and di Benedetto 2008) and suppliers (Chung

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41 A successful cooperation depends on variables such as communication management, commitment to the collaboration (Lam and Chin 2005), the intensity and media richness of communication (Badir et al. 2008, 2009; Oke and Idiagbon-Oke 2010; Thomas 2013), openness to change, willingness to cooperate, high trust level (Tomes et al. 1996; Jassawalla and Sashittal 1998; Schleimer and Shulman 2011), individual-level innovative work behavior and expertise and team-level innovation norms, cohesion, and decision-making autonomy (Stock 2014), informal social systems (Cui et al. 2013), comprehensiveness in contractual governance (Parker and Brey 2015), an alliance governance structure, partner technological capability, the competitiveness of market environments (Fang et al. 2015), lifecycle stage (Eng and Wong 2006; Pujari 2006), explorative vs. exploitative strategy (Lambe et al. 2009), shared problem-solving, psychological safety, management direction (Bstieler and Hemmert 2010), goal congruence, complementary capabilities, and inter-firm coordination efforts (Yan and Dooley 2014). For a framework for successful collaborative NPD, see Zolghadri et al. (2011b).

42 Classification patterns of coordination: (1) innovation intermediaries as brokers, mediators, collectors, and connectors (Colombo et al. 2015), (2) buyer as mediator, buyer-designer partnership, designer as integrator, and team design activities (Ateş et al. 2015), (3) single participation vs. dual participation, separate work vs. integrated work, project manager vs. team consensus (Gerwin and Ferris 2004).
and Kim 2003). Yet, a supplier is frequently better off (Yeniyurt et al. 2014). Thus, an intended cooperation requires intensive screening prior to negotiating contracts: for instance, a monetary assessment of suppliers’ offerings (Wynstra et al. 2012) and an assessment of suppliers’ power (Zolghadri et al. 2011a). The use and abuse of power causes mistrust and disappointment. If the decision to initiate a cooperation has been made, firms need to overcome barriers such as the resistance to sharing proprietary information and not-invented-here syndrome. This is possible through “shared education and training, formal trust development processes, formalized risk/reward sharing agreements, joint agreement on performance measurements, top management commitment from both companies, and confidence in the supplier’s capabilities. Overcoming these barriers also depends on asset sharing, including intellectual assets such as customer requirements, technology information, and cross-functional communication; physical assets such as linked information systems, technology, and shared plant and equipment; and human assets such as supplier participation on the project team and co-location of personnel” (Ragatz et al. 1997, p. 190; see also Cousins and Lawson 2007; Jayaram 2008; Yeniyurt et al. 2014; Lawson et al. 2015; Melander and Lakemond 2015).

In short, inter-firm cooperation is a prominent topic. Issues relating to collaborating with customers or suppliers are the dominant research schemes. There is little evidence about alliances (e.g. research collaborations) independent from the supply chain.

2.4.3.8 Firm-external: Coping with firm-external factors

Twenty-one articles examine how to cope with firm-external factors such as the management of uncertainty and market demands. Environmental dynamics are associated with inherent uncertainty that might reduce the contribution of other sources to competitive advantage (Lee and Wong 2011). Thus, uncertainty requires special focus in product development.

Market information processing mechanisms. Matching customer demands is the single most important success factor in NPD projects (Edgett et al. 1992). Thus, market orientation and customer orientation of NPD activities are found to contribute to product development success (Karakaya and Kobu 1994; Souder et al. 1997; Salomo et al.

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Thus, innovating companies benefit from adapting their NPD processes to uncertainty (Bstieler 2005). First, formalized scanning for market trends allows one to include external information in the NPD process and to guide managers’ attention to uncertainties (Cousins et al. 2011; Smits and Kok 2012). Second, influencing project priority within portfolio and flexibility to new products (the ability to easily switch from one technology to another), and reducing interdepartmental conflict improves market information processing (Veldhuizen et al. 2006). Third, balancing risk and project performance supports decisions about alternative project architectures (Martínez León et al. 2013). Fourth, managing project portfolios supports the processing of environmental dynamism (Abrantes and Figueiredo 2014). Den Hond (1998) proposes that, owing to pressure from the selection environment, development activities in different places result in similar inventions.

**Fuzzy front-end.** Definitions of fuzziness differ in their comprehensiveness. Fuzziness has up to four dimensions: uncertainty, equivocality, complexity, and variability (Chang et al. 2007). An early reduction of fuzziness positively impacts NPD project success in both radical and incremental projects (Verworn et al. 2008). One way to reduce fuzziness is by involving all departments in the NPD process early on, to enhance communication (Verworn 2009). Further, Huynh and Nakamori (2011) develop a tool to facilitate new product go/stop decisions at the fuzzy front-end, based on a linguistic approach. Comparable to open innovation, front-end fuzziness has been examined often in prior research, even if it was not labelled fuzzy.

**2.4.3.9 Firm-external: Consideration of strategic and cultural aspects**

Twelve articles study activities to consider strategic and cultural aspects in NPD.

**Managing global NPD.** Successful global NPD projects face geographical dispersion, with additional challenges. A firm’s innovation and globalization culture, resource commitment, top management involvement (de Brentani and Kleinschmidt 2004), and

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44 More recently, Racela (2015) develop that combining strategic orientations (i.e. customer, entrepreneurial, and IT orientations) is the most promising regarding performance. Pujari et al. (2003) propose that an additional ecological orientation can result in partial synergies of being simultaneously ecologically friendly and economically competitive.

45 *Innovation culture* is “involving entrepreneurship, risk taking, and openness to new ideas for new product development” (de Brentani and Kleinschmidt 2004 p. 312).

*Globalization culture* is an “international mindset and a global readiness […] to deal effectively with the complexities and opportunities that result from different national cultures, geographic dispersion of markets and participants, building trust and cooperation among dispersed affiliates, and cross-locational/cultural idea generation and resource utilization” (de Brentani and Kleinschmidt 2004, p. 313).
NPD process formality (Kleinschmidt et al. 2007) drive performance in international NPD projects. Thus, the integration of strategic and cultural aspects in globally oriented NPD processes can be considered a performance driver (de Brentani et al. 2010).

Project strategies. Studies maintain that NPD strategies might improve performance. Two sets of NPD-specific strategies are proposed: (1) differentiation, operational, and quality strategies (Yang 2012), and (2) product superiority, customer intimacy, and time-to-market strategies (Patanakul et al. 2012).


2.5 Trends in NPD performance research

We will now describe current trends in the NPD literature.

Inter-firm cooperation has seen increasing interest in research. While the performance effect of cooperating with customers was inconclusive (see Knudsen 2007), cooperating with suppliers was univocally confirmed to be (mutually) beneficial (Yeniyurt et al. 2014). In both cases, research builds awareness for powerful partners that might outperform in the relationship and proposes ways to detect this in time (see Song et al. 2013; Yeniyurt et al. 2014). There has recently been a focus on the collaborative competence – how to overcome internal barriers to create beneficial partnerships (Lawson et al. 2015; Melander and Lakemond 2015). Although (mainly structural) governance mechanisms are proposed, motivating beneficial individual behavior is expected to be subject to further research.

Within-firm cooperation has also gained attention. Settings and characteristics of beneficial cooperation between R&D and marketing has been the dominant issue (Ernst et al. 2010). In the past five years, other functional integrations have also gained attention; for instance, marketing-manufacturing (Kong et al. 2015), R&D-finance (Hempelmann and Engelen 2015), and design-integration (Sosa et al. 2015). Owing to
limited knowledge which effects are beneficial, we expect more research on the cooperation with functions besides marketing.

Development processes are experiencing increasing pressure to steadily accelerate speed-to-market, owing to shortening lifecycles. While archetypes and success factors of NPD processes have long been examined, the overarching focus has shifted from sequential to concurrent NPD processes. These are found to simultaneously increase speed-to-market and complexity. Thus, these are found detrimental in contexts of high uncertainty (Ahmad et al. 2013). Owing to the latent pressure on development time, we expect further research on how to facilitate concurrent NPD processes also in uncertain setting.

While the roles of intangible assets in the NPD process have consistently been highlighted (Ignatius et al. 2012) – especially knowledge generation through learning and the institutionalized knowledge management process – more recently, the focus has shifted to knowledge transfer within NPD teams and alliances. In both cases, an actor’s or team’s absorptive capacity is at the center of attention (Wang and Li-Ying 2014). Especially motivating the transfer of tacit knowledge is challenging (Schoenherr et al. 2014). As collaboration and intangible assets gain importance, we expect more research on how to improve an actor’s or a team’s absorptive capacity.

2.6 Directions for further research on NPD performance

From our literature analysis, we derive paths for future research. In contrast to the previous section (on current trends), these paths address a specific phenomenon or inconclusive evidence from a management control perspective.

Fostering we-ness in diverse NPD teams. The net effects of functional diversity on NPD performance through the opposing effects of increased goal adherence but decreased team cohesiveness are inconclusive (Keller 2001; Sivasubramaniam et al. 2012). This is subject to further research, how the MCS could foster team cohesiveness – a spirit of we-ness (Markham and Lee 2014) – in functionally diverse teams in order to offset the negative side-effects of diversity. In prior management control literature, trust was conceptualized as a cross-hierarchical construct between the NPD team and superiors (Atuahene-Gima and Li 2006; Haustein et al. 2014). Trust within the NPD team was previously not considered a mediating variable. However, evidence on the facilitative impacts of transformational leadership on trust (Dayan et al. 2009) might hint at enabling effects of more ‘positive’ controls such as interactive controls, which build on regular personal involvement of superiors, as well as certain autonomy and decision-
making authority (see Simons 1995). This could also add to best practice studies seeing demand for additional evidence on leadership in NPD teams (see Barczak et al. 2009).

**Increasing speed-to-market through concurrent NPD processes.** Shorter product lifecycles have put pressure on development time. Concurrent NPD activities bear the potential to shorten the development time, yet are subject to increased efforts and increased complexity. Especially in contexts of high uncertainty, concurrency is found to be detrimental (Bhuiyan et al. 2004; Ahmad et al. 2013). Yet, team autonomy positively increases speed-to-market in turbulent environments (Chen et al. 2015). Self-directed NPD teams can assume responsibility and authority for outcomes, which makes them react quickly. Thus, it is promising to examine how autonomous teams manage projects in concurrent NPD processes and whether speed-to-market increases. Concerning adequate MCS, Haustein et al. (2014) propose that decentralization – which equals team autonomy – requires results control, personnel control, and cultural control. This is to be tested.

**Increasing benefits from inter-functional cooperation.** Cooperation has received considerable research attention. It identifies potential in improving inter-functional communication (see Barczak et al. 2009), although studies mostly focused explicitly on R&D-marketing integration. Other functional integrations have barely been touched on; for instance, R&D-finance (Hempelmann and Engelen 2015), or design (Sosa et al. 2015). Especially cooperation with the finance function could deliver valuable insights, as increasing external pressure to generate returns from innovation requires alignment of the project pipeline with the sought portfolio returns. Further, cooperation is associated with additional coordination efforts. Identifying factors that reduce coordination (for instance, limited team autonomy; see Haustein et al. 2014) might increase the benefits from cooperating.

**Steering the evolution of alliances.** Inter-firm cooperation is a topic that has experienced significant attention. Especially the neighboring actors in the supply chain, customers, and suppliers are focused on. However, there is limited evidence on how alliances evolve (Marion et al. 2015). Since alliances are of recurring importance (Takayama et al. 2002), insights into successfully steering the founding phase (Marion et al. 2015) and overcoming internal (cognitive) barriers prove worthwhile investigating. For instance: how can trust in an alliance partner be created in order to overcome resistance to information-sharing (see Ragatz et al. 1997; Das and Teng 1998)?
Managing the fuzzy front-end. Managing the inherent uncertainty and variability of early project stages is of increasing scientific interest, since it drives project success and facilitates firm profitability (Verworn et al. 2008). However, evidence is limited. Best practice studies see the need to improve the management of the fuzzy front-end (Barczak et al. 2009). Thus, it is promising to examine the control implications of the tradeoff between early-stage rigidity, which saves costs but motivates incrementalism, and laissez-faire flexibility, which facilitates higher innovation but diminishes firm (short-term) profitability. How can weak signals be processed and managerial attention be guided to critical uncertainties?

Managing NPD costs. Although development costs are often referred to as a driver of project performance (see van Oorschot et al. 2011), no articles have focused primarily on adherence to budget. Costs and financial analyses are solely side-constructs (see Keller 2001; Mihm 2010; Gopalakrishnan et al. 2015), but were not the main subject of research in any of the analyzed articles. This lack of research was already emphasized in the meta-analysis by Montoya-Weiss and Calantine (1994). Operationalizing and controlling resource efficiency of NPD projects could depict a promising research field, yet it has seen little attention (see Swink et al. 2006), and is decisive, because efficient firms are more successful (Cruz-Cázares et al. 2013).

2.7 Conclusion

Management control research has claimed more comprehensive approaches than investigating single instruments and effects with conflicting or unclear results (Ferreira and Otley 2009). Yet, a holistic NPD performance framework is missing (Adams et al. 2006). Past reviews were either selective or have dated. We sought to develop a framework that illustrates the multidimensionality of NPD performance drivers in order to advance management control research to considering previously overlooked NPD characteristics that might nuance currently inconsistent findings. From a sample of 284 articles, we derived a framework (Figure 9) that composes NPD performance via nine clusters. The framework sets itself apart from prior reviews on two dimensions. First, we applied an inductive approach to the literature search. Since we did not limit the search to the management control literature, the analysis could inspire the own domain with findings from other disciplines that had not yet been transferred. Most prior reviews define the journals of interest, which limits the search results ex ante (see Haustein et al. 2014). Further, we derived the clusters from the articles and did not fit the articles to a given frame (see Montoya-Weiss and Calantine 1994; Ernst 2002). The latter might
distort phenomena in the database. Comparably, best practice studies solely test the hypothesized paths, which does not uncover ‘new’ drivers (see Cooper 1983; Cooper and Kleinschmidt 1995; Storey and Easingwood 1993; Kandemir et al. 2006; Barczak et al. 2009). Second, we illustrated the clusters in a framework that advocates the interrelationships among these and the context contingencies, which previous reviews proposed as an avenue for further research (Montoya-Weiss and Calantone 1994; Ragatz et al. 1997; Adams et al. 2006). Prior reviews have mostly skipped the illustration and have listed the factors as unconnected or as a loosely coupled system (see Montoya-Weiss and Calantone 1994; Ernst 2002; Adams et al. 2006; Haustein et al. 2014). The framework illustrates that researchers and managers should not treat NPD as a monolithic phenomenon (Davila et al. 2009). Complexity, uncertainty, volatility, and the interrelationship of elements that are illustrated in the framework do not allow the investment of resources and ideas as inputs that linearly produce new products as output. It is necessary to systematically control each of these aspects with individually adapted controls (Davila et al. 2009). Research on management controls concludes that not solely the control system design but also its use should be aligned with the larger product development setting (Simons 1995; Davila 2000). However, prior evidence in the NPD context has mainly focused on the global control-performance relationship, with only minor reconciliations to context contingencies or mediating elements (e.g. Davila 2000; Bisbe and Otley 2004; Bisbe and Malagueño 2009; Bedford 2015). Our framework (Figure 9) gathers diverse drivers of NPD performance. To nuance findings on the control-performance relationship, additional boundary conditions and mediating constructs must be assessed. Our research contributes to the management control literature by providing perspectives and explicit paths to further nuancing control research in NPD contexts.

Our review makes two contributions to the literature on the design and usage of MCS by identifying and structuring clusters of NPD performance drivers that should be considered in research and practice. First, it answers the call for a comprehensive assessment of management control phenomena (Ferreira and Otley 2009) and inductively illustrates the diverse NPD performance literature into a single framework. This distinguishes our study from past selective or dated reviews. Our framework illustrates a map of elements that drive NPD performance in order to organize current studies in ways that are useful to derive future research questions and to map findings. Second, we identified trends in the literature and formulated precise research questions based on located gaps. This review also addresses practitioners by providing a
framework according to which firms can evaluate their NPD activities. Empirically well-established factors that facilitate NPD performance might direct managers’ attention to elements that have to date been neglected.

This research has limitations. First, owing to the chosen methodological approach, and the associated design of the search algorithm, there might be relevant articles that were not considered in our analysis. Few articles from accounting journals are represented in the sample. This might be due to the fact that accounting articles’ titles refer often to innovation rather than new product development, which we considered in the algorithm. Nonetheless, we defined the algorithm in a structured way, and the sample size is sufficiently large, which supports the premise that articles are missing at random. Thus, we argue that this does not distort the general conclusion of the analysis. Second, we filter the articles according to the most current ABDC and JQ3 rankings. This means that a paper’s relevance is not defined according to its impacts via citations, but through a journal’s assessment, which is partly subjective. Further, the rankings are based on a status quo assessment, meaning that journal rankings might have changed during the observation period. Thus, we kept a broad window – the analysis of roughly half of the journals of both rankings – and did not base any analysis on ranking positions. Third, the classification of the articles into nine clusters is partly subjective. While in most cases the allocation is clear, in a few cases, there is a certain ambiguity. The authors discussed these cases and decided on the categorization. Generally, all classifications occurred through a four-eye principle. A meta-analytical approach (see Montoya-Weiss and Calantone 1994) would have generated statistical significance values for each driver, yet would not have considered evidence from qualitative studies.
### 2.8 Appendix

#### 2.8.1 Appendix 1: Assignment of keywords to articles

<table>
<thead>
<tr>
<th>Name of cluster</th>
<th>Keywords assigned to articles</th>
<th>Articles assigned to cluster</th>
</tr>
</thead>
<tbody>
<tr>
<td>Management of inter-firm cooperation</td>
<td>Configuration of collaboration; customer involvement (in the NPD team); risk evaluation when involving customers; supplier (environmental specialists) involvement; supplier / customer relationships in NPD process; M&amp;A and NPD integration; collaboration with innovation intermediaries; collaborative competence; conflict management in collaboration; creating tie strengths in alliances / collaborations; rational governance in collaborations; open innovation; success factors of inward technology licensing; governance of vertical coordination; communication / coordination among NPD partners; network competence; organization of NPD in alliances; formalization of collaboration; managerial guanxi (interpersonal relationships); learning in inter-firm teams</td>
<td>Ates et al. 2015; Badir et al. 2008; Badir et al. 2009; Badir and O’Connor 2015; Bstieler and Hemmert 2010; Bstieler and Hemmert 2015; Chen and Lin 2011; Chien and Chen 2010; Chung and Kim 2003; Colombo et al. 2015; Cousins and Lawson 2007; Cui et al. 2013; Eng and Wong 2006; Fang et al. 2015; Gerwin and Ferris 2004; Grönlund et al. 2010; Jassawalla and Sashittal 1998; Jayaram 2008; Knudsen 2007; Lam and Chin 2005; Lambe et al. 2009; Lawson et al. 2015; Lin and Huang 2013; Marion et al. 2015; Melander and Lakemond 2015; Mishra and Shah 2009; Mu 2014; Oke and Idiagbon-Oke 2010; Parker and Bray 2015; Petersen et al. 2005; Pujiari 2006; Pullen et al. 2012; Ragatz et al. 1997; Schleimer and Shulman 2011; Song and di Benedetto 2008; Song et al. 2013; Souder et al. 1998; Stock 2014; Takayama et al. 2002; Thomas 2013; Yan and Dooley 2014; Tomes et al. 1996; Tranekjer and Sondergaard 2013; Wynstra et al. 2012; Yeniyurt et al. 2014; Yu et al. 2014; Zolghadri et al. 2011a, 2011b</td>
</tr>
<tr>
<td>Article I</td>
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<tr>
<td><strong>Knowledge generation and management</strong></td>
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<tr>
<td>Continuous improvement in NPD process; organizational learning from NPD projects; development of technological competences; knowledge and information management, knowledge generation in NPD process; knowledge exchange in NPD process; information processing in NPD process; team learning in NPD process; absorptive capacity in supplier involvement; learning from competitors; knowledge transfer in collaborations; knowledge networks in NPD teams; knowledge management on team level; information-sharing of project managers; information dependencies in stage-gate processes</td>
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<tr>
<td><strong>Structural steering mechanisms</strong></td>
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<tr>
<td>Performance measurement; project monitoring and evaluation; performance assessment; evaluation of NPD team members; project review practices; incentive systems</td>
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<td></td>
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<tr>
<td>Supporting tools; forecasting success/failure from market data; assessment of NPD procedures; controlling mechanisms in NPD; target costing; control vs. creativity; project plan and control; IT tools in NPD; procedures to launch new NPD process; multi-project management; risk management at firm level; risk management at program level</td>
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<tr>
<td><strong>Management of teams and team characteristics</strong></td>
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<tr>
<td>Team characteristics; characteristics of team leaders; characteristics of team members; satisfaction in team cooperation; risk perception in teams; stress management within NPD teams; team autonomy; collocation vs. dispersion; trust among team members; transformational leadership in NPD teams; managers’ trust in NPD teams; team composition in inter-functional teams; team cognitive styles; collective efficacy in NPD teams; team reflectivity; flexible working hours in teams; team improvisation; team stability; we-ness in teams; team leader empowerment in alliances</td>
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<tr>
<td><strong>Management of inter-functional cooperation</strong></td>
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<tr>
<td>Managerial guanxi (interpersonal relationships); complementary effects of information systems in inter-functional cooperation; inter-functional cooperation; psychological drivers for cooperation; role of design in the NPD process; role of IT in global R&amp;D collaboration; trust in inter-functional collaboration; interaction between inter-functional teams</td>
<td></td>
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<tr>
<td>Article</td>
<td>Decision-making in the NPD process</td>
<td>Coping with firm-external factors</td>
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<td></td>
<td>Decision-making under risk; team intuition in decision-making; decision-making on portfolio level; tradeoffs in decision-making; risk perception in decision-making; reduction of escalation of commitment (cognitive biases); project breakoff decision (dependent on degree of innovativeness); firm-internal lobbying; collaborative decision-making; limiting decision alternatives; intervention decisions in late projects; decision traps</td>
<td>Scanning the environment for new innovations; management of front-end fuzziness and uncertainty; coping with regulatory mechanisms; impact of environmental dynamics on core competencies; considering context dynamics in the NPD process; inclusion of environment; customer orientation in NPD; processing of market information</td>
</tr>
</tbody>
</table>
2.9 References


References to articles that are included in the systematic review are marked with an asterisk (*).


3 Article II

The efficiency of new product development:
Evidence from prior research

BENEDIKT MÜLLER-STEWENS
3.1 Abstract

The efficiency of new product development (NPD) activities is of increasing interest, because it constitutes an antecedent to firm commercial performance. Especially NPD activities in incrementally innovative settings that face intensive competition are exposed to efficiency pressure. Currently, research relies on discussed rather than empirically proven relationships. Although efficiency is often touched on, its operationalization is rare and diverse. To further advance the field from qualitative efficiency assessments to quantitative evidence, a review of the literature that operationalizes NPD efficiency is necessary. Derived from the literature, the author clusters the articles into three approaches: (1) performance measurement systems facilitate efficient NPD processes through a proposed menu of metrics, (2) aggregate absolute metrics contrast spent inputs and received outputs, and (3) aggregate relative metrics contrast individual productivity with that of peers. Aggregate relative metrics apply data envelopment analysis. The classification of past research highlights the advantages of holistic operationalization of NPD efficiency, which can be reflected in aggregate relative metrics, and proposes ways to overcome common challenges. This contributes to research as well as to practice by sensitizing for approaches that might serve as a basis for future empirical research projects or that might be transformed into monitoring or steering tools.
3.2 Introduction

Innovative endeavors that form the basis of any business activity rely on a firm’s capability to convert a blueprint into a successfully commercialized product. It is agreed that having an efficient process that facilitates the management of uncertainties linked to new product development (NPD) is critical for a firm’s success (Adams, Bessant, & Phelps, 2006; Chiesa & Frattini, 2007). Despite much research arguing that NPD is vital for a firm’s long-term success, empirical evidence rarely evaluates NPD holistically, often limiting itself to uncover specific efficient and effective practices (Salomo, Weise, & Gemünden, 2007). Further, popular metrics regularly only build on linking inputs (e.g. R&D expenditures) to firm performance (see the metric R&D intensity\(^\text{47}\)) without considering the obtained outputs (e.g. products). Comparably, other metrics link outputs to firm performance without considering the effort needed (see the metric sales share of new products\(^\text{48}\)). However, NPD is a complex process that should be evaluated as such, rather than being limited to single indicators (Tidd & Bessant, 2009). Thus, ideas developed to conceptualize NPD performance more holistically represent a firm’s conversion ability from an idea to a commercialized product (Chandy, Hopstaken, Narasimhan, & Prabhu, 2006), linking causally related key inputs and outputs, quantifying an integral efficiency metric.

While efficiency has frequently been touched on, its operationalization in the NPD context is still in its infancy (Gwynne, 2015). If research relied on quantitative metrics rather than qualitative or semi-quantitative assessments via scores\(^\text{49}\), the approaches differed methodologically and conceptually, rendering the results incomparable. Thus, this emerging matter benefits from exposure to theoretical foundations in order to advance performance research from qualitative assessments to more harmonized quantitative indicators. The author of this paper aims to review key literature that conceptualizes and operationalizes NPD efficiency metrics and that illustrates paths to overcome common challenges. Being the first review of that literature, the author proposes an ad hoc classification that summarizes empirical observations (see Webster & Watson, 2009).

\(^{47}\) Defined as \(\text{R&D intensity} = \frac{\text{R&D expenses}}{\text{Sales}}\).

\(^{48}\) Defined as: \(\text{Sales share of new products} = \frac{\text{Sales of products younger than X years}}{\text{Total sales}}\).

\(^{49}\) See Kerssens-van Drongelen and Cook (1997, p. 354) for a definition of the typologies of metrics: quantitative methods use pre-defined algorithms to generate numeric measures; semi-qualitative methods convert a qualitative answer to a number by applying a rank or a score; qualitative methods result in subjective and intuitive measures (e.g. very good to very poor).
This paper derives three groups of approaches from the literature. Besides (1) performance measurement frameworks that hints at selecting specific metrics to facilitate efficient NPD activities, there are aggregate metrics that operationalize efficiency and result in a single value. These aggregate metrics are either (2) absolute or (3) relative – considering the relative efficiency of the unit in focus in relation to a peer group. Although the relative metrics, which are based on data envelopment analysis, are more holistic in their operationalization, both groups have in common that they rarely consider the time lag between resource investment and realization of benefits, mix output and outcome indicators, rely on output estimates in the context of ongoing projects, and do not consider strategic focus. Based on the literature, circumventions are illustrated.

This research contributes to the NPD performance measurement literature. Efficiency of NPD activities is among the most discussed issues in innovation measurement. Although empirical evidence finds that efficient processes drive firm commercial performance (Cruz-Cázares, Bayona-Sáez, & García-Marco, 2013), few studies have operationalized holistic metrics. This review summarizes prior approaches and illustrates how these might complement or replace qualitative assessments of efficiency with objective metrics. This might serve as a basis to develop empirically proven good practices that facilitate NPD efficiency. Besides research, this also addresses practitioners and will help them to establish, monitor, and steer their NPD portfolios, or to benchmark their firm performance with peers based on objective information on efficiency. The author aims to sensitize performance measurement practice and research for systematic approaches to quantify NPD efficiency.

### 3.3 Method

This study examines the operationalization of the efficiency of NPD activities for monitoring and steering purposes. Thus, the literature review focuses on project-level and firm-level analyses and excludes industry and regional levels that mostly address regulatory impacts on the innovation landscape. The review relies on the structured approach by Webster and Watson (2009). First, a keyword search on meta-databases, i.e. Web of Science and EBSCO-Host gathered a grand sample of articles on NPD efficiency. The search strings contained various combinations of innovation, product development, new product development, NPD, efficiency, productivity, and effectiveness. The search was limited to the titles and abstracts of academic journal publications. It became clear that the majority of these publications touch on efficiency, but remain fairly theoretical,
avoiding its operationalization. Thus, in a second step, the author manually filtered articles that operationalize efficiency and continued the search by checking the relevant articles’ backward (based on the articles’ reference lists) and forward citations (based on electronic databases, for instance Web of Science and Google Scholar). This resulted in the final sample, which is the basis for the analysis. In a third step, based on the literature, the author inductively derived groups of approaches that are methodologically comparable.

3.4 The evolution of Efficiency in new product development

NPD efficiency is defined from a resource-based perspective as the firm’s relative capability to transform its resources into outputs through the use of firm capabilities (Cruz-Cázares et al., 2013). Obviously, efficiency is not restricted to specific resources, but considers all firm resources. Efficiency has two aspects: (1) the productivity aspect of transforming input to output (2) and the performance aspect of relatively assessing productivity in relation to peers or target values (Fried, Lovell, & Schmidt, 1993). Thus, productivity is an inherent part of efficiency. Because productivity concepts can be used without methodological sophistication to assess efficiency, and both concepts are not distinguished clearly, this review accounts for the ambiguity in the literature by considering both productivity and efficiency labelled concepts.

While during the creative research phase, the effectiveness of activities and their strategic contribution to firm value are the critical performance variables, during the development phase, when the decision to pursue and commercialize an idea have been made, the focus becomes efficiency in reaching the goals (Chiesa & Frattini, 2007). This means that firms seek to reach pre-defined targets with the least possible resource input. If actions are directed to fulfil the firm’s strategy, the immediate focus is no longer on the project level. Still, the project’s effectiveness remains a critical dimension at the portfolio level.

A massive amount of research has sought to measure product development success (Adams et al., 2006; Ernst, 2002; Montoya-Weiss & Calantone, 1994; Werner & Souder, 1997). Yet there is little consensus about which measure is the most useful (Griffin & Page, 1996). This is partially associated with differing levels of analysis: the project versus portfolio perspective. While long-term financial success is the ultimate goal of

50 In contrast to research projects, NPD projects are (1) clearly specified through a business opportunity, a business case, and a pursued idea; are (2) typically within a staged development process; and (3) end in market launch (e.g. Cooper, 2008). The research on hand focuses on the NPD.
most firms, making it the overarching portfolio-level goal, individual project characteristics might justify goals besides sheer financial ones. The Fiat 500e electric car results in a loss of 14,000 US dollars losses per unit sold (Beech, 2014), while Fiat’s trading profit equaled 3,393 million Euros (Fiat, 2014). Obviously, Fiat had other goals in mind than pushing short-term group profitability when launching the 500e, for instance branding the firm as technologically advanced. Through the lens of financial efficiency, the Fiat 500e was less efficient in transforming the invested resources during NPD into financial returns than other models in the portfolio.

The debate about innovation efficiency has its origins in the 1980s, when industry massively accelerated its R&D expenditures (Jaffe, 1996) and was then confronted with market pressures to deliver increased returns from R&D through improved processes in terms of effectiveness and efficiency (Wheelwright & Clark, 1992). Foster et al. (1985) proposed the R&D Return Framework, a first approach to contrast technical progress and R&D investment in a value driver tree that results in a single metric with largely specified KPIs. Comparably, Brown and Svenson (1998) proposed looking at R&D as a system that requires one to consider process outputs in relation to spent inputs, and not in relation to only scientists’ behaviors or the achieved results. Further, some studies focused on formalizing innovation processes in order to harmonize activities and reduce slack and redundancies, thereby improving efficiency. A prominent example is the Stage-Gate Process, which structurally provides checkpoints with pre-defined deliverables and threshold values for inputs and outputs (Cooper, 2008). This has moved innovation processes from being managed as a black box to a highly structured process (Davila, Foster, & Oyon, 2009).

However, from the outset, there has been a debate between those who propose that NPD is controllable (Cooper, 1990) and those who generally refuse control techniques in innovative contexts (Damanpour, 1991; Roussel, Saad, & Erickson, 1991). The latter perceive controls from other business functions as detrimental to creativity through their exercised rigidity, and expect that these would harm innovation success. These concerns address the distinct character of innovation projects – the creative and unstructured process and the uncertain outcomes undermine the comparison of projects (Tidd & Bessant, 2009).

From this polarized initial position, empirical findings became more nuanced, legitimating both positions depending on the context conditions. First, the extent of project specificity was incorporated into the evaluation logic (Pappas & Remer, 1985), requiring research and development projects to have differing controls imposed. Thus, the more
mature a project and concrete its goals are, the more quantitative and tight the controls may be (Kerssens-van Drongelen & Cook, 1997).

Further, uncertainty and ambiguity not only characterize early-stage research projects, but also radically innovative projects that redefine a product context. Thus, the level of innovativeness requires differing control settings. For instance, Song and Montoya-Weiss (1998) find that, for radically new products, proficient business and market opportunity analyses may be counterproductive, since customers may not comprehend the innovation (Holahan, Sullivan, & Markham, 2014). While radical projects, due to their underlying flexibility and dynamism, rely on less formalized controls, incremental projects, which are more predictable, rely on formal controls that define project boundaries (Davila et al., 2009).

Summarizing these empirically strong findings suggests that quantified efficiency scoring, a formal control that is necessarily based on reliable project goals, is more beneficially implemented in contexts of incremental projects that are maturing into product development activities (see Figure 10).

51 Radical and incremental characterize NPD concerning an innovation’s novelty. While radical innovations might change market structures, create new markets, or make existing products obsolete (creates new business paradigm), incremental innovations improve the performance of existing products (within an existing paradigm) (Davila et al., 2009).
Efficiency is a prominent term in NPD research. However, the underlying definitions vary wholly, from focusing on the efficiency of a specific isolated dimension (e.g. cost) (Kumpe & Bolwijn, 1994), to considering an aggregate efficiency that incorporates an inclusive definition of multiple dimensions (Cruz-Cázares et al., 2013). Exemplary survey studies that operationalize project efficiency asks directly for schedule and budget adherence in a three-item construct (Salomo et al., 2007).\textsuperscript{52} Comparably, Hoegl and Parboteeah (2006) develop the five-item construct team performance efficiency, mainly asking for goal achievement regarding schedule and budget adherence.\textsuperscript{53} The inductively developed construct that operationalizes product innovation performance with eight items for efficacy and four items for efficiency takes an overarching perspective not asking for goal achievement, but absolute performance (Alegre, Lapiedra, & Chiva, 2007).

\begin{itemize}
  \item \textsuperscript{52} \textit{Project efficiency}: Met planned budget, met timetable, met time to market. (Salomo et al., 2007)
  \item \textsuperscript{53} \textit{Team performance efficiency}: From the company’s perspective, one could be satisfied with how the project progressed. Overall, the project was done in a cost-efficient way. Overall, the project was done in a time-efficient way. The project was within schedule. The project was within budget. (Hoegl & Parboteeah, 2006)
\end{itemize}
Since these constructs depend on the respondents’ qualitative assessments, which are subject to potential bias (Schmidt & Calantone, 2002), in the following literature analysis, the author focuses on quantitative approaches.

3.5 Major research approaches

Efficiency is commonly regarded as the output to input ratio. This logic is also present in R&D research. While performance measurement systems provide a framework to obtain an effective steering system, facilitating efficient NPD processes, aggregate measures offer operationalized efficiency scores (see Figure 11).

Figure 11: Three approaches to quantify NPD efficiency

![Diagram showing three approaches to quantify NPD efficiency: Performance measurement systems, Aggregate metrics, Absolute metrics, Relative metrics.]

Popular applications:
- European Foundation for Quality Management Framework
- R&D Lab
- Technology Value Pyramid

Popular applications:
- R&D Innovation Index
- Research Quotient
- Effectiveness Index
- R&D Return Framework
- R&D Productivity

Popular application:
- All articles follow DEA

54 Product innovation performance: (1) Efficacy: replacement of products being phased out; extension of product range within main product field through technologically new products; extension of product range within main product field through technologically improved products; extension of product range outside main product field; development of environment friendly products; market share evolution; opening of new markets abroad; opening of new domestic target groups. (2) Efficiency: average innovation project development time; average number of innovation project working hours; average cost per innovation project; global satisfaction degree with innovation projects efficiency. (Alegre et al., 2006)
3.5.1 Performance measurement systems

A performance measurement system is considered to be a “set of metrics used to quantify both the efficiency and effectiveness of actions” (Neely, Gregory, & Platts, 1995, p. 81). In the NPD literature, there are many frameworks, each of which seeks to implement strategy efficiently and effectively. However, there are large differences in the specification levels. While some concepts – such as the Balanced Scorecard (Kerssens-van Drongelen & Cook, 1997), the Quantum Performance Measurement Model (Hronec, 1993), or the Performance Prism (Neely, Adams, & Kennerly, 2002) – aim to structure the field’s complexity and to provide guidelines for firm-specific applications, others propose menus of metrics specifically for innovation settings. As the attention is on attempts to operationalize NPD efficiency, the focus is on performance measurement systems that propose metrics and explicitly address NPD specificities. In the following, three popular frameworks are summarized.

The European Foundation for Quality Management (EFQM, 2016) developed a framework of five inputs (i.e. enabling criteria: (1) leadership, (2) people, (3) strategy, (4) partnerships & resources, and (5) processes, products, and services) and four outputs (i.e. resulting criteria: (1) people results, (2) customer results, (3) society results, (4) business results) for business excellence, each of which is further broken down to sub-criteria. For survey purposes, the first-level criteria are associated with defined factor weightings, which generate an overarching performance score. The model seeks to identify strengths and potentials to be reached by continuous learning. Comparably, Brown and Svenson (1998) conceptualize the R&D Lab, a process-oriented system with recurring feedback loops to ensure learning. Besides the feedback loops, they distinguish five process elements: (1) inputs (raw materials or stimuli a system receives and processes), (2) processing system (the lab, which conducts research), (3) outputs (the immediate results from the research, as patents and new products), (4) receiving system (the consumers and users of the outputs, as marketing, manufacturing, or the academic community), and (5) outcomes (the accomplishments that have value for a firm, such as sales or cost savings). For each process step, they propose exemplary metrics. Both of these frameworks consider innovation as a process that transforms certain firm resources into

A similar yet more precise definition states that a performance measurement system provides “information that allows the firm to identify the strategies offering the highest potential for achieving the firm’s objectives, and align management processes, such as target setting, decision-making, and performance evaluation, with the achievement of the chosen strategic objectives” (Ittner, Larcker, & Randall, 2003, p. 715).
products. In contrast, with the *Technology Value Pyramid*, Tipping and Zeffren (1995) take a top-down perspective that is output-oriented, i.e. value creation is central to all innovation activities. The system provides a menu of 33 specified metrics that sustain R&D value creation on five dimensions, i.e. from top to bottom: value creation, portfolio assessment, integration with business, asset value of technology, and the practice of R&D processes to support innovation. Companies should select a set of metrics depending on their situation and their R&D dynamics.

In short, the systems have in common a portfolio-level perspective on value creation in an NPD context. They address practitioners with frameworks for structuring complexity and propose exemplary metrics that are linked through pre-defined weightings in the case of the EFQM framework. While the EFQM framework and the R&D Lab take a process-oriented perspective and contrast spent inputs and received benefits, the Technology Value Pyramid focuses on net value creation at different hierarchical levels. These frameworks primarily aim at facilitating efficient processes rather than operationalizing a specific score.

### 3.5.2 Aggregate metrics

Besides frameworks that facilitate efficient NPD processes, some reduce efficiency to a single and frequently aggregate metric. These approaches can be grouped as either an absolute metric or a relative metric that benchmarks in relation to a peer group.\(^{56}\) While absolute metrics are transparently defined and can be adopted by any firm 1:1, a relative approach requires certain manual tailoring.

#### 3.5.2.1 Absolute metrics

A broad variety of absolute efficiency metrics have developed. In the following, the author summarizes contributions that have received attention in the NPD management community. These metrics mostly contrast either revenue or profit and R&D expenses. A simplistic operationalization is promoted by Werner and Souder (1997), who contrast revenue of new products with R&D expenses.

\(^{56}\) Hammerschmidt (2005) groups the aggregate absolute metrics into first-generation approaches based on simple ratios, and the aggregate relative metrics into second-generation non-parametric approaches. In contrast to the classification at hand, Hammerschmidt distinguishes three classes of first-generation approaches: output-oriented metrics, input-oriented metrics, and simple ratios. Input-oriented and output-oriented metrics are not within the scope of this study, because these do not consider input-output transformation (see definition of efficiency). Further, Hammerschmidt considers parametric and non-parametric metrics as second-generation approaches. Yet, in the NPD context, the author did not identify parametric efficiency assessments.
**Article II**

\[
R&D \text{ Innovation Index} = \frac{\text{Revenue from products introduced in the last three years}}{\text{Total R&D costs}}
\]

Comparably, Knott (2012) proposes the *Research Quotient* and implements it for industry-wide benchmarks.

\[
\text{Research Quotient} = \frac{\text{Revenue increase}}{\text{R&D expenses}}
\]

McGrath and Romeri’s (1994) *Effectiveness Index* analyzes how beneficial R&D spending is. An index value larger than 1.0 suggests that new products generate more profits than the resources that are invested.

\[
\text{Effectiveness Index} = \frac{\text{Sales share of new products} \times \left(\text{profit margin} + \text{R&D intensity}\right)}{\text{R&D intensity}}
\]

Foster et al. (1985) define an aggregate metric of R&D return, of which the first two levels are pre-defined, while the remainder may be customized based on suggested drivers (see Figure 12). This driver tree looks deeper than mere financial metrics (i.e. costs, revenue) and proposes concrete causal effects.

*Figure 12: Foster et al.’s (1985, p. 14) R&D Return Framework*
Consultancies also promote metrics to quantify R&D efficiency. For instance, McKinsey publishes the *R&D Productivity Index*, which weights a contribution with the achieved maturity level (Hannon, Smits, & Weig, 2015). In contrast to the aforementioned metrics, which mainly quantify firm-level scores, this metric can be implemented at the project level.

\[
R&D\ Productivity = \frac{\text{Total gross contribution} \times \text{Achieved product maturity}}{\text{Consumed R&D costs}}
\]

While these aggregate measures work with information that is easy to obtain, how companies can use these, besides for benchmarking for internal steering purposes, remains an open question. These formulas disregard the causal relationships between input and output. Although there is an inherent time lag between R&D resource spending and received benefits, all the mentioned approaches ignore these intervals, yet assume consistently effective and strong R&D expense to revenue ratios. Further, these metrics do not approach efficiency holistically, but generically, only from a financial perspective. This criticism might have led to the low diffusion of these measures in the literature.

### 3.5.2.2 Relative metrics

Relative metrics that consider efficiency not in absolute terms, but in relation to peers, make up for the large majority of publications that operationalize NPD efficiency metrics. These mainly Asia-based publications consistently apply data envelopment analysis (DEA). DEA research in the innovation context dates back to 1996 (Cook, Kress, & Seiford, 1996), when the basic concept of DEA was presented and applied to an exemplary case in order to prioritize ideas for research projects. DEA is a non-parametric approach that maximizes a unit’s output to input ratio by optimizing the factor weights in relation to peer units, called decision making units (DMU) (Charnes, Cooper, & Rhodes, 1978). This results in an efficiency score that lies between zero and one and that quantifies the distance of a unit to the enveloping efficiency frontier. Thus, in each peer group, there is at least one efficient unit that defines the efficiency frontier. For further explanation, see Appendix 1.

Research can be divided into firm-level and project-level analysis (see Appendix 2).

#### Firm-level DEA application

Looking at the evolution of firm-level efficiency research, it becomes obvious that the methodological approaches quickly gain complexity. While, in their pioneering work, Guan et al. (2006) examine firm efficiency and scale effects solely based on DEA analyses, the following publications base their analysis on DEA outputs and supplement
these with other methods. Using DEA efficiency scores as independent variable in regression analysis shows that efficient firms are commercially more successful (Cruz-Cázares et al., 2013). Comparably, a logistic regression that integrates efficiency scores provides support that firm efficiency and innovation activities do not relate (Diaz-Balteiro, Herruzo, Martínez, & González-Pachón, 2006). Supplementing the analysis with the Malmquist productivity index provides insights into the temporal dynamics of the efficiency scores, while considering the shift of the efficiency frontier (Cruz-Cázares et al., 2013; Hashimoto & Haneda, 2008). Lastly, in combination with a network-based approach, authors have shown that a methodological practice favors evenly spread strengths over specialized competencies (Liu & Lu, 2010).

All articles besides that of Cruz-Cázares et al. (2013) apply input-oriented analyses, meaning that they minimize inputs, given a fixed amount of outputs. Further, all articles address backward-looking issues, dealing with actual values. Thus, these do not propose steering-relevant tools, but scientific findings to consider for future strategizing.

**Project-level DEA application**

The majority of articles positioned at the project level address *ongoing NPD projects* with steering-relevant tools based on expected values. In contrast to most research from an ex post perspective, these publications are highly relevant to practitioners. A prominent phenomenon is efficiency as a support tool for project selection. Linton, Walsh, and Morabito (2002) present a basic model that works with scenario values of the discounted cash-flow to support the select or reject decision about a project, supplemented in a follow-up publication with a grouping approach (i.e. based on sequential DEA) in order to cluster similar projects (Linton, Morabito, & Yeomans, 2007). Comparably, Eilat, Golany, and Shtub (2008) propose a more generalized approach that, besides project selection, also supports project evaluation throughout the innovation process with a specific link to firm strategy through variables explicitly derived from the Balanced Scorecard dimensions. Cao and Hoffman (2011) dig deeper into temporal efficiency in evaluating NPD projects. Lastly, Donthu and Unal (2014), in a laboratory experiment, prove that the objectified DEA scores of NPD project performance are in line with the managers’ subjective judgments, which is why the implementation of DEA in project steering might be a way to reduce cognitive bias.

In contrast to the practitioner-oriented studies from a concurrent perspective, publications that take an *ex post perspective* are of high scientific relevance and seek to understand specific phenomena, for instance the tradeoffs between the performance outcomes
time and quality (Swink, Talluri, & Pandejpong, 2006). Others emphasize the roles of contextual factors in analyzing efficiencies by considering the operating environment (Hsu & Hsueh, 2009), intellectual capital (Lu & Hung, 2011), as well as firm size and know-how in collaboration projects (Revilla, Sarkis, & Modrego, 2003).

Lastly, some publications are mainly methodologically motivated and advance DEA in an NPD context, for instance developing a model that considers ordinal and cardinal data (Cook et al., 1996), or reducing the number of input and output factors to facilitate sufficient sample sizes (Vitner, Rozenes, & Spraggett, 2006). 57

From a methodological perspective, the articles that focus on ongoing NPD projects differ from the articles from an ex post perspective, since the former do not focus specifically on the characteristics of scale returns, but consistently assume constant returns to scale (CRS). This could be due to the fact that CRS more strongly differentiates among projects than variable returns to scale (VRS), which rather overrates efficiencies (Dyson et al., 2001). Thus, differentiation might be desirable in steering-relevant tools, which can be supposed when taking a concurrent rather than an ex post perspective. In short, the models’ steering relevance might counteract the methodological advancements in the case of articles from a concurrent perspective.

3.6 Synthesis of NPD efficiency research and areas for future research

As the success of NPD efforts has been on the current agenda, the efficiency of NPD activities has seen increasing attention. NPD efficiency is found to be a driver of firms’ commercial success (Cruz-Cázares et al., 2013). Still, companies need to be sensitive to contexts that require efficient processes while, in other settings, efficiency might be detrimental to innovation success. Prior research supports the proposition that incrementally innovative settings of advanced development projects (in contrast to radically innovative research projects) might benefit from formal NPD efficiency assessments (Davila et al., 2009; Kerssens-van Drongelen & Cook, 1997). Despite hints about advantageous context conditions, it is largely vague what role efficiency plays in the NPD management cycle – even if there was an agreed upon and applicable efficiency metric: Does it have monitoring purposes on an NPD project level, or are the firm-level innovation activities benchmarked on those of competitors? Are there goals defined for the

57 The common threshold value for the minimum number of DMUs equals twice the sum of input and output factors (Golany & Roll, 1989).
measured efficiencies, or is it to diagnose critical developments? Who is using the metric? How can detrimental side-effects of formal metrics (e.g. rigidity and short-termism) be avoided?

The underlying scopes of efficiency analyses vary widely. While many articles focus on specific aspects of NPD efficiency (e.g. time-efficiency or cost-efficiency), fewer articles conceptualize efficiency holistically. This is surprising, since efficiency is a key attribute of a high-quality development process (e.g. Cooper, 2008). Thus, an overarching conceptualization is necessary to avoid performance implications that have negative side-effects. Such overarching conceptualization is provided by the performance measurement systems and the DEA-based aggregate relative measures. However, the systems develop frameworks as a facilitator tool, rather than metrics as a monitoring or steering tool. The aggregate absolute metrics fall short, due to their mere financial focus. There is only limited evidence (see Swink et al., 2006), how tradeoffs between performance dimensions (e.g. time, costs, quality) affect efficiency and how these can be managed. Thus, optimizing a unidimensional efficiency bears the risk of overlooking complementary performance dimensions. Analyzing current approaches, four major methodological drawbacks arise, which are subject to further refinements:

**Time lag:** Many publications do not consider the time lag between resource investment and the return flow. Because this models immediate resource transfers, this ignores causal relationships and can cause misinterpretations. Cruz-Cázares et al. (2013) consider this and include the four-year average input factors, contrasting these to the single-year output factors (i.e. return on assets). Articles that focus on ongoing projects regularly build on discounted metrics, for instance discounted cash-flow (e.g. Linton et al., 2002).

**Mixing output and outcome:** Efficiency metrics are set up by contrasting outputs and spent inputs. Prior research often mixes the immediate outputs (e.g. new products) with outcomes from the products’ commercialization (e.g. revenue) (see Brown & Svenson, 1998). Diaz-Balteiro et al. (2006) consider patents, product innovations, and process innovations (outputs) simultaneously with sales and before-tax profits (outcomes) in their DEA model. This undermines the comparability of the results with other studies because, due to project-specific weightings of outputs and outcomes, the driving factors of efficiency are not transparent. Evidence shows that a more differentiated bridge from input to output and, in a second step, to outcome can be built by either a sequential DEA (e.g. Liu & Lu, 2010) that calculates two models (model 1: input → output; model 2:
output → outcome), or by combining DEA with a regression of commercial outcomes on these efficiency scores (e.g. Cruz-Cázares et al., 2013).

**Reliability of estimates:** This especially refers to efficiency analyses of ongoing projects. Output factors are necessarily built on estimations, since the project is still in the development stage. This makes the efficiency metrics vulnerable to deterred scores. Considering scenario values that illustrate the sensitivity of data could weaken vulnerability (e.g. Linton et al., 2002). Further, data accuracy can be fostered through the assurance of the estimates by an uninvolved third party (Libby, Salterio, & Webb, 2004).

**Lack of strategic focus:** Most conceptualizations narrowly address NPD efficiency, without considering the strategic desirability of the achieved goals. Extending the focus to combine efficiency with the effectiveness of actions could be promising. For instance, Eilat et al. (2008) include Balanced Scorecard perspectives in their DEA analysis in order to consider the strategic target dimensions.

While the research on hand examined and grouped unidimensional and multidimensional approaches to operationalize NPD efficiency and gathered conditions in which efficient processes are desirable, there is much research that determines attributes of resource-efficient processes. Still, these publications have mostly applied a unidimensional efficiency concept (e.g. financial), which means that they might have overlooked obstructive side-effects. Thus, the verification and detailed analysis of these proposed antecedents to NPD efficiency from a holistic perspective is promising.

### 3.7 Conclusion

The review proposes three groups of approaches to quantify efficiency: (1) performance measurement systems that facilitate efficient processes and propose metrics for their quantification as well as (2) aggregate absolute metrics and (3) aggregate relative metrics that both result in a single efficiency score. Approaches resulting in an aggregate absolute number are easy to obtain and require little explanation for understanding, because the formulas are standardized. However, ignoring causal relationships and unit-specific settings, the compromise is large. On the other hand, relative approaches estimate the unit’s efficiency in relation to the peer group. These are dominated by DEA. These methods provide a transparent benchmark, with specific potentials derived, but

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58 See Perez-Freije and Enkel (2007, p. 17) for an overview of determinants of a resource-efficient innovation control system.
are more advanced and are therefore a hurdle for firm-wide communication or integration as part of a research project. Numerous levers (e.g. factor selection, scale effects, model orientation, peer group) allow customization but also undermine comparability and comprehensibility. In promoting holistic NPD efficiency as a relevant construct for innovation management research, standards might evolve on how to conduct DEA studies. There are general guidelines (e.g. Golany & Roll, 1989), but there are no standardized process models or well-established conceptual models that would facilitate comparability.

The review contributes to the NPD performance measurement literature, since it summarizes the prior debate on efficiency and circumvents common methodological challenges. The studies that operationalize efficiency scores provide valuable inputs to how innovation research might evolve. This paper sought to shift discussions in the literature from qualitatively assessing NPD efficiency and merely referring to it argumentatively, to quantitatively operationalizing it. This gives efficiency – an empirically proven antecedent to firm performance (Cruz-Cázares et al., 2013) – higher explanatory power. While efficiency is not the top decision criteria of every NPD project, resource efficiency is inevitable at the portfolio level. Thus, critical developments of holistic resource efficiency, which accounts for potential tradeoffs, might serve as a basis to direct managerial attention and firm actions based on more objective data. To have these concepts diffused broadly, further research is necessary, paths for which are highlighted.
3.8 Appendix

3.8.1 Appendix 1: The concept of data envelopment analysis

The data envelopment analysis (Charnes et al., 1978, p. 431) calculates relative efficiency scores ($E$) following the linear maximization of a ratio of weighted ($u$) outputs ($y$) to weighted ($v$) inputs ($x$). It is subject to the condition that the weights are determined from the data on all DMUs ($j$) in the reference set:

$$
\max E_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}
$$

Subject to:

$$
\frac{\sum_{r=1}^{s} u_r y_{rf}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1;
$$

$$
j = 1, \ldots, n
$$

$$
u_r, v_i \geq 0
$$

$$
r = 1, \ldots, s
$$

$$
i = 1, \ldots, m
$$
### 3.8.2 Appendix 2: Literature review of aggregate relative efficiency metrics

<table>
<thead>
<tr>
<th>Author</th>
<th>Sample</th>
<th>Level of analysis</th>
<th>Methodology</th>
<th>Analytical perspective (ex post vs. ongoing)</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cook et al., 1996</td>
<td>Concept development</td>
<td>Project level</td>
<td>DEA input-oriented (CRS)</td>
<td>Ongoing</td>
<td>3: Internal technical expertise; external technical expertise; technology availability</td>
<td>8: Energy efficiency; diversification; costs saved; environmental impact; technical capability; research profile; economic impact; impact on nuclear performance</td>
<td>Model development to incorporate ordinal data in DEA. Conceptual application: selection of R&amp;D projects</td>
</tr>
<tr>
<td>Linton et al., 2002</td>
<td>Single-case study (469 projects)</td>
<td>Project level</td>
<td>DEA output-oriented (CRS) / subjective value creation model</td>
<td>Ongoing</td>
<td>3: Discounted cashflow of investments; lifecycle stage of intellectual property; lifecycle stage of product</td>
<td>3: Discounted cashflow most likely / optimistic / pessimistic</td>
<td>Selection of R&amp;D projects in a large portfolio: select/reject decision support</td>
</tr>
<tr>
<td>Revilla et al., 2003</td>
<td>118 Spanish firms carrying out 277 collaboration projects with public centers</td>
<td>Inter-firm project level</td>
<td>DEA input-oriented (CRS; IRS; DRS)</td>
<td>Ex post</td>
<td>3: Firm revenue; number of employees; R&amp;D budget</td>
<td>3: Total income from project; new employees; patents from project</td>
<td>Efficiency of collaboration projects varies depending on firm size and level of firm knowledge</td>
</tr>
<tr>
<td>Guan &amp; Wang, 2004</td>
<td>21 Chinese research groups</td>
<td>Group level</td>
<td>DEA input-oriented (CRS)</td>
<td>Ex post</td>
<td>2: Budget; size of group</td>
<td>6: Number of publications; number of papers indexed; cumulative citation counts; average citation</td>
<td>Success factors of Chinese research groups. Identifica-</td>
</tr>
</tbody>
</table>

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59 Anchors were set according these characteristics: declining, widespread, emerging, future.
<table>
<thead>
<tr>
<th>Study</th>
<th>Sample Size / Context</th>
<th>Level / Approach</th>
<th>Ex Post Variables</th>
<th>Other Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Garg, Gupta, Jamal, Roy, &amp; Kumar, 2005</td>
<td>330 publicly funded research projects in India</td>
<td>Project level DEA input-oriented (CRS)</td>
<td>Ex post 2: Funding; number of projects</td>
<td>3: Publications (journals, conferences); patents</td>
</tr>
<tr>
<td>Guan et al., 2006</td>
<td>182 Chinese industrial firms</td>
<td>Firm level DEA input-oriented (CRS; IRS; DRS)</td>
<td>Ex post 5: R&amp;D; learning; manufacturing; marketing; organization</td>
<td>6: Market share; sales growth; export rate; profit growth; productivity; new product rate</td>
</tr>
<tr>
<td>Diaz-Balteiro et al., 2006</td>
<td>171 Spanish wood-based firms for 1998 to 2001</td>
<td>Firm level DEA input-oriented / logistic regression analysis</td>
<td>Ex post 5: Employees; share-holders’ funds; loans; R&amp;D expenditures; R&amp;D partnerships</td>
<td>5: Sales; profits before taxes; patents; product innovations; process innovations</td>
</tr>
<tr>
<td>Swink et al., 2006</td>
<td>137 NPD projects by U.S. manufacturing firms</td>
<td>Inter-firm project level Sequential DEA input-oriented (VRS)</td>
<td>Ex post 2: Development costs; product costs</td>
<td>7: Product quality (product manufacturability, quality, performance, innovative features, meet customer needs); project lead time (on-time performance; reduced development time)</td>
</tr>
<tr>
<td>Authors</td>
<td>Sample Size</td>
<td>Level</td>
<td>Methodology</td>
<td>Ongoing/Expost</td>
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<tr>
<td>Vitner et al., 2006</td>
<td>11 exemplar projects</td>
<td>Project level</td>
<td>Sequential DEA input-oriented</td>
<td>Ongoing</td>
</tr>
<tr>
<td>Linton et al., 2007</td>
<td>Single-case study (469 projects in 7 efficiency groups)</td>
<td>Project level</td>
<td>Sequential DEA</td>
<td>Ongoing</td>
</tr>
<tr>
<td>Eilat et al., 2008</td>
<td>36 exemplar projects</td>
<td>Project level</td>
<td>DEA input-oriented (CRS) with weight restrictions / Balanced Scorecard</td>
<td>Ongoing</td>
</tr>
<tr>
<td>Hashimoto &amp; Haneda, 2008</td>
<td>10 Japanese pharmaceutical companies (1983 to 1992)</td>
<td>Firm level</td>
<td>DEA input-oriented (CRS) / Malmquist index</td>
<td>Ex post</td>
</tr>
<tr>
<td>Hsu &amp; Hsueh, 2009</td>
<td>110 government-sponsored R&amp;D projects over</td>
<td>Project level</td>
<td>Two-step DEA input-oriented (CRS; VRS) / Tobit regression</td>
<td>Ex post</td>
</tr>
</tbody>
</table>

1: Financial return (estimated NPV)  
2: Published articles; patent stock  
3: Patents; sales; profits  
4: Project R&D staffing; government subsidy to project; profits  
5: Design; operations; training; documentation; project management  
6: Monitoring; risk level  
7: Technology; innovation; technology development  
8: Organizational; resource allocation; human resources  
9: Customer focus; brand; customer satisfaction; price competitiveness  
10: Discounted cashflow; customer focus feedback; performance improvement; congruence; importance; synergy; proprietary position; platform for growth; durability; probability of technological and commercial success (reduced to 5 dimensions)
<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Duration</th>
<th>Level</th>
<th>Methodology</th>
<th>Post-Project Period</th>
<th>Outputs/Outputs</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liu &amp; Lu, 2010</td>
<td>9 years in Taiwan</td>
<td>Firm level</td>
<td>Two-step DEA output-oriented (VRS) / network-based approach</td>
<td>Ex post</td>
<td>3: Advanced human resources; basic human resources; project time</td>
<td>(1) 3: Papers; research reports; patents (2) 3: License fees and royalties; industry service; production investment</td>
</tr>
<tr>
<td>Lu &amp; Hung, 2011</td>
<td>127 Taiwanese technology development programs (1999 to 2006)</td>
<td>Program level</td>
<td>Two-step sequential DEA output-oriented (CRS; IRS; DRS)</td>
<td>Ex post</td>
<td>3: Budget; human resources; time</td>
<td>(1) 3: Publications; patents; technology acquisitions (2) 3: Technology and patent transfers; firm investments; technology service</td>
</tr>
<tr>
<td>Cao &amp; Hoffman, 2011</td>
<td>Single-case study (20 projects)</td>
<td>Project level</td>
<td>DEA input-oriented (CRS)</td>
<td>Ongoing</td>
<td>4: Effort; project staffing; priorities; number of engineers; technical complexities</td>
<td>1: Project duration</td>
</tr>
<tr>
<td>Jiménez-Sáez, Zabala-Iturriagagoitia, Zofío, &amp; Castro-Martínez, 2011</td>
<td>36 to 49 Spanish research units from 1988 to 1999</td>
<td>Team level</td>
<td>DEA output-oriented (CRS; VRS)</td>
<td>Ex post</td>
<td>2: Personnel; public funding</td>
<td>5: Trained people; PhD theses; international papers; registered patents; R&amp;D contracts</td>
</tr>
<tr>
<td>Cruz-Cázares et al., 2013</td>
<td>415 Spanish manufacturing firms</td>
<td>Firm level</td>
<td>DEA output-oriented (VRS)</td>
<td>Ex post</td>
<td>2: R&amp;D capital stock; highly skilled staff</td>
<td>2: New products; patents</td>
</tr>
<tr>
<td></td>
<td>(1990 to 2005)</td>
<td>Malmquist index / regression</td>
<td></td>
<td></td>
<td></td>
<td>the efficiency with which they are developed</td>
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<tr>
<td>Donthu &amp; Unal, 2014</td>
<td>8 projects (laboratory experiments)</td>
<td>Project level</td>
<td>DEA output-oriented</td>
<td>Ongoing</td>
<td>3: Budget; people; dedication</td>
<td>2: Expected returns; progress</td>
</tr>
<tr>
<td>Lu, Kweh, Nourani, &amp; Huang, 2016</td>
<td>39 dual-use technology development programs in Taiwan</td>
<td>Program level</td>
<td>Network slacks-based measure DEA model (VRS)</td>
<td>Ex post</td>
<td>3: Research expenditure; research human resources; research duration</td>
<td>6: Academic performance; technological results; revenues; technology transfers; derivative value; revenue to pay national treasury</td>
</tr>
</tbody>
</table>

CRS: constant returns to scale; VRS: variable returns to scale; IRS: increasing returns to scale; DRS: decreasing returns to scale.
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Quantifying project efficiency in new product development:
Benefits and pitfalls

Benedikt Müller-Stewens
Klaus Möller
4.1 Abstract

New product development (NPD) is a major determinant of a company’s competitive advantage. However, weighting the relative importance of each of the multiple performance dimensions aggravates systematical assessments of ongoing NPD projects. Relying on decision heuristics to direct attention and action to critical projects, portfolio managers give space to subjectivity. Prior research finds that these decisions might be subject to cognitive biases that impede early reactions to critical project developments. This hinders successful projects, particularly in large portfolio contexts where managers are more detached from the individual project’s operations and rely on standardized procedures. We seek to reduce subjectivity in weighting metrics by testing an efficiency-based approach that systematically directs managerial attention to critical projects based on an aggregate indicator. The case study of a chemical company with more than 80 (incremental) innovation projects per year demonstrates that the data envelopment analysis (DEA) can be implemented in a product development context supplementing existing metrics. Common robustness tests support applicability. Using the Malmquist productivity index, we show that a dynamic perspective on the projects’ efficiency changes provides additional insights, over a merely static perspective on where to focus managerial attention. Derived from the case study, a promising implementation is required to address pitfalls: homogeneity of the project base; accuracy of the estimated output metrics; consistent data availability on project level; thoughtful interpretation of the results by experts; promotion of organizational acceptance of the metric. Our study adds to prior innovation performance measurement literature by being the first to prove the feasibility of quantifying DEA-based efficiency scores for steering purposes. We test the operationalization of a concurrent rather than lagged indicator of project efficiency – an antecedent to firm commercial performance. This adds to previous laboratory evidence, since DEA results might help to reduce managers’ cognitive biases and might focus managerial attention and action based on more objectified information.

Acknowledgements

We thank the participants of the 2016 ISPIM Innovation Conference in Porto, Portugal, and the workshop participants at the University of St. Gallen, Switzerland, for their feedback and constructive comments.
4.2 Introduction

New product development (NPD)\(^{60}\) is generally considered a major determinant of competitive advantage and organizational long-term performance (Ernst 2002). This has increased companies’ efforts to strive for successful NPD projects. However, interviews with six research-intensive industrial companies revealed that companies struggle to assess NPD project performance. It is transparent how well projects achieve their cost, time, and quality targets. Yet, it cannot be assured that this achievement is objectively good, because the achievement of quality standards might outweigh budgetary accuracy. This implies that decisions on where to direct managerial attention and consequential interventions largely rely on managers’ subjective judgments.

Research empirically shows that managers have difficulties assessing the relative importance of multiple metrics (Ittner and Larcker 1998; Banker, Hsisui, and Pizzini 2004; Dilla and Steinbart 2005; Cardinaels and van Veen-Dirks 2010). To simplify decision-making, managers rely on decision heuristics that replace the systematic evaluation of the tradeoffs among diverse metrics (Van Oorschot, Langerak, and Sengupta 2011). Yet, these individual heuristics are subject to potential judgmental biases, meaning that managers are not likely to intervene or terminate NPD projects, even if information hints at the commercial failure of NPD projects (Boulding, Morgan, and Staelin 1993; Schmidt and Calantone 2002). Only if managers cross a certain “threshold of dissatisfaction with existing conditions, they will initiate action to resolve their dissatisfaction” (Van de Ven 1986, p. 595). However, NPD is characterized by the rapid progression of project stages, which are associated with resource commitments that cannot be withdrawn ex post. Thus, having to cross a threshold value of dissatisfaction before reacting might be too late to ensure successful projects and concurrently avoid unnecessary costs.

Whereas in smaller companies with narrow project portfolios, an informal basis for control and coordination might suffice (see the simple control configuration by Bedford and Malmi 2015), larger companies with vast project portfolios, tall hierarchies, and centralized authority rely more on standardized procedures (see the action control configuration by Bedford and Malmi 2015). These configurations detach portfolio managers from individual projects and reduce their familiarity with project-specific characteristics. Thus, in these large portfolio contexts that mainly embrace exploitative projects (Davila,

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\(^{60}\) We focus on product development projects that are clearly specified and that close with market launch, rather than on basic research projects that provide input to subsequent product development activities (Chiesa and Frattini 2007). We refer to this process as \textit{new product development} (NPD).
Foster, and Oyon 2009), there is a distinct need to reduce subjectivity in assessing NPD project performance, in order to decrease potential cognitive biases through less room for interpretation regarding the relative weighting of performance measures.

NPD is considered a complex process, and should be evaluated as such, not limited to a single activity (Tidd and Bessant 2009). Neither relying solely on project input (e.g. R&D expenses), nor on output factors (e.g. number of new products), nor generalizing identical factor weightings for all projects is promising concerning long-term company performance (e.g. Ernst 2002). Building on this idea, Cruz-Cázares et al. (2013, p. 1248) empirically prove and claim “what really increases firm performance is the efficiency with which innovation inputs are transformed into innovation outputs”, thus connecting to prior literature underlining the roles of a firm’s conversion ability – the transformation of ideas into products (Chandy et al. 2006). Therefore, we argue that – overall – companies should seek to increase the efficiency of their NPD projects, because this facilitates long-term company performance. Exceptions might be strategically prioritized projects that, for instance, represent lighthouse projects that do not primarily seek commercial returns. However, there is currently no shared understanding of what the efficiency of ongoing development projects encompasses and if an overarching project efficiency score can reasonably apply in the NPD context, which is dynamic and uncertain. This observation provides input to our research project.

We seek to develop and test an approach that quantifies NPD project efficiency in order to provide a measure for NPD project performance that reduces subjectivity in the relative assessment of multiple metrics and directs managers’ attention on portfolio level to projects that objectively require such.

We apply the data envelopment analysis (DEA) in a single-case research setting on the project portfolio of a research-intensive chemical corporation. These incrementally innovative projects are in advanced phases (after agreeing on a business case) of a staged development process. Based on the operationalization of efficiency and the illustration of inter-year dynamics, we identify five pitfalls and propose promising project settings.

First, the reliability of the relative efficiency score depends on comparability within the project base. By approximation, statistical analyses can confirm tendencies of homogeneous project groups, but managerial judgment is irreplaceable in determining these. Thus, the approach is suitable for companies with large portfolios of projects that are incremental in their degree of novelty, because these have fewer unique features, and
are therefore more comparable than radical innovations. Further, quantifying accurate output metrics is a challenge. These are regularly based on estimations that can be subject to cognitive biases. As projects become more tangible the more progressed they are, the approach addresses projects within advanced stages of a structured development process with transparent goals, for instance, within a stage-gate process. In a daily setting, data availability limits the potential of DEA, which allows one to consider various metrics with differing units. At the project level, mostly financial metrics are consistently available. Lastly, the DEA approach is methodologically advanced and requires thoughtful handling of the organization to apply and interpret the results. Acceptance of the DEA analysis and derived conclusions are necessary for an effective application within the company (Kerssens-van Drongelen, Nixon, and Pearson 2000).

We contribute to the innovation performance measurement literature by proposing and proving the robustness of an approach to operationalize the efficiency of ongoing NPD projects for steering purposes. By transferring DEA, a prominent method mainly in areas outside the innovation field (Liu et al. 2013; Lampe and Hilgers 2015), the analysis considers multiple input and output variables simultaneously, without determining factor weightings a priori that could show preferential treatment of specific projects (Charnes, Cooper, and Rhodes 1978) and that could therefore be subject to biases (Ittner and Larcker 1998). Since the method is not limited to a single unit (e.g. financial KPIs), we address a common shortcoming in R&D performance measurement (Pearson, Nixon, and Kerssens-van Drongelen 2000; Henri 2006). This contributes to managerial practice. Our proposed approach facilitates a more objective assessment of project performance and, accordingly, the direction of managerial attention. Thus, the DEA efficiency measure bears the potential to counterbalance cognitive biases in determining the relative importance of multiple performance indicators (Schmidt and Calantone 2002; Donthu and Unal 2014). However, it does not replace traditional project performance indicators, but supplements these to reduce both subjectivity and complexity. A reduction of subjectivity might be particularly beneficial for mature companies with large portfolios of incrementally innovative projects (Davila, Foster, and Oyon 2009), the performance management configuration of which is characterized by action control: tall hierarchy, centralized authority, standardized procedures, and well-defined boundaries of conduct (Bedford and Malmi 2015) – characteristics that detach portfolio managers

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61 Radicality and incrementalism characterize NPD concerning innovation novelty. While radical innovations create a new business paradigm, incremental innovations improve within an existing paradigm (Davila, Foster, and Oyon 2009).
from operations. The efficiency metric serves as a basis for future research, since it quantifies a concurrent rather than lagged performance metric for ongoing NPD projects.

4.3 Theoretical background

4.3.1 Project performance evaluation in NPD

The performance assessment of NPD projects is a fundamental issue in NPD management research. On the one hand, the choice and definition of performance metrics influence decisions about resource allocation; on the other hand, the complexity and dynamism of the NPD process, with significant time lags between input and output, aggravate comprehensive assessments (Kerssens-van Drongelen, Nixon, and Pearson 2000). The multifaceted nature of product development activities contradicts the often unidimensional approaches to its measurement.

Performance measurement can be defined as the provision of “information that allows the firm to identify the strategies offering the highest potential for achieving the firm’s objectives, and align management processes, such as target setting, decision-making, and performance evaluation, with the achievement of the chosen strategic objectives” (Ittner, Larcker, and Randall 2003, p. 715). The information is obtained through specific procedures, measured via financial and non-financial metrics that are often referred to as key performance indicators (KPIs). These KPIs can be categorized (Kerssens-van Drongelen, Nixon, and Pearson 2000) as either subjective (relying on judgmental information, e.g. employee satisfaction) or objective (based on non-judgmental information, e.g. R&D expenses). Further, KPIs can be either quantitative (received through computational methods) or qualitative (received through assessments). Anchoring qualitative information (e.g. through scoring models) allows one to convert these into numerical values (e.g. employee satisfaction equals 80 percent).

Because no single metric can reflect a field’s complexity, research calls for the use of multiple performance measures (Moers 2005). Research found that a diverse set of applied metrics drives employee satisfaction and stock market performance (Ittner, Larcker, and Randall 2003). Comparably, Kolehmainen (2010) suggests including both subjective and objective metrics, since subjective metrics facilitate organizational dynamism. In contrast, Moers (2005) finds that subjective metrics lead to more lenient judgments. Lastly, a combination of financial and non-financial metrics proves promising in contemporary performance measurement (Franco-Santos, Lucianetti, and Bourne 2012).
4.3.2 Efficiency measurement approaches in NPD

The ability to convert ideas into products is subject to debate (Chandy et al. 2006). Cruz-Cázares et al. (2013) empirically show that NPD portfolio efficiency drives company performance. Thus, a company’s motivation lies in increasing its NPD efficiency, argued from a resource-based view: transforming the company’s resources into outputs through the use of company capabilities. Clearly, efficiency is not limited to specific resources, but inclusively considers all resources.

NPD efficiency was previously mostly either accessed at the country (e.g. Guan, Zuo, Chen, and Yam 2016) or the company level (e.g. Cruz-Cázares et al. 2013). Both fields have received much attention in terms of publications. Further, a number of approaches address project efficiency conceptually but do not quantify a metric, mention key success factors instead (e.g. Blindenbach-Driessen, van Dalen, and van den Ende 2010).

Although efficiency analysis is of increasing interest in performance measurement (Lampe and Hilgers 2015), our literature review illustrates (see Appendix 2) that, in an innovation context, there is seldom a focus on quantified project efficiencies.62 These studies often took an ex post perspective on NPD projects, analyzing closed projects regarding specific phenomena. The publications that do take a concurrent perspective on ongoing projects mostly seek to facilitate project selection (Cook, Kress, and Seiford 1996; Linton, Walsh, and Morabito 2002; Linton, Morabito, and Yeomans 2007) rather than managing agreed-upon projects. The latter studies address specific phenomena, for instance the connection between NPD activities and strategy (Eilat, Golany, and Shtub 2008) or temporal efficiencies (Cao and Hoffman 2011). In short, to our best knowledge, besides the laboratory experiment by Donthu and Unal (2014), no publication measures nor conceptualizes NPD efficiencies of ongoing projects for steering purposes in an integrated way.

Regarding applied methods to quantify project-level efficiencies, DEA is the dominant approach. It is applied in minor variances with certain extensions, for instance, sequential DEA (Swink, Talluri, and Pandejpong 2006), or in combination with other concepts, for instance the Balanced Scorecard (BSC; Eilat et al. 2008). While, at other levels of analysis, the methods vary more, for instance stochastic frontier analysis (Bai 2013), at

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62 The literature review focuses on approaches that explicitly address NPD projects and that holistically operationalize efficiency, not merely KPIs that contrast unidimensional factors (e.g. net present value or return on investment). Thus, we omit approaches that do not consider the complexity of innovation (Moers 2005; Franco-Santos, Lucianetti, and Bourne 2012).
the project level, DEA is the sole previously applied mathematical approach to quantify efficiency.

4.4 Research methodology

This single-case research (Yin 2014) builds on the data envelopment analysis (DEA). We demonstrate the concept of DEA in Appendix 1, which for illustrative purposes considers two inputs and one output. DEA is a linear programming technique that determines relative efficiency scores by optimizing the weightings of the output-to-input ratio of multiple input and output factors in relation to a homogeneous set of decision making units (DMU; Charnes et al. 1978). This results in an efficiency frontier that is defined by the DMUs – in this case, NPD projects – with the largest relative ratios. These units are 100 percent efficient. The units’ distance to the frontier represents the deviation from 100 percent efficiency. An advantage of DEA is that, owing to its non-parametric character, it does not require conditions of factor normality and equal variance. Further, factor weightings are obtained via mathematical optimization rather than ex ante determination.

Since it was first published by Charnes, Cooper, and Rhodes (1978), DEA research has advanced into a broadly acknowledged academic field with numerous methodological developments (Liu et al. 2013). From 1978 to 2009, approximately 4,500 papers using and addressing DEA were published (Liu et al. 2013). These are positioned in various research fields, such as banking, education, and healthcare (Emrouznejad, Parker, and Tavares 2008). There have also been previous applications in the innovation context, mostly at the industry level, but only a few at the project level. In short, the analysis’ characteristics, together with prior empirical evidence from different contexts, make DEA a promising approach for ongoing NPD projects.

We chose a case study design owing to the limited knowledge in the field of NPD project efficiency and in order to test if the DEA approach applies in an innovation context of ongoing projects. The case company, which is in the chemical industry, offers a large array of innovation projects (more than 80 tracked projects per year). These incremental projects are in advanced phases of a stage-gate process (from definition of a business case to product launch), with detailed and comprehensive reporting from 2007 to 2014 in a proprietary archival dataset. This facilitates diverse project grouping alternatives and highlights minor notions in the approach’s applicability.
4.5 Conceptualizing and analyzing NPD project efficiency

4.5.1 Factor selection

Inspired by Golany and Roll’s (1989) DEA application process, we first conducted eight semi-structured interviews with innovation experts from the case company, in order to learn about the company’s context and to compile a long list of inputs (30 factors) and outputs (16 factors) of NPD projects, irrespective of operationalization and data availability (see Appendix 3). In close cooperation with the case company, we checked the consistent and reliable data availability of these factors at the project level, which reduced a diverse set to mainly financial measures. Based on these measures, we set up a conceptual model (see Figure 13) consisting of two input factors (R&D expenses, capital expenditures) and three output factors (net present value, cash flow, success probability). DEA requires inputs to be minimized and outputs to be maximized. All variables are part of the project-specific reporting that the NPD team is accountable for. Since all projects run within a structured stage-gate process, the data is reconfirmed at least annually by an operationally uninvolved third party. This fosters data reliability (Libby, Salterio, and Webb 2004), which is necessary because, owing to the focus on ongoing projects, the variables represent expected values rather than observed values.

Figure 13: Conceptual model

The figure depicts the extracted input and output factors from the gathered long list (see Appendix 3). For these factors, data was consistently and reliably reported at the project level in the case company. These factors do not represent a best practice selection of factors for future DEA applications, but a case-specific selection.

63 Success probability is a firm-specific index composed of the probability of commercial and technical success. Both dimensions have defined anchors.
Second, to reduce the risk of non-homogeneous units within the grand set of running innovation projects (Dyson et al. 2001), we statistically validated homogeneous sub-samples based on the NPD projects’ progress. This means that we grouped recently started projects (≥ 3 years to market launch; 22 projects in 2014), mature projects (0 < X ≤ 2 years to market launch; 36 projects in 2014), and projects due (≤ 0 years to market launch; 21 projects in 2014). In untabulated tests, we proved significant differences between these subgroups on four dimensions of the conceptual model, with exception of net present value. That the NPD projects from different business units operate in unlike environments might bias results (Dyson et al. 2001). However, neither significant differences between the business units, nor abnormalities in the DEA output (for instance, a business unit that is constantly more efficient than the rest) could be revealed. These tests suggest comparability and credibility of the relative efficiency scores.

In a next step, we approached DEA modeling using the ‘projects due’ subgroup as exemplar. Pairwise correlation analysis (see Table 3) among the five factors revealed moderate and partly significant values. As the maximum correlation arose between two output factors, cash flow and net present value (correlation = 0.86), there is the potential of a substitution effect that might overemphasize a specific effect in the model (Scheel 2000). However, more recent research avoids omitting variables on grounds of correlation (Dyson et al. 2001). Even if two sets of data are highly correlated, minor variations in data might not change the correlation score but the DEA efficiency score significantly. Further, factor weightings show that neither factor was fully excluded from the analysis (average weighting cash flow: 54.66 percent; net present value: 13.38 percent). Thus, we kept both variables in the model. Furthermore, there are negative but insignificant correlations with success probability that contradict the requirement for monotonous data (Dyson et al. 2001). In untabulated analyses, we prove, first, that the efficiency scores in a trimmed four-factor model without success probability correlate highly (correlation = 0.83) with the original model and, second, that the scores do not differ significantly (p = 0.40). Thus, we build on the grand model, including success probability.

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We also tested for differences between pre-defined groups of strategic buckets (Cooper 2008). Although the grouping showed significant differences, DEA resulted in multiple large super-efficiency scores (Andersen and Petersen 1993) that suggest outliers, hinting at a heterogeneous sample.
Table 3: Correlation analysis of projects due in 2014

<table>
<thead>
<tr>
<th></th>
<th>R&amp;D expenses</th>
<th>Capital expenditures</th>
<th>Cash flow</th>
<th>Net present value</th>
<th>Success probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D expenses</td>
<td>Pearson correlation</td>
<td>1</td>
<td>0.282</td>
<td>0.375</td>
<td>0.187</td>
</tr>
<tr>
<td></td>
<td>Sig. (two-tailed)</td>
<td>n/a</td>
<td>0.215</td>
<td>0.094</td>
<td>0.418</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>21</td>
<td>21</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>Capital expenditures</td>
<td>Pearson correlation</td>
<td>0.282</td>
<td>1</td>
<td>0.353</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>Sig. (two-tailed)</td>
<td>0.215</td>
<td>n/a</td>
<td>0.117</td>
<td>0.995</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>21</td>
<td>21</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>Cash flow</td>
<td>Pearson correlation</td>
<td>0.375</td>
<td>0.353</td>
<td>1</td>
<td>0.859**</td>
</tr>
<tr>
<td></td>
<td>Sig. (two-tailed)</td>
<td>0.094</td>
<td>0.117</td>
<td>n/a</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>21</td>
<td>21</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>Net present value</td>
<td>Pearson correlation</td>
<td>187</td>
<td>0.002</td>
<td>0.859**</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Sig. (two-tailed)</td>
<td>0.418</td>
<td>0.995</td>
<td>0.000</td>
<td>n/a</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>21</td>
<td>21</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>Success probability</td>
<td>Pearson correlation</td>
<td>-0.381</td>
<td>-0.280</td>
<td>-0.016</td>
<td>0.288</td>
</tr>
<tr>
<td></td>
<td>Sig. (two-tailed)</td>
<td>0.088</td>
<td>0.219</td>
<td>0.945</td>
<td>0.205</td>
</tr>
<tr>
<td></td>
<td>N</td>
<td>21</td>
<td>21</td>
<td>21</td>
<td>21</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (two-tailed).

We model the efficiencies by applying an input-oriented DEA, a model that minimizes inputs given a fixed amount of outputs, with constant returns to scale (CRS; Charnes, Cooper, and Rhodes 1978). Since the purpose of the analysis is to direct managerial attention to critical project developments, we used CRS, because in the case of variable returns to scale (VRS; Banker, Charnes, and Cooper 1984), the efficiencies of small and large projects are often over-rated\(^\text{65}\) (Dyson et al. 2001). Since we seek to reduce the cognitive biases of over-estimating project performance, we preferably underestimate efficiencies and, after having manually checked, remove the project from the consideration set.

The analysis of the 21 projects due results in an average efficiency score of 50.78 percent and six projects located on the efficiency frontier (see Appendix 4). Guided by Andersen and Petersen (1993), the analysis of the super-efficiency\(^\text{66}\) scores shows that two of these efficient projects might be outliers (Project 5; Project 18), with super-efficiency scores of above 40,000 percent. Having adjusted the sample for these two supposing outlying projects and rerunning the analysis with 19 projects, the average deviation of efficiency

\(^{65}\) A VRS model results in 13 (out of 21) efficient units with an average score of 67.77 percent.

\(^{66}\) Super-efficiency aims to further differentiate among units on the efficiency frontier that originally all scored 100 percent. It follows the same logic as the original DEA approach, but the unit under evaluation is excluded from the reference set, which results in previously efficient units obtaining scores of or above 100 percent (Andersen and Petersen 1993). This super-efficiency measure has been widely utilized to evaluate sensitivities (Zhu 2001).
scores between the original and the adjusted sample equals 5.94 percent. This means that, despite two outlying projects that could distort efficiency scores, the scores are robust. Thus, we continue our analysis with the unadjusted sample of 21 projects.

DEA does not offer fit indices or significance values. Thus, we further validated the results using ex post robustness checks and sense-making together with the case company innovation experts. During each step of the analysis, we were in close contact with these company experts.

To account for differences in efficiency scores, which established distance measures might result in, we correlated the scores and project ranks of three distance measures, i.e. radial distance, minimizing distance, maximizing distance (see Table 4). This resulted in very high conformance of the scores (correlation > 0.92). We conclude that the distance measure in use, the commonly applied radial distance, does not distort the overall picture, and the efficiency scores prove to be robust.

Lastly, extreme factor weightings might structurally exclude single variables from the model (Dyson et al. 2001). Overall, we found average factor weightings between 45.18 percent and 54.82 percent for input factors, and between 13.38 percent and 54.66 percent for output factors, which can be regarded as evenly spread. Still, there are several case-specific extreme weightings. This common phenomenon can be manually controlled (Dyson and Thanassoulis 1988). However, constraining goes along with subjectivity in determining the weight restriction that obstructs the linear optimizations – one of the main characteristics and advantages of DEA. Lastly, this aggravates interpretability of results (Dyson et al. 2001). Thus, we waived such restrictions in the model at hand.

### Table 4: Correlation of efficiency scores and ranks applying varying distance measures of projects due

<table>
<thead>
<tr>
<th></th>
<th>Radial distance</th>
<th>Minimizing distance</th>
<th>Maximizing distance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Eff. score</td>
<td>Ranks</td>
<td>Eff. score</td>
</tr>
<tr>
<td><strong>Pearson correlation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radial distance</td>
<td>1</td>
<td>1</td>
<td>0.991**</td>
</tr>
<tr>
<td>Sig. (two-tailed)</td>
<td>n/a</td>
<td>n/a</td>
<td>0.000</td>
</tr>
<tr>
<td>N</td>
<td>21</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>Minimizing distance</td>
<td>0.991**</td>
<td>0.932**</td>
<td>1</td>
</tr>
<tr>
<td>Sig. (two-tailed)</td>
<td>0.000</td>
<td>0.000</td>
<td>n/a</td>
</tr>
<tr>
<td>N</td>
<td>21</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>Maximizing distance</td>
<td>0.951**</td>
<td>0.990**</td>
<td>0.941**</td>
</tr>
<tr>
<td>Sig. (two-tailed)</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>N</td>
<td>21</td>
<td>21</td>
<td>21</td>
</tr>
</tbody>
</table>

**. Correlation is significant at the 0.01 level (two-tailed).
* . Correlation is significant at the 0.05 level (two-tailed).

We processed data of previously defined projects due in 2014.
4.5.2 Presentation and analysis of results

After having proven the robustness of the efficiency scores, we demonstrate an illustrative presentation of the scores.

Färe et al. (1994) developed a method to compare efficiency scores of different dates concerning efficiency and technological changes (see Appendix 5). Thus, the method accounts for technological developments in the environment that shift the overall efficiency frontier independently of the project’s characteristics. This means that a decrease in the annual efficiency score can still result in an increase in overall productivity if there was an overall increase in efficiency, i.e. a shift of the efficiency frontier. We apply the so-called Malmquist productivity index, the product of efficiency and technological changes, to the exemplary projects due in 2014 subset in comparison to their 2013 status. We calculated the same input-oriented model with constant returns to scale, because these have higher discriminatory power and prevent systematic biases, in contrast to models that have variable returns to scale (Grifell-Tatjé and Lovell 1995).

The analysis provides insights into the dynamics of the subsample (see Table 5). Concerning overall productivity, 13 of 21 projects are declining. This mainly originates from diminishing efficiencies (12 of 21 projects decline). Although technological change positively contributed to overall productivity (15 of 21 projects increase), it cannot outweigh the losses in efficiency. This can reasonably be argued for, since we focus on projects due that might already have postponed their launch dates, meaning that, for instance, comparable outputs necessitated additional inputs.
Table 5: Malmquist productivity index applied to projects due

<table>
<thead>
<tr>
<th>Project efficiency status</th>
<th>2013</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of efficient projects</td>
<td>9</td>
<td>6</td>
</tr>
<tr>
<td>Number of inefficient projects</td>
<td>12</td>
<td>15</td>
</tr>
<tr>
<td>Number of efficient projects remaining efficient 2013 and 2014</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>Average efficiency score</td>
<td>67.24%</td>
<td>50.78%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Productivity change</th>
<th>Malmquist productivity index</th>
<th>Efficiency change</th>
<th>Technological change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Improve</td>
<td>4</td>
<td>4</td>
<td>15</td>
</tr>
<tr>
<td>Decline</td>
<td>13</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>Equal</td>
<td>4</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Project 1</td>
<td>0.56</td>
<td>0.54</td>
<td>1.03</td>
</tr>
<tr>
<td>Project 2</td>
<td>0.87</td>
<td>1.00</td>
<td>0.87</td>
</tr>
<tr>
<td>Project 3</td>
<td>0.34</td>
<td>0.17</td>
<td>1.95</td>
</tr>
<tr>
<td>Project 4</td>
<td>0.76</td>
<td>0.49</td>
<td>1.56</td>
</tr>
<tr>
<td>Project 5</td>
<td>1</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Project 6</td>
<td>0.60</td>
<td>2.67</td>
<td>0.22</td>
</tr>
<tr>
<td>Project 7</td>
<td>0.74</td>
<td>0.47</td>
<td>1.58</td>
</tr>
<tr>
<td>Project 8</td>
<td>1.27</td>
<td>1.24</td>
<td>1.02</td>
</tr>
<tr>
<td>Project 9</td>
<td>1</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Project 10</td>
<td>1.82</td>
<td>1.23</td>
<td>1.48</td>
</tr>
<tr>
<td>Project 11</td>
<td>0.73</td>
<td>0.70</td>
<td>1.03</td>
</tr>
<tr>
<td>Project 12</td>
<td>0.31</td>
<td>0.21</td>
<td>1.50</td>
</tr>
<tr>
<td>Project 13</td>
<td>0.33</td>
<td>0.22</td>
<td>1.54</td>
</tr>
<tr>
<td>Project 14</td>
<td>0.14</td>
<td>0.10</td>
<td>1.50</td>
</tr>
<tr>
<td>Project 15</td>
<td>0.70</td>
<td>0.47</td>
<td>1.49</td>
</tr>
<tr>
<td>Project 16</td>
<td>0.72</td>
<td>0.42</td>
<td>1.70</td>
</tr>
<tr>
<td>Project 17</td>
<td>7.03</td>
<td>4.95</td>
<td>1.42</td>
</tr>
<tr>
<td>Project 18</td>
<td>1</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Project 19</td>
<td>1.06</td>
<td>0.59</td>
<td>1.80</td>
</tr>
<tr>
<td>Project 20</td>
<td>1</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Project 21</td>
<td>0.33</td>
<td>0.22</td>
<td>1.48</td>
</tr>
</tbody>
</table>

An index score greater (lower) than unity indicates that efficiency has increased (decreased) relative to the previous year.

Illustrating productivity changes in relation to de facto efficiency scores provides additional insights (see Figure 14; Han, Asmild, and Kunc 2014). This helps to direct attention to efficient projects declining (deteriorating group), efficient projects gaining (leading group), inefficient projects declining (lagging group), or inefficient projects gaining (improving group). Thus, managers can further break down the overall sample and can decrease complexity. This facilitates a focus on projects that require managerial attention based on objectively determined critical dynamics, without subjectively assessing overall performance based on the evaluation of multiple de-linked measures.
**Figure 14:** Dynamic perspective on efficiency applying the Malmquist productivity index to the projects due

Black lines indicate exemplary threshold values that distinguish efficient projects from inefficient ones (based on the input-oriented CRS model) and efficiency increasing from decreasing ones (based on input-oriented CRS Malmquist productivity index). We centralized the Malmquist productivity index in a way that unity equals 0. Adapted from Han et al. (2014).

**4.5.3 Discussion**

We illustrate a DEA-based approach to obtain NPD project efficiencies. This represents a method to reduce managers’ judgmental leeway, which might be subject to cognitive biases. Although the approach can help to guide managerial attention, in the context of the case study, we identified pitfalls that researchers and practitioners need to be aware of:

*Comparability:* The reliability of the efficiency scores and the derived potentials depend on the homogeneity of the sample regarding projects’ characteristics and their contexts, because DEA is extremely sensitive to outliers (Dyson et al. 2001; Brown 2006). Statistical analysis (e.g. cluster analysis and analysis of variance) can confirm tendencies for subgroups. However, these still need to be ratified through expert judgment.

*Output factor accuracy:* Projects’ outputs are inherently uncertain. If the subjects of analysis are ongoing projects, outputs are necessarily based on estimations that themselves might be subject to biases. Still, data accuracy is a key facilitator of reduced cog-
nitive biases (Hermans, Cools, and van den Abbeele 2016). Among others, data accuracy can be fostered through the assurance of an uninvolved third party (Libby, Salterio, and Webb 2004).

**Data availability:** Lacking data consistency across business units and for the focal period, as well as the common emphasis on financial data, limit the possibilities of the methodology, which allows for factors with differing units. Close cooperation with experts on the company’s performance measurement ensured a reasonable model conceptualization. Achieving acceptance of the DEA-based efficiency scores might help one to collect more variables consistently. Thus, the conceptual framework may grow over the years.

**Thoughtful handling:** DEA outputs are a powerful tool. However, a number of determinants influence these outputs. This variability needs to be considered when handling DEA outputs and deriving actions from these. Methodological characteristics (e.g. the concept of project-specific linear optimizations) undermine the broad communication of outputs, since there is the risk that outsiders might interpret results hastily.

**Acceptance:** The advanced methodological characteristics impede broad organizational acceptance of the DEA. In contrast to other, easily comprehensible metrics, employees might avoid DEA because they might see it as a black box (Kerssens-van Drongelen, Nixon, and Pearson 2000).

Derived from the abovementioned pitfalls, we can formulate propositions for contexts in which DEA applications methodologically face promising settings. The required homogeneity of NPD projects necessitates a large project portfolio from which comparable subgroups can be built. This is further emphasized by the statistical requirements that suggest a minimum sample size of twice the sum of input and output factors for effective discrimination, in case $2 \times (2 \text{ inputs} + 3 \text{ outputs}) = 10 \text{ projects}$ (Golany and Roll 1989). Comparability is further supported by incrementally rather than radically innovative projects that have unique characteristics in comparison to the remainder of the portfolio (Kerssens-van Drongelen, Nixon, and Pearson 2000). Further, the formalized structure of such a method-driven approach, despite its enabling use (Adler and Borys 1996), is more suited to exploit existing knowledge (Davila, Foster, and Oyon 2009; Bedford and Malmi 2015). Radical innovation projects can neither be reliably depicted in quantified estimates nor benchmarked to comparable peers. Our case study has demonstrated that data availability is a limiting factor. **Structured innovation pro-**
cesses (e.g. the stage-gate process) facilitate consistent data for the focal portfolio, because these have standardized project status reports. DEA’s methodologically advanced character suggests the analysis and interpretation by an *expert team* that is fully aware of the organization’s strategic objectives (Banker, Hsisui, and Pizzini 2004; Dilla and Steinbart 2005; Cardinaels and van Veen-Dirks 2010). An operationally uninvolved expert team that cross-checks estimations for input and output measures reduces these evaluations’ subjective biases (Libby, Salterio, and Webb 2004). Lastly, the DEA outputs serve as a high-level call to further investigations at the project level. This accentuates that the DEA is a *supplement* rather than a substitute to existing metrics.

### 4.6 Conclusion

We sought to develop an approach that effectively directs managerial attention by reducing ambiguity in assessing the relative importance of multiple performance metrics of NPD projects. We built on prior laboratory evidence by Donthu and Unal (2014) and have provided, to our knowledge, the first study to prove the robustness of DEA-based efficiency scores in a real NPD context of ongoing projects. This addresses doubts that NPD projects’ characteristics – for instance, the inherent uncertainty, dynamism, and uniqueness – would obstruct objective and integrated measures because these ignore the context’s complexity (Tidd and Bessant 2009). The DEA-based approach is neither limited to a single performance dimension (e.g. financial), nor to a common unit (Charnes, Cooper, and Rhodes 1978), which addresses prominent shortcomings of R&D performance management (Pearson, Nixon, and Kerssens-van Drongelen 2000; Henri 2006). Further, by mathematically optimizing factor weightings, the approach eliminates managers’ estimation of relative weightings (Ittner and Larcker 1998) and concurrently considers NPD projects’ individual characteristics (Charnes, Cooper, and Rhodes 1978). This ensures that assigned benchmarks do reflect a project’s characteristics.

The approach assists portfolio managers and innovation officers by opening the black box of NPD project performance. It especially addresses contexts of vast portfolios of incrementally innovative projects, tall and centralized hierarchies, and standardized procedures that, taken together, detach managers from NPD projects’ operations (Bedford and Malmi 2015). DEA reduces a manager’s leeway of judging the relative importance of multiple KPIs, which might be subject to cognitive biases (Schmidt and Calantone 2002; Donthu and Unal 2014). Illustrating relative dynamics in efficiency changes directs managerial attention at the portfolio level to particular projects that stand out, either positively or negatively. Even if managers assume, for instance, low efficiency scores
for certain projects, this approach makes these notions explicit and discloses ways for relative efficiency improvements. Our method facilitates early reactions to critical project developments that could otherwise generate avoidable costs. In contrast to subjective weighting and assessment of multiple performance metrics, this approach results in a single indicator that can be manipulated for scenario purposes. DEA does not replace traditional project performance indicators, but has the potential to supplement the current toolbox with an aggregate measure.

No study is free from limitations. First, having conducted an in-depth case study, our observations and conclusions apply to the case company. This also refers to the conceptual framework, which is case-specific. However, the approach’s generalizability is supported by thoroughly describing the methodological steps. By identifying pitfalls and proposing contextual factors that facilitate successful implementation, we addressed generalizability concerns. Second, the applied factors were based on estimations and are therefore subject to judgmental biases, which might have distorted the DEA results. To reduce that risk, we ensured that the estimations and analyses were not done by the same experts (Schmidt and Calantone 2002). Because outputs are in the future, these are necessarily based on estimations. Comparably, past DEA of ongoing projects were also based on estimated outputs (see Appendix 2, e.g. Linton et al. 2007, 2002). Third, we demonstrated that DEA can be reasonably implemented at the project level as a concurrent rather than lagging performance metric. However, we cannot show empirically whether, in a field setting, Donthu and Unal’s (2014, p. 212) findings that “DEA is an objective and automatic tool that makes managers’ decisions free from bias and less time consuming” prove viable. Considered in isolation, DEA does not necessarily reduce judgmental biases solely through better information (Schmidt and Calantone 2002). Besides the quality of the information, which we focused on, its presentation, its organizational integration, its addressees, and the measurement processes determine the impact of cognitive biases (Schmidt and Calantone 2002; Franco-Santos, Lucianetti, and Bourne 2012). This necessitates further research on promising practices.
4.7 Appendix

4.7.1 Appendix 1: Data envelopment analysis

Data envelopment analysis (Charnes, Cooper, and Rhodes 1978, p. 431) calculates relative efficiency scores ($E$) following the linear maximization of a ratio of weighted ($u$) outputs ($y$) to weighted ($v$) inputs ($x$). It is subject to the condition that the weights are being determined by the data on all DMUs ($j$) in the reference set:

$$\max E_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1;$$

$$j = 1, \ldots, n$$

$$u_r, v_i \geq 0$$

$$r = 1, \ldots, s$$

$$i = 1, \ldots, m$$
### 4.7.2 Appendix 2: Literature review of quantified efficiency approaches at the project level

<table>
<thead>
<tr>
<th>Author</th>
<th>Sample</th>
<th>Methodology</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Perspective</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cook, Kress, and Seiford (1996)</td>
<td>Concept development</td>
<td>DEA input-oriented (CRS)</td>
<td>Internal technical expertise; external technical expertise; technology availability</td>
<td>Energy efficiency; diversification; costs saved; environmental impact; technical capability; research profile; economic impact; impact on nuclear performance</td>
<td>Ongoing</td>
<td>Model development to incorporate ordinal data in DEA. Conceptual application: selection of R&amp;D projects</td>
</tr>
<tr>
<td>Linton, Walsh, and Morabito (2002)</td>
<td>Single-case study (469 projects)</td>
<td>DEA output-oriented (CRS) / subjective value creation model</td>
<td>Discounted cash-flow of investments; lifecycle stage of intellectual property; lifecycle stage of product[^67^]</td>
<td>Discounted cash-flow most likely / optimistic / pessimistic</td>
<td>Ongoing</td>
<td>Selection of R&amp;D projects in a large portfolio: select/reject decision support</td>
</tr>
<tr>
<td>Revilla, Sarkis, and Modrego (2003)</td>
<td>118 Spanish firms carrying out 277 collaboration projects with public centers</td>
<td>DEA input-oriented (CRS; IRS; DRS)</td>
<td>Firm revenue; number of employees; R&amp;D budget</td>
<td>Total income from project; new employees; patents from project</td>
<td>Ex post</td>
<td>Efficiency of collaboration projects varies depending on firm size and level of firm knowledge</td>
</tr>
<tr>
<td>Guan and Wang (2004)</td>
<td>21 Chinese research groups</td>
<td>DEA input-oriented (CRS)</td>
<td>Budget; size of group</td>
<td>Number of publications; number of papers indexed; cumulative citation counts; average citation counts; percentage cited by others vs. uncited; papers with more than five citations</td>
<td>Ex post</td>
<td>Success factors of Chinese research groups. Identification of three indicators of knowledge management</td>
</tr>
<tr>
<td>Garg, Gupta, Jamal, Roy, and Kumar (2005)</td>
<td>330 publicly funded research projects in India</td>
<td>DEA input-oriented (CRS)</td>
<td>Funding; number of projects</td>
<td>Publications (journals, conferences); patents</td>
<td>Ex post</td>
<td>Communication channels of academic research. Researchers prefer to present research study results at conferences rather than in journals</td>
</tr>
<tr>
<td>Swink, Talluri, and Pandejpong (2006)</td>
<td>137 NPD projects by U.S.</td>
<td>Sequential DEA input-</td>
<td>Development costs; product costs</td>
<td>Product quality (product manufacturability, quality, performance, innovative features,</td>
<td>Ex post</td>
<td>Performance tradeoffs among NPD performance outcomes are stronger in very efficient</td>
</tr>
</tbody>
</table>

[^67^] Anchors were set according these characteristics: declining, widespread, emerging, future.

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# Article III

<table>
<thead>
<tr>
<th>Manufacturing firms</th>
<th>Oriented (VRS)</th>
<th>Meet customer needs); project lead time (on-time performance; reduced development time)</th>
<th>Projects compared to inefficient projects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linton, Morabito, and Yeomans (2007)</td>
<td>Single-case study (469 projects in 7 efficiency groups)</td>
<td>Sequential DEA</td>
<td>Financial return (estimated NPV)</td>
</tr>
<tr>
<td>Eilat, Golany, and Shhtub (2008)</td>
<td>36 exemplary projects</td>
<td>DEA input-oriented (CRS) with weight restrictions / Balanced Scorecard</td>
<td>Investments</td>
</tr>
<tr>
<td>Hsu and Hsueh (2009)</td>
<td>110 government-sponsored R&amp;D projects over 9 years in Taiwan</td>
<td>Two-step DEA input-oriented (CRS; VRS) / Tobit regression</td>
<td>Project R&amp;D staffing; government subsidy to project; project budget from recipient company; post-project period</td>
</tr>
<tr>
<td>Cao and Hoffman (2011)</td>
<td>Single-case study (20 projects)</td>
<td>DEA input-oriented (CRS)</td>
<td>Effort; project staffing; priorities; number of engineers; technical complexities</td>
</tr>
<tr>
<td>Donthu and Unal (2014)</td>
<td>8 projects (laboratory experiments)</td>
<td>DEA output-oriented</td>
<td>Budget; people; dedication</td>
</tr>
</tbody>
</table>

*The Review is an excerpt from an extensive literature review on NPD efficiency by Müller-Stewens (2016). CRS: constant returns to scale; VRS: variable returns to scale; IRS: increasing returns to scale; DRS: decreasing returns to scale.*
### Appendix 3: Long list of input and output factors

<table>
<thead>
<tr>
<th>Input factors (30 factors)</th>
<th>Output factors (16 factors)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Financial factors</strong></td>
<td>Research</td>
</tr>
<tr>
<td>R&amp;D expenses</td>
<td>Patents</td>
</tr>
<tr>
<td>Innovation expenses</td>
<td>Inventions</td>
</tr>
<tr>
<td>Capital expenditures</td>
<td>Lab reports</td>
</tr>
<tr>
<td><strong>Proprietary research</strong></td>
<td>Generated knowledge</td>
</tr>
<tr>
<td>Licenses</td>
<td></td>
</tr>
<tr>
<td>Patents</td>
<td></td>
</tr>
<tr>
<td><strong>Idea</strong></td>
<td>Process</td>
</tr>
<tr>
<td>Communication</td>
<td>Success probability</td>
</tr>
<tr>
<td>Creativity</td>
<td></td>
</tr>
<tr>
<td>Information</td>
<td></td>
</tr>
<tr>
<td>Know-how</td>
<td></td>
</tr>
<tr>
<td>Iteration of idea generation</td>
<td></td>
</tr>
<tr>
<td><strong>Strategic directions</strong></td>
<td>Marketing</td>
</tr>
<tr>
<td>Market potentials</td>
<td>Unique selling proposition</td>
</tr>
<tr>
<td>Search field analysis</td>
<td>People</td>
</tr>
<tr>
<td><strong>External competences</strong></td>
<td>Societal value added</td>
</tr>
<tr>
<td>Open innovation</td>
<td></td>
</tr>
<tr>
<td>Consultants</td>
<td></td>
</tr>
<tr>
<td>Supporter</td>
<td></td>
</tr>
<tr>
<td>Research funds</td>
<td></td>
</tr>
<tr>
<td>Development partner</td>
<td></td>
</tr>
<tr>
<td>Patent research</td>
<td></td>
</tr>
<tr>
<td>Literature research</td>
<td></td>
</tr>
<tr>
<td><strong>Capacity</strong></td>
<td>Ecology</td>
</tr>
<tr>
<td>Tangible means</td>
<td>Emission</td>
</tr>
<tr>
<td>Marketing resources</td>
<td>Waste</td>
</tr>
<tr>
<td>Logistics</td>
<td>Water</td>
</tr>
<tr>
<td>Laboratory capacity</td>
<td></td>
</tr>
<tr>
<td><strong>Time</strong></td>
<td>Number of products</td>
</tr>
<tr>
<td>Time to launch</td>
<td>Number of launches</td>
</tr>
<tr>
<td>Time to market</td>
<td></td>
</tr>
<tr>
<td><strong>Labor force</strong></td>
<td>Economy</td>
</tr>
<tr>
<td>Headcount</td>
<td>Net present value (NPV)</td>
</tr>
<tr>
<td>Cross-functional teams</td>
<td>Commercial value</td>
</tr>
<tr>
<td>Geographic diversity of teams</td>
<td>Cash flow</td>
</tr>
<tr>
<td>Individual incentive structure</td>
<td>Sales</td>
</tr>
<tr>
<td>Qualification of employees</td>
<td></td>
</tr>
</tbody>
</table>

The table represents the unfiltered listing of input and output factors that were mentioned in eight expert interviews without considering operationalization. These do not reflect data availability. The grouping was done ex post to structure the listing. The classification as inputs and outputs stems from the interviews and is not linked to DEA logic.

Consistent data available on project level for 2013 and 2014.
4.7.4 Appendix 4: Efficiency scores of projects due in 2014

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Eff. score</td>
<td>Rank (decreasing)</td>
</tr>
<tr>
<td>Project 1</td>
<td>1.38</td>
<td>-0.56</td>
<td>-0.56</td>
<td>-0.22</td>
<td>-0.88</td>
<td>50.90%</td>
<td>10</td>
</tr>
<tr>
<td>Project 2</td>
<td>1.48</td>
<td>-0.56</td>
<td>0.49</td>
<td>0.05</td>
<td>-1.67</td>
<td>100.00%</td>
<td>1</td>
</tr>
<tr>
<td>Project 3</td>
<td>1.33</td>
<td>-0.54</td>
<td>2.83</td>
<td>3.20</td>
<td>0.58</td>
<td>17.41%</td>
<td>15</td>
</tr>
<tr>
<td>Project 4</td>
<td>-0.76</td>
<td>-0.40</td>
<td>-0.45</td>
<td>-0.63</td>
<td>-0.17</td>
<td>21.17%</td>
<td>13</td>
</tr>
<tr>
<td>Project 5</td>
<td>-0.92</td>
<td>-0.56</td>
<td>-0.80</td>
<td>-0.66</td>
<td>1.43</td>
<td>100.00%</td>
<td>1</td>
</tr>
<tr>
<td>Project 6</td>
<td>-0.26</td>
<td>0.03</td>
<td>-0.80</td>
<td>0.50</td>
<td>0.99</td>
<td>0.08%</td>
<td>21</td>
</tr>
<tr>
<td>Project 7</td>
<td>-0.90</td>
<td>-0.56</td>
<td>-0.74</td>
<td>-0.61</td>
<td>-0.99</td>
<td>46.87%</td>
<td>11</td>
</tr>
<tr>
<td>Project 8</td>
<td>-0.73</td>
<td>-0.56</td>
<td>-0.78</td>
<td>-0.74</td>
<td>1.43</td>
<td>100.00%</td>
<td>1</td>
</tr>
<tr>
<td>Project 9</td>
<td>-0.68</td>
<td>-0.56</td>
<td>0.49</td>
<td>1.03</td>
<td>0.99</td>
<td>100.00%</td>
<td>1</td>
</tr>
<tr>
<td>Project 10</td>
<td>-0.78</td>
<td>-0.56</td>
<td>-0.18</td>
<td>0.11</td>
<td>0.99</td>
<td>94.90%</td>
<td>7</td>
</tr>
<tr>
<td>Project 11</td>
<td>0.89</td>
<td>-0.56</td>
<td>-0.46</td>
<td>-0.64</td>
<td>0.00</td>
<td>70.40%</td>
<td>9</td>
</tr>
<tr>
<td>Project 12</td>
<td>-0.84</td>
<td>-0.49</td>
<td>-0.64</td>
<td>-0.59</td>
<td>-0.52</td>
<td>20.84%</td>
<td>14</td>
</tr>
<tr>
<td>Project 13</td>
<td>2.26</td>
<td>1.14</td>
<td>-0.08</td>
<td>-0.82</td>
<td>-0.61</td>
<td>2.29%</td>
<td>20</td>
</tr>
<tr>
<td>Project 14</td>
<td>0.58</td>
<td>2.86</td>
<td>-0.17</td>
<td>-1.09</td>
<td>-1.24</td>
<td>3.49%</td>
<td>19</td>
</tr>
<tr>
<td>Project 15</td>
<td>0.06</td>
<td>2.46</td>
<td>2.62</td>
<td>1.80</td>
<td>0.01</td>
<td>26.69%</td>
<td>12</td>
</tr>
<tr>
<td>Project 16</td>
<td>0.98</td>
<td>0.15</td>
<td>0.31</td>
<td>0.25</td>
<td>-0.03</td>
<td>6.03%</td>
<td>18</td>
</tr>
<tr>
<td>Project 17</td>
<td>-0.49</td>
<td>-0.56</td>
<td>-0.18</td>
<td>0.18</td>
<td>0.36</td>
<td>81.00%</td>
<td>8</td>
</tr>
<tr>
<td>Project 18</td>
<td>-0.92</td>
<td>-0.39</td>
<td>-0.59</td>
<td>-0.66</td>
<td>-1.69</td>
<td>100.00%</td>
<td>1</td>
</tr>
<tr>
<td>Project 19</td>
<td>-0.66</td>
<td>0.08</td>
<td>-0.49</td>
<td>-0.32</td>
<td>0.99</td>
<td>9.60%</td>
<td>17</td>
</tr>
<tr>
<td>Project 20</td>
<td>-0.87</td>
<td>-0.56</td>
<td>-0.29</td>
<td>0.14</td>
<td>0.98</td>
<td>100.00%</td>
<td>1</td>
</tr>
<tr>
<td>Project 21</td>
<td>-0.14</td>
<td>0.67</td>
<td>0.48</td>
<td>-0.28</td>
<td>-0.97</td>
<td>14.67%</td>
<td>16</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>50.78%</td>
<td></td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1.8</td>
<td>12.6</td>
<td>11.9</td>
<td>31.1</td>
<td>0.2</td>
<td>0.41</td>
<td></td>
</tr>
</tbody>
</table>

The table shows the values of the mean-centered input and output factors of the subgroup of projects due. [I] represents inputs and [O] outputs. DEA suggests robustness of the original efficiency scores when comparing these to the scores of the adjusted sample that was reduced by two supposing outlying projects (Projects 5; Project 18). The Malmquist productivity index corresponds to the values in Table 5.
4.7.5 Appendix 5: The concept of the Malmquist productivity index

The figure depicts for illustrative purposes the reasoning behind the Malmquist productivity index (Färe et al. 1994). The index is composed of an efficiency change and a technology change component, the product of which is the Malmquist productivity index. The efficiency change is calculated as the ratio of the annual efficiency scores relative to their respective technology. A value below unity reflects an efficiency decline:

\[
Efficiency \ change = \frac{0X_{2016}}{0b} \div \frac{0X_{2015}}{0c}
\]

In contrast to the efficiency change that compares to years isolated, the technology change component accounts for overall changes in productivity, i.e. it operationalizes the efficiency frontier shift between two years. A value above unity reflects in a technological improvement:

\[
Technological \ change = \sqrt{\frac{0b}{0a}} \times \frac{0d}{0c}
\]

The generally applicable formula of the Malmquist productivity index \(M\) for a DMU \((\theta)\) with inputs \((x)\), outputs \((y)\), and a technology \((d)\) between the moments \((t)\) and \((t+1)\) reads (Färe et al. 1994, p. 71):

\[
M_0 = Efficiency \ change \times Technological \ change
\]

\[
M_0 = \frac{d_0^{t+1}(y_{t+1}, x_{t+1})}{d_0^t(y_t, x_t)} \times \left( \frac{d_0^t(y_t, x_t)}{d_0^{t+1}(y_{t+1}, x_{t+1})} \times \frac{d_0^{t+1}(y_{t+1}, x_{t+1})}{d_0^t(y_t, x_t)} \right)^{\frac{1}{2}}
\]
4.8 References


The role of controls in innovation: An examination of diagnostic use, interactive use, and dynamic tension

Benedikt Müller-Stewens
Sally K. Widener
Jan-Christoph Steinmann
Klaus Möller
5.1 Abstract

The purpose of this paper is to empirically investigate the relationship between different uses of control systems, the alignment of the product development process, and innovativeness in terms of product newness and innovation rate. The paper builds on the levers of control framework by Simons (1995) and suggests that, in addition to the individual uses of controls, using controls jointly can result in dynamic tension that enhances innovativeness. Using data from a survey of 695 R&D professionals from North America and Europe, this study uses structural equation modelling to examine whether diagnostic use, interactive use, and dynamic tension (the joint use) are positively related to innovativeness through process alignment. The results show that process alignment is a strong predictor of innovativeness, which is driven by interactive and diagnostic uses. Exploratory analysis emphasizes the role of process alignment in technologically turbulent environments. The results show that dynamic tension is positively associated with product newness and innovation rate, but the relationship is not mediated by process alignment.

Acknowledgements

We thank the conference participants of the 2015 Doctoral Colloquium and the 2016 Annual Conference for Management Accounting Research, as well as workshop participants at Clemson University. We also thank Josep Bisbe, Antonio Davila, and Vincent Chong for their feedback and constructive comments. The support of the Basic Research Fund at the University of St. Gallen is gratefully acknowledged.
5.2 Introduction

Product innovation is a means to gain competitive advantage and thus ensure long-term growth and enhanced business performance (Dyer et al., 2009; Stock et al., 2013). However, fewer than three out of four initiated product development projects are launched to the market (Barczak et al., 2009). While the preponderance of recent evidence indicates that product development may benefit from a well-designed management control system (MCS) (Bedford, 2015; Ylinen and Gullkvist, 2014), there are still inconsistent and even contradictory findings on the relationship between formal controls and innovation outcomes. For instance, Bisbe and Otley (2004) find no evidence of a positive association between interactive controls and firm performance, while Bedford (2015) does, especially in high-innovating firms (see also Henri, 2006). Thus, gaining more insights into the role that MCS play in providing discipline and enhancing the innovation process is of increasing interest (Szymanski et al., 2007).

In this study, we focus on product development projects that are characterized by (1) being clearly specified through a business opportunity, a business case, and a pursued idea, that are (2) typically within a staged development process, and that (3) end in market launch (e.g., Cooper, 2008). We refer to the conversion process, which begins with a concept and culminates in the development of a marketable product, as new product development (NPD) (Bisbe and Malagueño, 2015). Therefore, the creative phase of basic research projects that provide input to subsequent product development activities is not part of the scope (see Bisbe and Malagueño, 2015; Chiesa and Frattini, 2007); nor is the financial success of the project.

In this NPD process, firms design a process architecture intended to facilitate innovativeness. The process architecture (also referred to as innovation control) is comprised of two parts: “the elements of a process (activities) and their pattern of interaction” (Browning and Eppinger, 2002, p. 428). Examples of activities include assessing what customers value, designing the product, estimating costs and sales volumes, developing specifications, building prototypes, and sourcing materials. Interaction refers to the information exchanges that take place and focuses on the use of information from these process control activities. It is common to decompose the process into its constitutents of the underlying architecural elements and information.

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68 Innovation control is a more familiar term in the MCS literature while process architecture is a more familiar term in the innovation literature. In the conceptual part of this paper we use the term 'process architecture'.
use (Browning and Eppinger, 2002). In this study, we consider the architectural elements as being in place and focus, instead, on the role MCS play in the effective use of the information from these underlying architectural elements. As Tessier and Otley (2012) point out, the underlying architecture is neutral; what is important is how the information from these activities is used. Given the low ratio of product launches, it is important to gain more insight into the NPD process itself. Moreover, in examining the use of information from the underlying elements of the process, the study responds in part to Davila et al. (2009, p. 297), who call for future research that “examine(s) the intersection between innovation and control […] to take a process perspective”.

One way that MCS may promote innovation is by using information from the underlying process architecture to enhance the quality of the NPD process. Using information from the process architecture appropriately can help one to ensure that the NPD process is transparent to the NPD team; they then understand the process that guides the development of new products as well as the innovation goals that the organization has set for itself. Through transparency and understandability of the process and innovation goals, one gains alignment between the NPD team and the organization, thereby facilitating innovativeness (e.g., Sammerl, 2006; Schultz et al., 2013). We refer to this as process alignment.

It is critical that the NPD process is aligned so the development team understands the direction it must take and the innovation objectives that top management wants to achieve, which studies argue will facilitate innovativeness (Sammerl, 2006). Best practice studies investigating NPD capabilities consistently find that the NPD process is a key factor in determining firm performance (Barczak et al., 2009; Cooper, 1998; Cooper et al., 2004; Cooper and Kleinschmidt, 1987, 1991, 1995; Griffin, 1997; Kahn et al., 2006). However, to date, there is limited evidence on the role MCS play in the implementation of the NPD process (e.g., Bisbe and Malagueño, 2015; Davila, 2000; Davila et al., 2009; Jørgensen and Messner, 2010). We contend that MCS bridge, through their effective use of information, the gap between the elements of the process architecture and its beneficial implementation, which facilitates innovativeness. Accordingly, to advance understanding of the inconclusive relationships between MCS
and innovation outcomes, we examine the mediating role of process alignment in the role between MCS use and innovation outcomes.69

Existing research argues that there are different control types, each of which influences innovation outcomes differently (Bedford, 2015; Ylinen and Gullkvist, 2014). A growing body of empirical research proposes that organizations need to balance flexibility and discipline, thereby blending seemingly opposing control mechanisms in order to enhance performance (Bedford, 2015; Henri, 2006; Lewis et al., 2002; Mundy, 2010; Rijsdijk and van den Ende, 2011; Simons, 1994; Ylinen and Gullkvist, 2014). Employing a mix of control types that serve different purposes will create dynamic tension (Simons, 1995), thus facilitating the achievement of flexibility while also ensuring predictability. Accordingly, different control types likely influence the NPD process in different ways.

Drawing on the levers of control framework by Simons (1995), this study adopts the concepts of diagnostic and interactive uses of controls to capture two opposing types of control usage. Diagnostic use relies on formal feedback systems to monitor process outcomes, in order to ensure predictable goal achievement. Interactive use incentivizes regular and personal involvement of superiors during decision activities, in order to provoke the emergence of new initiatives and stimulate search and learning. We follow Simons’ (1995) argumentation that both control uses work together to create dynamic tension and drive product innovativeness. We hypothesize that the effect on innovativeness is achieved through process alignment. The interactive and diagnostic use of controls identify and reduce information asymmetry (Jaworski and Macinnis, 1989) and ambiguity in the organization’s goals (Jaworski et al., 1993), enhancing decision-making clarity (Schultz et al., 2013), which aligns development processes and ultimately results in increased product innovativeness (Cooper and Kleinschmidt, 1986).

To conceptualize innovativeness, we build on Stock et al.’s (2013) three layer understanding of newness, frequency, and value, which taken together, form product innovativeness. We focus on the internal assessment of innovativeness and, therefore, examine two of these variables: the frequency of new product launches (i.e., innovation rate) (e.g., Kessler and Bierly, 2002; Langerak and Hultink, 2006) and these products’ degree of newness of (i.e., product newness) (Szymanski et al., 2007). Product value

69 We focus on the mediating role of process alignment because extant literature holds that it is associated with innovativeness (Cooper and Kleinschmidt, 1986). Thus, we are interested in understanding whether MCS use works through process alignment to affect innovation outcomes.
assesses the benefits the innovation provides customers with and is excluded from the analysis on hand, because it is based on customer appreciation, which is also affected by factors such as marketing that dilute the direct impact of process alignment. Empirical evidence considers innovativeness a predecessor of new product performance (Szymanski et al., 2007); thus, we focus on the more proximate measure of innovativeness since, without internal performance on innovation, there can be no external value.

This research study develops a conceptual model and tests it using structural equation modelling (SEM) on a sample of 695 research-intensive companies from North America and Europe. Our results show that the diagnostic and interactive uses of control are directly associated with innovation rate and product newness. We also find that these relationships are partially mediated by process alignment. Finally, we find that dynamic tension, or the joint use of diagnostic and interactive control uses, is directly associated with both innovation rate and product newness.

This study makes two primary contributions to the accounting literature. First, our results provide insights into why controls are important for the NPD process by distinguishing between the process architecture designed to guide the process and its effective implementation, which is affected by control use. We demonstrate that the diagnostic and interactive uses of information enhance NPD team members’ perceptions that the processes in place are transparent and understandable (Simons, 1995) and facilitate the effective alignment of development activities with the overarching organizational goals (i.e., enhance process alignment). Gaining insights into the effects of control uses and their combinations on NPD process alignment is considered a major issue, yet one that has received little attention (Rijsdijk and van den Ende, 2011). The results show that diagnostic and interactive uses individually facilitate process alignment, which, in turn, facilitates the development of new products and the speed at which they are developed. However, finding that dynamic tension (i.e., the combination of control uses), affects innovation outcomes directly, but not through process alignment, suggests that there is more to be learnt at the intersection of control and NPD processes.

Second, in examining the role of controls in the NPD process, we provide more nuanced findings on both innovativeness and the levers of control framework. We examine two specific dimensions of innovativeness, product newness and innovation rate, which allows for more specific implications to be drawn. Simons (1995) emphasizes the importance of interactive use of controls in ensuring innovation project success, but does
not distinguish between different types of impact of the use of MCS, nor is such research known concerning product innovation (i.e., Bedford, 2015; Ylinen and Gullkvist, 2014). The results indicate that the interactive and diagnostic control uses facilitate both dimensions of innovativeness. Our results also help to reconcile previous ambiguities in the literature. In contrast to the largely inconsistent literature and Henri’s (2006) findings, we show that diagnostic use and dynamic tension are generally positively related to innovativeness. Upon further examination, we find that this direct effect of diagnostic use only holds for companies in technologically stable environments. However, diagnostic and interactive uses of controls both impact innovativeness through process alignment in sub-samples of firms in technologically turbulent environments, providing transparent direction in contexts of high uncertainty. Thus, we nuance Henri’s (2006) findings by showing that the diagnostic use of control is important in the NPD process and how this influential role is characterized.

The paper proceeds as follows: First, we review existing literature on MCS, process alignment, and innovativeness. We also present the conceptual model and develop arguments describing the impact of control uses on process alignment and innovativeness. We then describe our research methods. Subsequently, we discuss the empirical analysis which tests the hypotheses. Finally, we conclude by evaluating the results, discussing the limitations, and indicating avenues for future research.

5.3 Theoretical background and hypotheses development

5.3.1 Background literature

The purpose of this study is to examine whether MCS affect product innovativeness by facilitating process alignment, and, in doing so, improve our understanding of the use of controls in NPD environments. The proposed research model is illustrated in Figure 15. We begin this section with a discussion of MCS and process alignment. We then build on these concepts to develop the hypotheses.
5.3.1.1 The levers of control framework

MCS can be defined as “the formal, information-based routines and procedures used by managers to maintain or alter patterns in organizational activities” (Simons, 1987, p. 358; Simons, 1994, p. 170). There is diverse research on MCS in the innovation context. Controls can facilitate coordinating and controlling the development process and stimulating dialogue and idea generation to enhance innovation outcomes (Bedford, 2015). Still, some researchers propose that controls and innovation are incompatible, since innovation is a unique, creative, and unstructured process and controls may restrict or harm creativity (see Kerssens-van Drongelen and Bilderbeek, 1999). This criticism mainly addresses the imposed formalization through controls on research or on the early stages of product development projects, where creativity plays a central role (see Chiesa and Frattini, 2007). It has become well-accepted in the literature that there are multiple types of controls that carry differing characteristics and functionalities. Recent research attempts to develop a finer-grained perspective of the role control has in innovation and distinguishes control configurations as depending on differing project characteristics, for example, the stage of development (Chiesa et al., 2009), the level of innovativeness (Ylinen and Gullkvist, 2014), or the modes of innovation (Bedford, 2015).

Simons’ (1994) frequently cited levers of control framework identifies four unique forms of control levers – beliefs, boundary, diagnostic, and interactive systems. In the innovation context, beliefs systems convey the overarching values and mission of innovation activities. Boundary systems define the behavioral rules of how to (or not to) conduct an NPD project (e.g., a code of conduct). Interactive systems refer to the mechanisms that managers use to regularly involve themselves in decision activities to challenge the underlying data and assumptions of NPD. Diagnostic systems cover the
formal outcome-oriented measuring tools, which are applied to monitor project progress.

Although there are four levers of control, research on the use of controls often considers the dichotomy of diagnostic and interactive control uses (e.g., Chenhall, 2003; Chong and Mahama, 2014; Simons, 1995). Tessier and Otley (2012) suggest that this is due to differing characteristics. While beliefs systems and boundary systems are rather structural in nature, interactive and diagnostic controls refer to the applications or uses of controls. Simons (1990) suggests that most corporations have similar MCS, but differ concerning how the controls are used. He further argues that the same MCS can be used both diagnostically and interactively. We focus on the diagnostic and interactive control levers, both singularly and as a combination.

The diagnostic use of controls seeks to align individual behavior with organizational objectives by systematically monitoring and correcting deviations from pre-defined targets (Simons, 1995). It requires low top management involvement, because managerial attention is guided by periodic monitoring (e.g., at gates) or triggered by exceptional cases (e.g., deviations). Because diagnostic control relies on past periods’ data, it is considered a ‘backward-looking’ system. Diagnostic control constitutes a negative force, because it focuses on mistakes and variances (Henri, 2006; Simons, 1995; Widener, 2007). It constrains behavior and imposes a monitoring and evaluating device on employee behavior.

Interactive controls seek to challenge underlying assumptions and goals that drive activities, in order to uncover emerging opportunities and uncertainties (Simons, 1995), which is why it is labelled ‘forward-looking’ (Widener 2007). According to Henri (2006, p. 533), interactive controls have four characteristics: “[…] (i) the information generated is a recurrent and important agenda for top managers; (ii) frequent and regular attention is fostered throughout the organization; (iii) data are discussed and interpreted among organizational members of different hierarchical levels; and (iv) continual challenge and debate occur concerning data, assumptions and action plans”. Interactive control is based on frequent and intense two-way communication between managers and their teams. It enables managers to create an informational environment that generates dialogue and encourages information-sharing across hierarchical levels, which is why it constitutes a positive force (Simons, 1995). Frequent dialogue brings together individuals with differing information sets about the firm’s profile, which allows for the identification of ambiguities and the reduction of mutual information asymmetries (Jaworski and Macinnis, 1989). However, owing to continuous managerial attention,
interactive controls are considered to be time-consuming and therefore costly (Widener, 2007).

Although each control lever has a distinct and specific purpose, Simons (1995) hypothesizes that their power resides not in their isolated application but in the ways they complement each other through their interdependencies (see also Milgrom and Roberts, 1995). He argues that integrating the positive control levers (interactive control and beliefs systems) with the negative control levers (diagnostic control and boundary systems) creates dynamic tension. By creating tension via integrating controls that motivate and inspire employees to take action with controls that constrain and focus behavior, predictable goal achievement is facilitated with the concurrent search for innovative solutions (Henri, 2006; Simons, 1995). However, there is limited insight into these potentially reinforcing effects within the levers of control framework (e.g., Henri, 2006; Kruis et al., 2016; Mundy, 2010; Speklé and Widener, 2016; Tuomela, 2005; Widener, 2007), especially in the innovation context (e.g., Bedford, 2015). Besides Bedford (2015), Kruis et al. (2016), Speklé and Widener (2016), and Widener (2007), large-sample research has tended to focus on particular isolated levers of control such as interactive control (e.g., Bisbe and Otley, 2004; Bisbe and Malagueño, 2009). Studies that suggest a substitution effect between diagnostic and interactive control uses (Li et al., 2010) argue that diagnostic use reduces individual opportunism at the cost of higher bureaucratic expenses. Thus, in firms with high intra-firm trust levels, the additional bureaucratic expenses outweigh the benefits from further reduced opportunistic behavior. On the other hand, proponents of the complementary effect argue that the diagnostic use of controls represents the foundation for guiding employee behavior, but provides limited flexibility for adaptations in case of unforeseen occurrences, which can be compensated for by interactive control usage. Henri (2006) and Widener (2007) empirically conclude that there is dynamic tension within the levers of control framework, which results in a complementary effect.

5.3.1.2 Process alignment

Our hypotheses posit that control uses influence innovativeness through process alignment. To develop these hypotheses, we first discuss process alignment and its relationship with innovativeness in terms of rate and newness. Following which, in the theoretical development, we will develop the relationships between each of the control uses and innovativeness through process alignment.
Holahan et al. (2014) and van der Panne et al. (2003) propose that, among other factors, a high-quality development process determines innovation success. Process quality not only depends on the elements of the process architecture, but also on its implementation (Browning and Eppinger, 2002; Kahn et al., 2006; Schultz et al., 2013). Kahn et al. (2006) note that a disciplined process usage within the organization complements an effective process architecture in firms that have achieved the most progress concerning their NPD process benchmarks. In the next section, we contend that an important determinant of development process quality is effective information use, since it will facilitate NPD process alignment, in which the development process is transparent to the NPD team; they understand it and the innovation goals they are striving towards (see Sammerl, 2006).

A transparent process is one in which NPD team members have clarity regarding the goals they seek to achieve and the requirements necessary to pass through the predefined process gates (e.g., Barczak et al., 2009). A comprehensible process is one in which the involved parties understand the characteristics of a firm’s NPD process (e.g., Kerssen-van Drongelen and Cook, 1997). Lastly, a structured process is one where the NPD team members perceive a formalized frame that guides projects within a clearly defined development process through a stage-specific goal system (Cooper and Kleinschmidt, 1986; Salomo et al., 2007). Taken together, these three characteristics result in the NPD team working in alignment with the firm’s process requirements and innovation goals, which comprises a high-quality development process (Sammerl, 2006).

Process alignment is a precursor to innovativeness. The transparent and comprehensible goals and the structured NPD process of a well-aligned process facilitate NPD teams’ ability to work productively in the desired manner, increasing the firm’s innovation outcomes (i.e., product newness and innovation rate). Knowing and understanding a project’s short-term goals in relation to awareness of a firm’s long-term targets aligns the NPD team’s efforts with the firm’s intentions and motivates long-term thinking, which results in innovative endeavors. NPD teams and their managers develop higher trust levels through the perceptions that the process has sufficient structure to facilitate precise ‘track records’ of the NPD team’s performance (Das and Teng, 1998). Since the NPD team understands the specified strategic direction and explicitly defined goals, their motivation is positively affected (see Bonner et al., 2002). Together, trust and motivation creates goal commitment in the NPD team (see Hoegl and Parboteeah, 2006). Although conveying a formal structure, process alignment leaves sufficient space for innovative endeavors because while goals are defined at the gates, how the goals are to
be reached is not specified (Mundy, 2010). Accordingly, process alignment facilitates innovation newness.

Research shows that detailed outlines regarding goals, timeliness, hurdles, and responsibilities result in greater NPD performance (Dvir et al., 2003; Shenhar et al., 2002), because when NPD teams believe they understand the structure they are to work within, their motivation increases (e.g., Bonner et al., 2002), their attention is focused, and they are not as easily distracted (Thieme et al., 2003). Thus, unsurprisingly, Eisenhardt and Tabrizi (1995) show that frequent reassessments of the project state through formal milestones can accelerate the pace of product development. Having an understanding of clearly structured development process tasks limits task ambiguity (Jaworski et al., 1993). Thus, detailed process specifications reduce unproductive activities, since they limit long and continuous discussions about details (Thieme et al., 2003). This calibrates an NPD team’s activities and results in fewer errors and delays (Filippini et al., 2004). The reduction of slack impacts development cycles, the length of which can then be shortened (e.g., Eisenhardt and Tabrizi, 1995). Operational focus is ensured through a process structure that harmonizes internal calibrations, increasing cost and time efficiencies. In sum, transparent and well-understood (comprehensible) goals and a structured development process facilitate an NPD team’s ability to work productively in the desired way. Accordingly, process alignment facilitates the speed at which new products are launched.

5.3.2 Development of hypotheses

Drawing on the discussion of the relationship between process alignment and innovativeness, in the following sub-sections, we develop the theory relating the diagnostic, interactive, and joint uses of controls to process alignment and, thus, to innovativeness through process alignment. In each sub-section, we first discuss the inconclusive nature of the direct relationship between the control uses and innovativeness. We then draw on studies that relate the control uses to process alignment, which allows us to predict a positive relationship between control uses and innovativeness through process alignment.

5.3.2.1 The diagnostic use of controls and product innovativeness through process alignment

Increasing the predictability of an NPD team’s activities is the purpose of diagnostic control usage (Simons, 1995). Detailed definitions of market needs and project specifications enable transparent processes and provide clear direction. This level of
structure minimizes unproductive discussions, because objectified information replaces subjective perceptions (Zirger and Maidique, 1990). Thus, it is argued that, in the case of reliable information from performance measurement, rigid outcome control (i.e., diagnostic use of controls) limits deviations from project goals (Salomo et al., 2007). Further, despite the control’s rigidity, Mundy (2010) finds that NPD teams are free, within the defined gates’ boundaries, concerning how to reach their goals and are therefore receptive to novel means to achieve these. Combined with the continuous focus on goals, the diagnostic use of control may drive NPD efficiency.

In contrast, there is a large consensus in the control literature that detailed planning, associated with the diagnostic use of control, has either a negative effect on innovation (Henri, 2006; Song and Montoya-Weiss, 1998) or a generally insignificant effect on innovativeness (Ylinen and Gullkvist, 2014). Thus, it is argued that the diagnostic use of controls is especially detrimental in explorative projects (Bedford, 2015) because diagnostic use motivates short-term goal achievement, while highly innovative products cannot be properly translated into short-term goals and necessitate space for experimentation. Strictly enforced goals keep projects from responding to changing context conditions, which leads to failures in learning and has negative effects on the performance of novel products (Sethi and Iqbal, 2008). Additionally, empirical evidence shows that planning for schedule attainment does not accelerate the pace of development (Eisenhardt and Tabrizi, 1995).

In sum, research emphasizes the role of the diagnostic use of controls in driving goal achievement (Simons, 1995), but also warns about its weakening influence on innovativeness (Calantone et al., 2010). Since there is a large consensus that the direct relationship between diagnostic use and innovativeness is inconclusive, we propose, instead, that the diagnostic use of information facilitates perceptions of the process architecture such that it positively aligns the NPD process with the innovation objectives and, thus, has a positive effect on innovation outcomes through process alignment. In essence, process alignment translates the more ‘positive’ aspects of diagnostic use to innovativeness.

We contend that the diagnostic use of information from the underlying process architecture increases the quality of the development process (i.e., process alignment) because it increases an NPD team’s understanding of the process, the NPD goals, and the underlying structure. The diagnostic use of controls monitors processes, with a specific focus on deviations from preset targets (Simons, 1995), which are defined in stage-specific goal systems (e.g., the stage-gate system; Cooper, 2008). Through the use
of measures and targets, the NPD team perceives that a formal system is in place to monitor and track its performance. An NPD team’s goals, timelines, hurdles, and responsibilities become transparent through the specification of targets. An NPD team seeks to understand the goals and their underlying assumptions, which inspires decision-making clarity (Schultz et al., 2013) and aligns its activities accordingly. Thus, a high level of diagnostic use of control provides clear direction (Zirger and Maidique, 1990) and facilitates predictability of development activities (Simons, 1995), which are aligned with the firm’s innovation goals. Process alignment is achieved which, in turn, facilitates innovativeness through the team’s increased productivity, commitment, trust, and understanding of the innovation goals. Thus, the diagnostic use of controls facilitates the team’s conversion ability and, in turn, the efficiency and effectiveness of NPD activities. Therefore, we formally hypothesize:

**H1a:** The diagnostic use of controls has a positive effect on product newness acting through process alignment.

**H1b:** The diagnostic use of controls has a positive effect on innovation rate acting through process alignment.

5.3.2.2 *The interactive use of controls and product innovativeness through process alignment*

Research emphasizes that the interactive use of information provides the needed flexibility for firms to react to changing contextual conditions and still achieve its long-term goals (Bisbe and Otley, 2004; Simons, 1995). It provides NPD teams with a deep understanding of the firm’s goals and activities. Thus, when combined with flexibility, NPD teams are able to adapt to a dynamic context (Simons, 1995), and managers gain access to knowledge that supports the development of future NPD plans and strategies. Especially in the knowledge-based context of innovation, communication about tacit notions is necessary, since these can hardly be depicted in objectified measures (Ditillo, 2004). The problem-oriented focus of interactive control can also be used to discuss and solve challenges, rather than to remain silent on disagreements and to come into open conflict, which increases productivity and thus innovation outcomes. However, the research also concludes that interactive control can distract employees from their immediate goals, risking a loss of focus. For instance, Ayers et al. (1997) argue that the interactive use of controls may lead to unfocused development efforts, resulting in a loss of innovativeness, which can obstruct new product success.
In short, similar to the inconclusive direct relationship between diagnostic use of controls and innovation outcomes, the literature is also inconclusive about the direct relationships between interactive use of controls and innovation outcomes. Accordingly, we propose that the interactive use of controls relates positively to process alignment and thus positively affects innovation outcomes indirectly through process alignment. In essence, we propose that process alignment translates the ‘positive’ aspects of interactive use to innovativeness.

Through managers’ regular personal involvement (Simons, 1995) in an NPD team’s decision activities, the NPD team members perceive that the development process has structure. The discussions use formalized information and data to inform dialogue on top manager and NPD team member concerns in the NPD process. Through this interactive control, top managers are able to signal their concerns vertically throughout the organization and to share and discuss these concerns with development team members. Through this structured process, Simons (2000) holds that opportunities and threats are communicated vertically throughout the organization and thus become transparent to the development team and the top managers. This two-way transfer of knowledge reduces information asymmetries (Jaworski and Macinnis, 1989), as the NPD team gains understanding of the activities, timelines, and goals in the innovation process that are important to top managers (Tatikonda and Montoya-Weiss, 2001; Thieme et al., 2003), and top management learns about perceived contextual uncertainties from the NPD team. The formalization achieved through the interactive use of control provides direction to the NPD team, which means that it aligns its understanding of the project goals between the firm and the team (Ayers et al., 1997; Lewis et al., 2002; Turner and Makhija, 2006). Equipped with certain decision-making authority, an NPD team has increased flexibility and autonomy, and thus perceives that its superior has trust in them (see Atuahene-Gima and Li, 2006). These feelings motivate employees to strive to accomplish the commonly understood goals (Bonner et al., 2002).

In short, the interactive use of controls facilitates transparency and a team’s comprehension of innovation goals. As interactive use of controls builds on two-way communication, this also sensitizes managers to uncertainties and emerging opportunities in the project context (Simons, 1995). This is especially important in an environment that is as knowledge-intensive as the NPD context. The tacit nature of innovation is less codifiable in objective measures, which requires communication about nuanced and subtle matters (Ditillo, 2004). Thus, interactive controls facilitate the adaptation of innovation goals and strategy according to the NPD team’s information,
which aligns perceptions and activities within the firm. Accordingly, we propose that the interactive use of controls facilitates innovativeness through increased transparency, comprehension, and formalization; that is, it helps to align the development process. Thus, we formally hypothesize:

**H2a:** The use of interactive control systems has a positive effect on product newness acting through process alignment.

**H2b:** The use of interactive control systems has a positive effect on innovation rate acting through process alignment.

### 5.3.2.3 The combination of diagnostic and interactive uses of controls and product innovativeness through process alignment

In isolation, the diagnostic use of controls is beneficial to achieving plans (e.g., Chenhall, 2003; Simons, 1995), but if used in too rigid of a manner may constrict employees, which can negatively affect innovativeness (Sethi and Iqbal, 2008). In their recent meta-analysis, Calantone et al. (2010) find ambiguous results on the effect of formalization on innovativeness. Some attribute the ambiguous results to formalized plans that become too detailed. If the structure dictates how activities should be conducted, rather than only defining the goals, then team flexibility is limited, which might constrain creative freedom, thus reducing the level of product newness (e.g., Bonner et al., 2002). On the other hand, in isolation, the interactive use of controls, while encouraging knowledge generation leading to alternative ways to solve problems or address dynamics (e.g., Chenhall, 2003), may result in uncoordinated efforts in the search for opportunities if the usage is too unstructured. Thus, individually, both approaches offer benefits but may also incur unintended side effects, which supports our reasoning for hypothesizing the indirect effects of each type of control use on innovativeness through process alignment. In addition, though, the joint use of controls may offset the inherent weaknesses of each, and thus have a more positive influence on innovativeness through process alignment than either control use by itself.

We discussed how the combination of controls is thought to create positive ‘dynamic tension’ (Henri, 2006; Simons, 1995). That is, combining diagnostic use (a negative control) with interactive use (a positive control), may offset potential negative side effects (Simons, 1995). The possible rigidity an NPD team may perceive in the diagnostic use of controls is offset by the freedom and autonomy to respond to changing uncertainties, fostered through the interactive use of controls. Yet, these boundaries contained in diagnostic control usage simultaneously serve to place bounds on the
freedom and flexibility found in the interactive use of controls. This serves to channel efforts towards more fruitful directions.

While diagnostic use mainly defines the structural boundaries by enforcing predefined and transparent goals at the gates, interactive use facilitates adaptability by mainly fostering understanding and transparency of these goals, while also sensitizing an NPD team to the firm’s long-term targets. Thus, interactive use allows one to respond flexibly to emerging trends concerning the firm’s long-term targets, while rigidly enforced goals ensure focus. Together, both control uses create dynamic tension and may complement each other’s characteristics so as to increase process alignment.

Following extant literature (e.g., Henri, 2006; Simons, 1995; Widener, 2007), we propose that the combined use of both diagnostic and interactive use of controls will reduce the individual negative side effects and thus maximize product innovativeness through the individual mechanisms as hypothesized in H1a/b and H2a/b. We formally hypothesize:

**H3a:** The interaction of the diagnostic and interactive uses of controls (i.e., dynamic tension) is positively related to product newness acting through process alignment.

**H3b:** The interaction of the diagnostic and interactive uses of controls (i.e., dynamic tension) is positively related to innovation rate acting through process alignment.

### 5.4 Research methodology and design

#### 5.4.1 Sampling frame

Data sources include survey data and data from the databases *Amadeus* and *Onesource*. We addressed the survey to North American and European firms within R&D-intensive industries. These industries were selected according to their definition as ‘R&D-intensive’ in the NACE classification (Nomenclature statistique des activités économiques dans la communauté européenne) of 2008. These industries correspond to industrial sectors 20 to 21 and 26 to 30 of this classification:

- Manufacturer of chemicals and chemical products (20)
- Manufacturer of basic pharmaceutical products and preparations (21)
- Manufacturer of computer, electronic, and optical products (26)
- Manufacturer of electrical equipment (27)
- Manufacturer of machinery and equipment (28)
• Manufacturer of motor vehicles, trailers, and semi-trailers (29)
• Manufacturer of other transport equipment (30)

In Europe, the use of NACE is common. In the U.S., the ISIC (International Standard Industrial Classification of all Economic Activities) standard has been used. The NACE categories were derived from the ISIC categories and matched to their highest classification level. Since we only use the highest level, we selected exactly the same industries across Europe and the U.S. for this study.

We identified the European companies via the platform Amadeus, and selected the North American companies via the platform Onesource. A prerequisite for selection was the number of employees, which had to exceed 500 to ensure the existence of an R&D department with management control structures (e.g., Bouwens and Abernethy, 2000; Davila, 2005; Davila et al., 2010). This resulted in a total sample of 3,230 institutions.

5.4.2 Survey and respondents

We used a six-page fully standardized online survey, which we simultaneously pre-tested on seven companies within the targeted research pattern as well as sequentially on twelve business researchers for clarity, comprehensibility, ambiguity, and face validity (Dillman, 2007). Based on the feedback, we integrated minor changes to the formulations of particular items. We excluded the companies included in the pretest from the data.

Within the sample companies’ R&D departments, we targeted R&D project managers, R&D middle managers, and innovation team coordinators. With this specific focus, we ensured that the participants were involved in the NPD process, had managerial responsibility, and thus set goals and applied controls, but concurrently also faced development goals and were subject to controls. Thus, the addressees occupied a position in which they had knowledge about the items we asked in the survey, for instance, the management control structures. From the 3,230 institutions originally identified, we dropped 1,069 companies owing to the absence of a R&D function, no identifiable contact, or the absence of a willing participant. As an incentive to respond, we offered to provide the participants with a benchmarking report on their firm’s relative performance to the sample.

We first contacted the remaining 2,161 companies via phone and then invited the targeted participants per e-mail to the online survey. Alternatively, the respondents could also answer the questionnaire physically and return it by mail. If a respondent did
not answer after one week, we sent a first e-mail reminder, followed by a second and third e-mail reminder within two-week periods. The reminder e-mails increased the response rate significantly, since about 80 percent of the responses were generated via reminders. The process resulted in 845 responses; Forty-three responses came from the same business unit. We retained the most suitable responses based on job description and eliminated the other responses. Further, respondents from other cultural regions than proposed in the database were, if possible, recoded (11) or eliminated (66), in order to avoid confounding effects owing to cultural differences. Due to fragmented (more than 20 percent missing) and inconsistently answered responses (analyzing responses on reverse-coded items within the constructs), we removed another 31 responses. Lastly, ten respondents indicated that they did not use MCS, as they marked all related items with one. These were also isolated from analysis. This results in a response rate of approximately 32 percent (695 responses). Finally, as the number of missing values (13 of 22,956 total items) was very small and analysis showed that the data was missing completely at random (chi-square 211.86; df 219; \( p = 0.623 \)), we replaced the missing data using the mean imputation approach (e.g., Ylinen and Gullkvist 2014).

We investigated the presence of non-response bias by comparing non-respondents (2,535) to respondents (695) using archival size data (i.e., the number of employees and sales volume). The data were taken from the databases Amadeus and Onesource. The results presented in panel A of Table 6 show that there are no statistically significant differences between the characteristics of respondents and non-respondents concerning size. We also compared early and late respondents, based on the return time, as the number of days from the invitation via mail to the completion of the survey. The results are shown in panel B of Table 6. With exception of interactive use (4.54 vs. 4.33, \( p = 0.090 \)) and innovation rate (4.83 vs. 4.64, \( p = 0.099 \)) there are no statistically significant differences between early and late respondents concerning sales, number of employees, and all survey constructs. The overall results support the absence of significant bias.
Table 6: Non-response bias test

<table>
<thead>
<tr>
<th>Variable</th>
<th>Respondents (n = 695)</th>
<th>Non-respondents (n = 2,535)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Respondents vs. non-respondents</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of employees [absolute]</td>
<td>6,648.41</td>
<td>5,527.42</td>
</tr>
<tr>
<td>Sales [in Mio. USD]</td>
<td>2,969.27</td>
<td>2,470.38</td>
</tr>
<tr>
<td><strong>Panel B: Early respondents vs. late respondents</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of employees [absolute]</td>
<td>6,231.13</td>
<td>5,355.90</td>
</tr>
<tr>
<td>Sales [in Mio. USD]</td>
<td>2,444.34</td>
<td>3,055.10</td>
</tr>
<tr>
<td>Process Alignment</td>
<td>4.93</td>
<td>4.79</td>
</tr>
<tr>
<td>Diagnostic Use</td>
<td>5.13</td>
<td>4.99</td>
</tr>
<tr>
<td>Interactive Use</td>
<td>4.54*</td>
<td>4.33*</td>
</tr>
<tr>
<td>Product Newness</td>
<td>4.72</td>
<td>4.59</td>
</tr>
<tr>
<td>Innovation Rate</td>
<td>4.83*</td>
<td>4.64*</td>
</tr>
</tbody>
</table>

* Sample was divided into early, middle, and late respondents based on the return period of the survey.
* Means are significantly different at p-value < 0.1 (two-tailed significance).

Since all constructs are gathered through the same channel, the results could be subject to common method bias and could therefore trigger systematic measurement error. Thus, we followed procedural recommendations to mitigate the potential for biases (Podsakoff et al., 2003; Podsakoff and Organ, 1986). A separate cover letter explained the survey context, ensured respondents of full anonymity, and asked respondents to give estimates “as best possible”. The survey title was abstract and did not give any idea of the research questions. We positioned dependent and independent constructs in an unsystematic order. We reverse-coded three items. To avoid ambiguity or complexity in the items, we thoroughly pretested the items and adapted the formulations slightly where necessary. In sum, these efforts mitigate the common causes of bias: implicit theory, consistency motif, and social desirability (Podsakoff et al., 2003). Ex post to the survey design, we employed the Harman’s single-factor test, one of the most widely used statistical techniques to test for common method bias. We ran an unrotated exploratory factor analysis on all 33 survey questions (see Appendix 1). Based on eigenvalues > 1, the solution yielded five factors, with the first factor explaining 38.6 percent of the total variance. Thus, the one-factor solution explains considerably less than the majority of the data. We also conducted the Harman’s test using confirmatory factor analysis, which revealed more obvious differences between the single-factor and the multi-factor models. The single-factor model has a chi-square of 4,027.1 (df 460) whereas, assessed using the chi-square difference test, the multi-factor model fits significantly better, with
a value of 1,313.11 (df 478). Other fit indices provide similar evidence (one-factor model: CFI = 0.797 and RMSEA 0.106; multi-factor model: CFI = 0.953 and RMSEA 0.050). The ex ante steps combined with the ex post statistical evidence show that there is a low risk of common method bias (Podsakoff et al. 2003).

Demographic data (see Table 7) shows that the largest proportion of participating business units is from the machinery and equipment industries (30 percent), followed by computer, electronic and optical products (19 percent), and chemicals and chemical products (15 percent). The average respondent works in an organization with 6,648 employees and realizes revenue of $2.97 billion on average. 79 percent of the total sample comes from Europe, 34 percent of which is from Germany. The remaining 21 percent come from North America, mainly from the U.S.

Table 7: Demographic data

<table>
<thead>
<tr>
<th>Industries (NACE code)</th>
<th>Respondents</th>
<th>Avg. sales [in Mio. USD]</th>
<th>Avg. number of employees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemicals and chemical products (20)</td>
<td>102</td>
<td>3,385.3</td>
<td>5,109.0</td>
</tr>
<tr>
<td>Basic pharmaceutical products and pharmaceutical preparations (21)</td>
<td>61</td>
<td>3,132.4</td>
<td>6,899.8</td>
</tr>
<tr>
<td>Computer, electronic, and optical products (26)</td>
<td>129</td>
<td>5,083.5</td>
<td>1,054.9</td>
</tr>
<tr>
<td>Electrical equipment (27)</td>
<td>76</td>
<td>1,232.3</td>
<td>4,967.4</td>
</tr>
<tr>
<td>Machinery and equipment (28)</td>
<td>206</td>
<td>2,107.3</td>
<td>5,392.8</td>
</tr>
<tr>
<td>Motor vehicles, trailers, and semi-trailers (29)</td>
<td>79</td>
<td>3,407.8</td>
<td>7,944.9</td>
</tr>
<tr>
<td>Other transport equipment (30)</td>
<td>42</td>
<td>1,598.6</td>
<td>4,803.5</td>
</tr>
<tr>
<td>Total</td>
<td>695</td>
<td>2,969.3</td>
<td>6,648.4</td>
</tr>
</tbody>
</table>

5.4.3 Variable measures

To assess the validity of the survey variables, we tested for content and construct validity (Nunnally, 1978). Based on a thorough understanding of the literature, we screened the relevant articles for previously validated constructs that fit our purpose. All used constructs were scientifically published. We discussed the topic prior to the survey with practitioners and academics in order to gain more hands-on knowledge of the domain; they also screened the survey for the explicit purpose of eliminating ambiguity from the questions’ formulation. Lastly, we empirically tested the data for content and construct validity. Appendix 2 contains the survey questions. We created the latent variables by taking the arithmetic mean of the corresponding measured variables. Descriptive analyses of these variables are reported in Appendix 3.
5.4.3.1 Control systems

We built on the validated constructs by Henri (2006) to measure the diagnostic use and interactive use of control systems. To ensure that the respondents understood the context of the reflective constructs, these were introduced by “please rate the extent to which information from innovation control in your organization is used for the following purposes” (see Appendix 2). Diagnostic use is a four-item construct, and interactive use a seven-item construct. Henri (2006) did not apply the constructs in a product development context, but in a general changing business context, so we made minor adaptations to ensure the questions applied to the R&D context (i.e., we rephrased the items referring to the ‘organization’ to refer to the ‘innovation department’). We used an exploratory factor analysis (see Appendix 1) across all study items so as to ensure discriminant validity. Analysis supports the constructs and suggests two separate factors for diagnostic and interactive use containing the hypothesized items. There are minor cross-loadings. D_use4 (“Information is used to review key measures”), a diagnostic item, cross-loads on interactive use (0.269) and i_use1 (“Information is used to enable discussion in meetings of superiors, subordinates and peers”), an interactive item, cross-loads on diagnostic use (0.282); however, these loadings are below the common threshold value of 0.3. The constructs are highly reliable with Cronbach’s alphas of 0.88 (diagnostic use) and 0.92 (interactive use) and explain a high percentage of the variance, i.e. 74.5 percent (diagnostic use) and 66.4 percent (interactive use). Additionally, the average variance extracted (AVE) of both constructs is high: 66.4 percent (diagnostic use) and 60.9 percent (interactive use).

The interaction effect of the diagnostic and interactive uses of controls, labelled as dynamic tension, is modeled as a product term between the two constructs. We followed prior empirical research analyses, findings, and implications (Henri, 2006; Ylinen and Gullkvist, 2014) and model a multiplicative rather than additive effect on product innovativeness.

5.4.3.2 Process alignment

Based on the discussions about the characteristics of a high-quality development process with structural and behavioral aspects (see Kahn et al., 2006), we built on Sammerl’s (2006) theoretical understanding of the structured, comprehensive, and transparent process. The eight-item construct ‘innovation process management’ (Sammerl 2006; Sammerl et al., 2008) served our needs, since the underlying understanding of the latent variable is consistent with our conceptualization of process alignment. NPD team
members’ perceptions of the level of structure of the process and its controls are included in all items (reflected by verbs as, e.g., defined, structured, or controlled), however, mostly in items i_pro 1, 2, and 4, for instance i_pro 1 “in innovation projects we define operative process flows with clear tasks”. Comprehensibility of the process is addressed in five items, especially asking in i_pro 6 if the “innovation processes are [...] understood by all involved”. Transparency of the goals and the associated innovation and control activities is covered by four items, for instance i_pro 8 “operative tasks and goals […] are […] communicated to all involved”. We used all eight items that are adapted from prior literature (e.g., Cooper and Kleinschmidt, 1991, 1995; Ernst, 2002) and relabeled the construct for our purposes as ‘process alignment’. This label is more inclusive than that used by Sammerl (2006). Sammerl’s (2006) label only suggests the presence or absence of process management and ignores the part of the construct that captures the NPD team’s perceptions of the process implementation; our label overcomes this.

The items were adapted from prior questions originally designed in German and we translated these to English. The exploratory factor analysis (see Appendix 1) shows very high reliability (Cronbach’s alpha: 0.95) for an eight-item factor consisting of all the items. This factor explains 73.4 percent of the variance with an AVE of 69.6 percent.

5.4.3.3 Product newness and innovation rate

Product newness is a previously published construct. We followed the five-item conceptualization by Stock et al. (2013), since it explicitly focuses on the aspect of newness within the overarching understanding of innovativeness and therefore fits our conceptualization. Stock et al. (2013) built on relevant prior studies by Cooper (1979) and Olson et al. (1995). Based on feedback from pre-tests, we rephrased one negatively termed item from “new products of our company are not predictable” to “new products of our company are not innovative”. Exploratory factor analysis (see Appendix 1) shows that the five items load as one construct, with a Cronbach’s alpha reliability of 0.91 and explaining 73.8 percent of the variance. The AVE is 67.3 percent.

Innovation rate, which addresses the frequency with which the product program is being updated, was measured through a composite construct. We took nine well-published items from studies by Harmancioglu et al. (2010), Homburg and Stock (2004), and Stock et al. (2013) that all focus on innovation frequency. Exploratory factor analysis (see Appendix 1) shows high convergent reliability of this composite construct, which is
reflected in a Cronbach’s alpha of 0.92 with an explained variance of 64.6 percent. The AVE equals 57.0 percent.

5.4.3.4 Summary of constructs

All constructs were measured on 1 to 7 Likert scales. Descriptive statistics show that the available range was fully used for every item. Further, the constructs have univariate normality, since they did not exceed threshold values for skewness (|3.0|) or kurtosis (|10.0|) (Kline, 2005). Exploratory factor analysis supports each of the hypothesized constructs with only minor cross-loadings (i.e., none of these cross-loadings exceed 0.3). Cronbach’s alphas were sufficient for each construct and support internal consistency. The AVEs all exceed the common threshold value of 50 percent (Fornell and Larcker, 1981). Still, these factors can correlate with one another and dilute discriminant validity. Thus, we followed Widener (2007) and analyzed whether the five constructs are empirically different using the multitrait matrix in Table 8 (Churchill, 1979). The results show that the internal reliability is higher than the inter-construct reliability. Correlations range up to 0.66, while the Cronbach’s alphas begin at 0.88. Further, the constructs’ AVEs consistently exceed the squared inter-construct correlations (Fornell and Larcker, 1981). Based on these analyses, we conclude that there is strong support for discriminant validity. In cross-sectional studies, significant correlations likely occur between the independent and the moderating variables, in case between the uses of controls (correlation 0.66). This alone is not a phenomenon that validates or rejects a moderation model (Burkert et al., 2014).

Table 8: Multitrait matrix.

<table>
<thead>
<tr>
<th></th>
<th>Diagnostic Use</th>
<th>Interactive Use</th>
<th>Process Alignment</th>
<th>Innovation Newness</th>
<th>Innovation Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnostic Use</td>
<td><strong>0.88</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interactive Use</td>
<td>0.66***</td>
<td><strong>0.92</strong></td>
<td></td>
<td><strong>0.91</strong></td>
<td></td>
</tr>
<tr>
<td>Process Alignment</td>
<td>0.63***</td>
<td>0.55***</td>
<td><strong>0.95</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product Newness</td>
<td>0.31***</td>
<td>0.35***</td>
<td>0.33***</td>
<td><strong>0.91</strong></td>
<td></td>
</tr>
<tr>
<td>Innovation Rate</td>
<td>0.32***</td>
<td>0.36***</td>
<td>0.32***</td>
<td>0.60***</td>
<td><strong>0.92</strong></td>
</tr>
</tbody>
</table>

*The diagonal of the matrix is the Cronbach’s alpha for each variable. The remainder of the tables reports the bivariate Pearson correlation coefficients.

*** Correlation is significant at the 0.01 level (two-tailed significance).
5.5 Results

We used the software program AMOS with maximum likelihood estimation to calculate the model illustrated in Figure 15. We used SEM, since it results in a fit index for the whole model rather than partial robustness when applying multiple regression analyses (Kline, 2005). Since we are modeling the interaction of controls, we treat the constructs as manifest variables, which are created through the arithmetic mean of the underlying items. Considering the presence of a product term representing the dynamic tension, the literature recommends (Aiken et al., 1991; Henri, 2006; Little et al., 2007) centering the multiplied variables around the mean (i.e., diagnostic and interactive uses of control) prior to creating the product term. This reduces multicollinearity between the product term and the constituent variables, and facilitates the interpretation, without affecting the significance of the coefficients. After mean centering the first-order variables, the product term, dynamic tension, correlates at a maximum of |0.39| (reduced from max. |0.92| before centering) with interactive and diagnostic uses of controls.70

Appendix 4 presents the results of five structural equation models. We calculated multiple models to identify the inter-model differences. We began with model A, which models the direct effects of interactive and diagnostic use as well as its interaction effect, dynamic tension, on innovation rate and newness. Model B integrates the hypothesized mediator, process alignment, and the direct effects. Model C trims Model B by the insignificant paths and Model D by the interaction effect, dynamic tension. Model E estimates the full mediation model, excluding the direct paths (Baron and Kenny, 1986). Models A, B, and D do not provide fit measures owing to model saturation, which is reflected in zero degrees of freedom (Kline, 2005). Models C and E demonstrate good model fits, considering the large sample size.

5.5.1 Hypothesis tests

Mediations are a key issue in the hypotheses. “Mediation hypotheses posit how, or by what means, an independent variable affects a dependent variable through one or more potential intervening variables, or mediators” (Preacher and Hayes, 2008, p. 879). We assessed the hypothesis tests by complementing Baron and Kenney’s (1986) causal steps approach with the more recent mediation tests by Zhao et al. (2010) as well as Preacher and Hayes (2008). First, we tested whether there is a significant direct effect between...
the use of controls and innovativeness. Subsequently, we tested how these paths change when including the indirect effect through process alignment. We assessed the significance of the indirect effect using the Sobel test (Sobel, 1982, 1987) and bootstrapping (Hayes, 2009; Preacher and Hayes, 2008). Bootstrapping (Appendix 5) provides a response to criticisms of the Sobel test, which implies normal distribution of the indirect effect and is designed fairly conservatively concerning rejecting hypotheses (Zhao et al., 2010). In contrast, the bootstrapping procedure of non-parametric resampling does not require normality of the sample (Preacher and Hayes, 2008). Lastly, we provided evidence for the moderation form of fit of the control uses concerning innovativeness (see Burkert et al., 2014).

Hypothesis 1 predicts that the diagnostic use of controls relates positively to innovativeness through process alignment. Model A (see Appendix 4) suggests highly significant standardized direct effects of diagnostic control on both product newness (0.163; \( p < 0.01 \)) and innovation rate (0.188; \( p < 0.01 \)). Model B considers the mediating effect through process alignment and shows that the direct effects lose strength and significance. The effect of diagnostic control on product newness loses its significance fully (\( p = 0.14 \)), while the effect of diagnostic control on innovation rate decreases from 0.188 (\( p < 0.01 \)) to 0.120 (\( p < 0.01 \)). In combination with the fully significant positive effect through process alignment (0.468; \( p < 0.01 \)) on product newness (0.182; \( p < 0.01 \)) and innovation rate (0.221; \( p < 0.01 \)), analysis suggests a full mediation of the diagnostic use of controls acting through process alignment on product newness and a partial mediation on innovation rate (Baron and Kenny, 1986). The Sobel test supports significance of the indirect effects on product newness (\( p < 0.01 \)) and innovation rate (\( p < 0.01 \)). Finally, we tested mediation, as suggested by Preacher and Hayes (2008), using bootstrapping of 10,000 samples. The 95 percent confidence intervals are shown in Appendix 5. We again found consistent evidence. The confidence intervals do not embrace zero, which documents significance of the direct and indirect effects (i.e., the product of the mediated paths), except that the direct effect on product newness (the effect is likely to range from -0.035 to 0.189; \( p = 0.169 \)). Together, these findings fulfill the conditions (Preacher and Hayes, 2008) that process alignment fully mediates the effect of diagnostic use on product newness (H1a), and partially mediates the effect on innovation rate (H1b).

Hypothesis 2 predicts that the interactive use of controls relates positively to innovativeness through process alignment. Appendix 4, Model A, suggests highly significant standardized direct effects of interactive control on both product newness
(0.263; \( p < 0.01 \)) and innovation rate (0.256; \( p < 0.01 \)). Integrating the mediating effect through process alignment into the model (Model B) shows that the direct effects lose strength. The effect of interactive use of control on product newness decreased from 0.263 (\( p < 0.01 \)) to 0.218 (\( p = 0.01 \)) while the effect on innovation rate decreased from 0.256 (\( p < 0.01 \)) to 0.221 (\( p < 0.01 \)). The fully significant standardized positive effect on process alignment (0.243; \( p < 0.01 \)) and of process alignment on product newness (0.182; \( p < 0.01 \)) and innovation rate (0.145; \( p < 0.01 \)) supports a partial mediation of the interactive use of controls acting through process alignment on both product newness and innovation rate. The results are qualitatively similar in the more parsimonious Model C. The indirect effect is supported by the Sobel test, which in both cases is highly significant (\( p < 0.01 \)). Bootstrapping provides consistent evidence for the indirect and direct effects, which confirms that the effects of interactive use of controls on product newness (H2a) and innovation rate (H2b) are partially mediated by process alignment.

Hypothesis 3 predicts that the interaction of diagnostic and interactive uses of controls (i.e., dynamic tension) relates positively to innovativeness through process alignment. Appendix 4, Model A, depicts a significant direct effect of dynamic tension on both product newness (0.083; \( p < 0.05 \)) and innovation rate (0.083; \( p < 0.05 \)). The strengths or significances of these effects are surprisingly not affected by integrating process alignment as a mediator into the model (see Model B). However, the indirect effect through process alignment on innovativeness is nonexistent, since the combination of controls is not significantly associated with process alignment (-0.009; \( p = 0.776 \)). This is confirmed through bootstrapping, which rejects significance for the indirect effect concerning both dimensions of innovativeness (product newness (H3a): from -0.014 to 0.010, \( p = 0.753 \); innovation rate (H3b): from -0.011 to 0.008, \( p = 0.729 \)). In conclusion, consistent evidence shows that process alignment is not a mediator to dynamic tension’s effect on innovativeness, which is why we reject both H3a and H3b. Thus, we could not show evidence of a mediated moderation (Baron and Kenny, 1986) and conclude that the indirect effects of interactive and diagnostic use through process alignment are not conditional on the value of one or the other.

However, the results show that the interaction effect has a significant direct effect on innovativeness (product newness 0.085, \( p < 0.05 \); innovation rate 0.085, \( p < 0.05 \)). Bootstrapping confirms the direct effects of dynamic tension on product newness (\( p < 0.05 \)) and innovation rate (\( p < 0.1 \)). Further, a simple slope test (Aiken et al., 1991; Dawson, 2014) provided evidence of the significance of the interaction effect throughout the spectrum of values for all four possible models. Since the interaction is
symmetrical, there are four possible models: “This implies that if $X_2$ moderates the relationship between $X_1$ and $Y$, then $X_1$ necessarily also moderates the relationship between $X_2$ and $Y$. It is because of this symmetry that the neutral expression refers to an ‘interaction’ of $X_1$ and $X_2$ to affect $Y$” (Hartmann and Moers, 1999, p. 294). Thus, the four models represent the linear monotonic relationships of interactive (diagnostic) use on innovativeness (product newness; innovation rate) as moderated by the diagnostic use (interactive use) (Burkert et al., 2014). In conclusion, the effect of interactive use on innovativeness is more positive when diagnostic use is increasing, and vice versa. For plots of the moderating effects (Aiken et al., 1991; Dawson, 2014) see Appendix 6.

In sum, H1a/b and H2a/b are supported.\footnote{Model D in Appendix 4 proves robustness of the hypothesized effects when trimming the grand model, Model B, for dynamic tension.} While we could not find support for H3a/b (dynamic tension affecting innovativeness through process alignment), we did find that dynamic tension is directly associated with product newness and innovation rate. We also show that, in three of four instances, process alignment partially mediates the diagnostic and interactive uses of control on innovation rate and product newness, and in the fourth instance, there is a fully mediated effect. Generally, evidence supports the theoretical model, suggesting that process alignment is an antecedent of both the degree and frequency of product innovativeness, and that diagnostic and interactive uses of control are positively associated with innovativeness through process alignment. However, dynamic tension was only directly associated with innovativeness.

To ensure that the SEM results are robust, we performed several validity tests. First, untabulated analyses of the measurement model confirmed robustness of the structural model’s results, since statistical inferences remain unchanged.\footnote{In an untabulated analysis, we tested the robustness of the path coefficients of the grand model (see Appendix 4) when excluding items of process alignment that mainly refer to structural aspect (i.e., i_pro 1, i_pro 2, i_pro 4). All effects remain stable, except the level of significance of d_use on i_rat decreases from $p < 0.01$ to $p < 0.05$.} Second, we substantiated the illustrated model by controlling for cultural effects (respondents from North America vs. Europe: $p = 0.65$) and size effects (low vs. high number of employees: $p = 0.86$; low vs. high firm sales: $p = 0.70$). The model differences of these groups, applying a chi-square difference test, were not significant.\footnote{In an untabulated analysis, we tested whether the model fit was significantly different due to country effects or size effects (employee or size effects).} Third, we examined whether industry drove our results by removing each industry individually and re-running the model. We compared the reduced models to the full model. In all seven
cases, the models do not differ significantly \( (p > 0.1) \); thus, we concluded that no one industry (in isolation) drove the effects.

### 5.5.2 Exploratory analyses

Recent research suggests that firms in stable and turbulent environments are likely to experience the influence of controls and coordination mechanisms differently (see Bisbe and Malagueño, 2012; Chenhall, 2003; Jansen et al., 2006; Lee and Wong, 2011; Shenhar et al., 2002). Thus, the relationships between the use of controls, process alignment, and innovativeness may be moderated by technological turbulence\(^74\), a type of environmental uncertainty (Song et al., 2005). Technologically turbulent environments are characterized by “short cycles of technological innovation and obsolescence” (Song et al., 2005, p. 263). In turbulent environments organizational inflexibility resulting from formalization might cause learning failure, which lowers innovativeness (e.g., Sethi and Iqbal, 2008), while on the other hand, formal controls provide organizations with the necessary direction (Chenhall, 2003). Since there has been little empirical research and theory is thus not developed to the extent that we can hypothesize directional effects, further exploratory investigation is reasonable.

To test significance of the model difference, we first compared a fully restricted model to a model that allows parameters to vary freely across the groups with low and high technological turbulence. To test significance of the difference in the specific paths of interest, we then compared a restricted model in which the specific parameters for the paths of interest are forced to be equal across the groups with a model that allows these parameters to vary freely (Burkert et al., 2014; Fan et al., 1999). We used the chi-square difference as a test to examine the effect the moderator variable, technological turbulence, has on the paths. The results are presented in Appendix 7. We found that the models differ significantly \( (p < 0.05) \). In the following subsections, we explore the results of the moderation analysis.

#### 5.5.2.1 Control uses and product newness through process alignment

The empirical results suggest that the positive indirect effects of interactive and diagnostic uses of control through process alignment on product newness are stronger in the context of high technological turbulence \( (p < 0.05) \). This is surprising, since prior research has emphasized the risk of formality through predefined and rigid project

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\(^74\) Untabulated exploratory factor analyses have shown high levels of discriminatory and convergent reliability of the construct Technological Turbulence that was adapted from Song et al. (2005) (see Appendix 2).
parameters to constrain flexibility and thereby detract from innovativeness (Sethi and Iqbal, 2008). This argumentation holds especially in contexts of high uncertainty where flexibility plays a more important role. However, the results suggest that when an NPD team perceives that the development process is structured, transparent, and understandable, the degree of product newness increases, especially in contexts of high turbulence. Shenhar et al. (2002) argue that highly uncertain environments require, among other factors, special attention on project definition, milestones, and documentation, which all are elements of process alignment. Chenhall (2003, p. 138) proposes that the more “turbulent the external environment the greater the reliance on formal controls and […] traditional budgets”. Thus, it appears reasonable that, especially in contexts of high technological turbulence, which is perceived as uncertainty, clearly structured processes as well as transparency and comprehensibility of the development goals provide NPD teams with clear direction, which results in increased product newness. This leads to the conclusion that a comprehensive structural frame is necessary for product newness in contexts of high technological turbulence. This also highlights the importance of both interactive and diagnostic uses of controls, because both drive process alignment, which positively influences product newness.

5.5.2.2 Interactive use and innovation rate

The results show that the interactive use of controls has a significant direct effect on innovation rate, especially when there is high technological turbulence ($p < 0.05$). Chapman (1998) argues that changing conditions in the case of technological turbulence unfold unpredictability, which requires substantial interaction between managers to align with the context. Similarly, Chenhall (2003) proposes that, in uncertain environments, rigid controls are used together with interpersonal interaction, which interactive controls are characterized by. Thus, interactive use of controls fosters interaction among managers and the NPD team, which allows them to adapt flexibly to the changing context conditions.

5.5.2.3 Diagnostic use and product newness

The direct effect of diagnostic use on product newness is only significant in technologically stable environments ($p < 0.05$). This means that the rigid outcome control that enforces predictability is especially influential in stable environments but also not destructive in turbulent environments. In this case, the influence of diagnostic use on product newness is indirect, fully mediated by process alignment. We nuance prior research that found insignificant effects of diagnostic controls (i.e., mechanistic
controls) on innovativeness (Ylinen and Gullkvist, 2014) by showing that this holds only for turbulent environments, but not stable environments in which diagnostic controls positively affect product newness.

5.5.3 Discussion

First, the study results strongly suggest that an interactive use of controls drives both dimensions of product innovativeness – innovation rate and product newness. Indeed, by focusing a business unit’s attention on strategic priorities and stimulating dialogue, controls foster the transfer of knowledge and aligned understandings (Turner and Makhija, 2006), which contribute to faster and more efficient product development processes (Ayers et al., 1997; Rijsdijk and van den Ende, 2011). This conclusion is supported by the finding of an increased innovation rate. Further, the flexibility that interactive control brings ensures continuous adaptations to a changing context, which increases market value of the provided products (Rijsdijk and van den Ende, 2011). This is emphasized through the positive relationship between interactive use and product newness. This finding complements previous evidence from the literature, which also shows a positive relationship between the interactive use of controls and more general innovativeness (Henri, 2006; Ylinen and Gullkvist, 2014). To an extent, this result also extends Bisbe and Otley (2004), who focus on the effect of interactive use of MCS on performance through innovation. While they confirm the importance of innovation for performance, they found no general support for the positive effect of interactive use on innovation. They even provide opposing evidence for high-innovating firms. We provide evidence for a partially mediated positive effect of interactive control on innovativeness through process alignment.

Second, the results show (especially in technologically stable environments) a positive direct effect of the diagnostic use of controls on product innovativeness, and an indirect effect through process alignment. This result supports our hypotheses and is interesting, since research is ambiguous on this relationship (Henri, 2006; Ylinen and Gullkvist, 2014). The differences in results could be due to the larger sizes of our sample firms relative to Henri’s (2006) sample75, a specific focus on the research department in our sample, a more narrowly defined industry focus (Ylinen and Gullkvist (2014) also

75 The average firm in the Henri (2006) sample had 796 employees, in contrast to 6,648 employees in our sample. In untabulated tests, though, we do not find significant differences between sub-samples of small (avg. 1,117 employees) and large (avg. 11,965 employees) companies, which substantiates the positive effect of diagnostic controls on innovativeness.
considered service firms), or differing contextual dynamics of the sample companies (Ylinen and Gullkvist (2014) focused on the fairly dynamic high-tech industry).

Third, dynamic tension does not have the expected effect on product innovativeness through process alignment owing to its insignificant association with process alignment. The insignificant result suggests fully independent effects of interactive and diagnostic controls on process alignment. However, we found significant positive direct effects of dynamic tension on product newness and innovation rate. This hints at a mediating variable other than process alignment, the identification of which is a subject for further research. Similar to the result found for H2, the result for H3 is not consistent with the results of Henri (2006), who explored the association between dynamic tension and a more general formulation of innovativeness. For the sub-sample of small firms that are more comparable in size to Henri’s (2006) sample, we support the insignificant effect found. However, for the sub-sample of large firms, the effects of dynamic tension on both innovation rate and newness are significant and positive. Although the paths are not significantly different between the samples, this might provide hints. Large firms benefit from the complementary balance between seemingly opposing control mechanisms.

Lastly, our empirical evidence strongly suggests that process alignment is an antecedent of product innovativeness. Thus, we support and extend prior findings by Schultz et al. (2013). We show that formalization drives innovativeness through increased transparency and concreteness. Thus, we overcome reservations concerning the resulting rigidity (e.g., Calantone et al., 2010) and show that process alignment is beneficial for research-intensive companies.

5.6 Conclusion

We sought to open the ‘black box’ of the relationship between management control and innovativeness by examining the role of MCS in the development process. Overall, the results suggest that controls used in a diagnostic and interactive fashion contribute positively to innovativeness directly and indirectly through process alignment. From their joint use, dynamic tension emerges (Simons, 1995), which directly drives both product newness and innovation rate.

This study contributes to current research at the boundary of management accounting and innovation management in two different ways. First, we shed light on the mechanisms of how control usage relates to innovativeness by introducing the mediator process alignment. The role of the development process within this relationship is
considered a major issue, yet it has received little attention (Rijsdijk and van den Ende, 2011). We show that interactive and diagnostic control uses are positively associated with innovativeness in terms of product newness and innovation rate, because they align an NPD team’s activities with a firm’s innovation objectives. The requirements of the innovation process are transparent to the NPD team, the team understands these requirements and perceives that the process has a defined structure. We provide additional insights into the relatively open question of what the effects are of combining diagnostic and interactive controls. We find that the combined use of controls – the dynamic tension – directly affects innovativeness but not through process alignment. In short, the trend towards efficient NPD processes has increased the need for research on how the use of control practices can drive sound new product development processes, thus achieving efficiency (Davila, 2000; Davila et al., 2009). This study partially addresses this need.

Second, we applied the influential levers of control framework to the R&D context. Simons’ framework (1995) is often associated with triggering innovation performance outcomes. Still, to our best knowledge, only a few studies have explicitly focused on the R&D context (e.g., Bedford, 2015; Bisbe and Malagueño, 2015; Bisbe and Otley, 2004). Nonetheless, this is crucial, since the R&D function has its own dynamics, which must be explicitly addressed by control systems. We provide more nuanced findings on the levers of control framework and innovativeness by examining two specific dimensions that comprise innovativeness, product newness and innovation rate, which allows for more specific implications to be drawn. Our results indicate that the control uses drive both dimensions of innovativeness: newness and rate. These results also help to overcome previous ambiguities in the literature, especially accentuating the important role of diagnostic control uses that prior literature attested consentaneously obstructive (e.g., Henri, 2006; Song and Montoya-Weiss, 1998) or insignificant effects (e.g., Ylinen and Gullkvist, 2014) on innovativeness to. Contrary to the findings of Henri (2006), we found that diagnostic use and dynamic tension are generally positively related to innovativeness. Upon further examination, we found that this direct effect of diagnostic use only holds for companies in stable environments but that, individually, both uses of controls impact innovativeness through process alignment in sub-samples of firms in technologically turbulent environments. Thus, we are able to nuance Henri’s (2006) findings by showing under which conditions and in what ways diagnostic controls are beneficial within the NPD process.
This study also has implications for managerial practice. Awareness of the value drivers is key for companies in uncertain contexts, i.e. the product development context. Keeping track of fast-changing market conditions is a critical challenge for development units. For such companies, this means that innovation must be a core capability. This study provides empirical evidence that generally underscores the importance of interactive and diagnostic control in the development context, to improve process alignment and increase innovativeness. We found that the individual control usages and the joint use of controls (i.e., dynamic tension) drive product innovativeness. In greater nuance, we underline the importance of aligned development activities especially in technologically turbulent context conditions. Awareness of these results can enable managers to consciously guide development activities, to ensure goal predictability and also short-term flexibility.

As with other empirical studies, this study has potential limitations. We have elaborated on the relationships between controls, innovativeness, and the mediating effect through process alignment. Nonetheless, other mediators would also have been plausible. Owing to the research setting, causalities were based on the literature and were hypothesized accordingly. There is no methodological approach to ensure causality in cross-sectional survey analysis. We have assessed innovativeness qualitatively via subjective assessments by project managers. This could be subject to common method bias, although we designed the survey to avoid bias and conducted tests to confirm the absence of a significant bias. Further, we tested the model on a general set of (likely) incremental innovation projects, which means that the conclusions drawn do not necessarily apply for radically innovative projects. Due to their inherent uncertainty of creating new paradigms, radical innovation projects require different MCS, for instance, less rigid goals, timelines, and hurdles (Davila et al., 2009). Finally, the conceptualized ‘dynamic tension’ is modeled as a product term, which is a proxy. To our best knowledge, there are no elaborated scales that directly assess dynamic tension.

The study results provide guidance for future research. We deliver evidence that the impacts of controls on innovativeness are contingent on technological dynamism. Shedding more light on this contingency is promising, in order to also understand the prior ambiguous findings on the roles of diagnostic controls and process alignment in an innovation setting. Further, we have shown that dynamic tension directly affects product newness and innovation rate. However, the hypothesized antecedent process alignment is not affected. Little is known about the effects of this tension. Thus, more research is required to understand how the mechanisms behind these relationships work.
Qualitative methodologies could provide valuable input for future conceptualizations. These future research paths will lead to a richer understanding of how controls, dynamic context variables, and outcome variables interact, in order to support innovation activities.
### 5.7 Appendix

#### 5.7.1 Appendix 1: Exploratory factor analysis

<table>
<thead>
<tr>
<th>Items</th>
<th>Process Alignment</th>
<th>Innovation Rate</th>
<th>Interactive Use</th>
<th>Product Newness</th>
<th>Diagnostic Use</th>
</tr>
</thead>
<tbody>
<tr>
<td>i_pro2: process flows with clear tasks</td>
<td>0.913</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_pro3: systematic project management</td>
<td></td>
<td>0.900</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_pro4: process/stage specific goal system</td>
<td></td>
<td></td>
<td>0.867</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_pro6: processes are clearly structured and understood</td>
<td></td>
<td></td>
<td>0.849</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_pro1: controlled/progressive implementation process</td>
<td></td>
<td></td>
<td></td>
<td>0.839</td>
<td></td>
</tr>
<tr>
<td>i_pro5: situation-appropriate and multi-stage integrating project management</td>
<td></td>
<td></td>
<td>0.787</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_pro8: tasks and goals defined clearly and communicated to all involved</td>
<td></td>
<td></td>
<td>0.739</td>
<td>0.111</td>
<td></td>
</tr>
<tr>
<td>i_pro7: activities coordinated based on performance- and goal-orientation</td>
<td>0.678</td>
<td></td>
<td>0.157</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_rat7: frequently replenish or add novel products</td>
<td></td>
<td>0.869</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_rat1: product offer is continuously updated</td>
<td></td>
<td></td>
<td>0.811</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_rat5: products are continuously supplemented with new features</td>
<td></td>
<td></td>
<td>0.803</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_rat8: introduce many innovative products</td>
<td></td>
<td>0.786</td>
<td></td>
<td>0.114</td>
<td></td>
</tr>
<tr>
<td>i_rat4: every year we launch new products</td>
<td></td>
<td></td>
<td>0.785</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_rat3: continuously improve the attributes of the products</td>
<td></td>
<td></td>
<td>0.743</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_rat6: introduce more novel products than strongest competitors</td>
<td>-0.106</td>
<td></td>
<td>0.685</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_rat2: products are subject to permanent innovations</td>
<td></td>
<td>0.674</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_rat9: introduce several new products on the market during the next five years</td>
<td>0.553</td>
<td>-0.141</td>
<td>0.102</td>
<td>0.144</td>
<td></td>
</tr>
</tbody>
</table>
**Article IV**

<table>
<thead>
<tr>
<th>Item</th>
<th>Loadings</th>
<th>Cross-loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>i_use5: enable to focus on common issues</td>
<td>0.922</td>
<td>-0.110</td>
</tr>
<tr>
<td>i_use4: tie innovation activities together</td>
<td>0.863</td>
<td></td>
</tr>
<tr>
<td>i_use7: develop a common vocabulary</td>
<td>0.804</td>
<td>-0.104</td>
</tr>
<tr>
<td>i_use6: enable to focus on critical success factors</td>
<td>0.786</td>
<td></td>
</tr>
<tr>
<td>i_use3: provide a common view</td>
<td>0.773</td>
<td></td>
</tr>
<tr>
<td>i_use2: enable continual challenge and debate</td>
<td>0.606</td>
<td>0.191</td>
</tr>
<tr>
<td>i_use1: enable discussion</td>
<td>0.439</td>
<td>0.282</td>
</tr>
<tr>
<td>i_deg5: products are innovative</td>
<td></td>
<td>0.849</td>
</tr>
<tr>
<td>i_deg3: products differ significantly from existing products</td>
<td>0.834</td>
<td></td>
</tr>
<tr>
<td>i_deg2: products are inventive</td>
<td>0.794</td>
<td></td>
</tr>
<tr>
<td>i_deg4: products are exceptional</td>
<td>0.765</td>
<td></td>
</tr>
<tr>
<td>i_deg1: products are novel</td>
<td></td>
<td>0.739</td>
</tr>
<tr>
<td>d_use2: monitor results</td>
<td>0.887</td>
<td></td>
</tr>
<tr>
<td>d_use1: track progress towards goals</td>
<td>0.798</td>
<td></td>
</tr>
<tr>
<td>d_use3: compare outcomes to expectations</td>
<td>0.707</td>
<td></td>
</tr>
<tr>
<td>d_use4: review key measures</td>
<td>0.269</td>
<td>0.538</td>
</tr>
</tbody>
</table>

This table reports results of exploratory factor analysis. The formulations of the items are shortened. For complete formulations, see Appendix 2. We used maximum likelihood with promax rotation to calculate the factor analyses and to extract all factors with eigenvalues > 1. Loadings > 0.3 are bolded and are used in the subsequent analysis. We report the Cronbach’s alpha of the bold constructs, the corresponding variance extracted, and the AVE. Cross-loadings below absolute 0.1 are suppressed.

Extraction method: maximum likelihood.
Rotation method: promax with Kaiser normalization.
Rotation converged in 7 iterations.
### Appendix 2: Survey items and constructs

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interactive Use (i_use)</td>
<td>Please rate the extent to which information from innovation control in your organization is used for the following purposes. Information is used 1. ...to enable discussion in meetings of superiors, subordinates and peers. 2. ...to enable continual challenge and debate underlying data, assumptions and action plans. 3. ...to provide a common view in innovation activities. 4. ...to tie innovation activities together. 5. ...to enable the innovation department to focus on common issues. 6. ...to enable the innovation department to focus on critical success factors. 7. ...to develop a common vocabulary within innovation activities.</td>
<td>Henri (2006)</td>
</tr>
<tr>
<td>Diagnostic Use (d_use)</td>
<td>Please rate the extent to which information from innovation control in your organization is used for the following purposes. Information is used to 1. …track progress towards goals 2. …monitor results 3. …compare outcomes to expectations 4. …review key measures</td>
<td>Henri (2006)</td>
</tr>
<tr>
<td>Process Alignment (i_pro)</td>
<td>Please evaluate the following statements regarding the organization of innovation projects 1. Innovation projects run here through a controlled and progressive implementation process. 2. In innovation projects we define operative process flows with clear tasks. 3. In our organization innovation projects get controlled by a systematic project management. 4. For innovation projects we carefully develop a process and stage specific goal system (e.g., specification of performance, cost and time goals). 5. Innovation projects are accompanied by a situation-appropriate and multi-stage integrating project management. 6. Our innovation processes are clearly structured and understood by all involved. 7. Individual activities within the innovation process are coordinated based on performance- and goal-orientation. 8. Operative tasks and goals in the innovation process are defined clearly and communicated to all involved.</td>
<td>Sammerl (2006)</td>
</tr>
<tr>
<td>Product Newness (i_deg)</td>
<td>Please evaluate the following statements regarding the product program of your company. New products of our company… 1. …are novel. 2. …are inventive. 3. …differ significantly in terms of their newness from existing products/services of competitors. 4. …are exceptional. 5. …are innovative.</td>
<td>Stock et al. (2013)</td>
</tr>
</tbody>
</table>
### Innovation Rate (i_rat)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Our product offer is continuously updated with new products.</td>
<td>Harman-cio-glu et al. (2010)</td>
</tr>
<tr>
<td>2. Our products are subject to permanent innovations.</td>
<td>Stock et al. (2013)</td>
</tr>
<tr>
<td>3. We continuously improve the attributes of the firm’s products.</td>
<td>Homburg and Stock (2004)</td>
</tr>
<tr>
<td>4. Almost every year we launch new products that are based on new tech-</td>
<td></td>
</tr>
<tr>
<td>nologies.</td>
<td></td>
</tr>
<tr>
<td>5. Our products are continuously supplemented with new features.</td>
<td></td>
</tr>
<tr>
<td>6. Our company has introduced more novel products during the last five</td>
<td></td>
</tr>
<tr>
<td>years than our strongest competitors.</td>
<td></td>
</tr>
<tr>
<td>7. Our company frequently replenishes or adds novel products to its</td>
<td></td>
</tr>
<tr>
<td>product offer.</td>
<td></td>
</tr>
<tr>
<td>8. Our company introduces many innovative products in the market.</td>
<td></td>
</tr>
<tr>
<td>9. Our company plans to introduce several new products on the market</td>
<td></td>
</tr>
<tr>
<td>during the next five years.</td>
<td></td>
</tr>
</tbody>
</table>

### Technological Turbulence (t_turb)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. The technology in our industry is changing rapidly.</td>
<td></td>
</tr>
<tr>
<td>2. Technological changes provide big opportunities in our industry.</td>
<td></td>
</tr>
<tr>
<td>3. It is very difficult to forecast where the technology in our industry</td>
<td></td>
</tr>
<tr>
<td>will be in the next 2–3 years.</td>
<td></td>
</tr>
<tr>
<td>4. Technological developments in our industry are rather minor.</td>
<td>Song et al. (2005)</td>
</tr>
</tbody>
</table>

---

In the introduction to the survey, innovation control was defined as follows: Innovation control in this questionnaire subsumes all information processing methods from the field of business administration (scorecards, innovations assessments, budget control, etc.) to support innovation activities.

Reverse-coded item.
### 5.7.3 Appendix 3: Descriptive statistics

<table>
<thead>
<tr>
<th>Items</th>
<th>$N$</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean MV repl.</th>
<th>Mean incl. MV</th>
<th>Std. deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Diagnostic Use</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>d_use1: track progress towards goals</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>5.01</td>
<td>5.01</td>
<td>1.329</td>
</tr>
<tr>
<td>d_use2: monitor results</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>5.24</td>
<td>5.24</td>
<td>1.500</td>
</tr>
<tr>
<td>d_use3: compare outcomes to expectations</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>5.22</td>
<td>5.22</td>
<td>1.477</td>
</tr>
<tr>
<td>d_use4: review key measures</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.95</td>
<td>4.95</td>
<td>1.533</td>
</tr>
<tr>
<td><strong>Interactive Use</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_use1: enable discussion</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>5.24</td>
<td>5.24</td>
<td>1.500</td>
</tr>
<tr>
<td>i_use2: enable continual challenge and debate</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.98</td>
<td>4.98</td>
<td>1.491</td>
</tr>
<tr>
<td>i_use3: provide a common view</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.60</td>
<td>4.60</td>
<td>1.578</td>
</tr>
<tr>
<td>i_use4: tie innovation activities together</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.30</td>
<td>4.30</td>
<td>1.598</td>
</tr>
<tr>
<td>i_use5: enable to focus on common issues</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.29</td>
<td>4.29</td>
<td>1.562</td>
</tr>
<tr>
<td>i_use6: enable to focus on critical success factors</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.44</td>
<td>4.44</td>
<td>1.647</td>
</tr>
<tr>
<td>i_use7: develop a common vocabulary</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.05</td>
<td>4.04</td>
<td>1.714</td>
</tr>
<tr>
<td><strong>Process Alignment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_pro1: controlled/progressive implementation process</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>5.14</td>
<td>5.14</td>
<td>1.537</td>
</tr>
<tr>
<td>i_pro2: process flows with clear tasks</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.96</td>
<td>4.96</td>
<td>1.551</td>
</tr>
<tr>
<td>i_pro3: systematic project management</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.99</td>
<td>4.99</td>
<td>1.588</td>
</tr>
<tr>
<td>i_pro4: process/stage specific goal system</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>5.00</td>
<td>5.00</td>
<td>1.610</td>
</tr>
<tr>
<td>i_pro5: situation-appropriate and multi-stage integrating project management</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.78</td>
<td>4.78</td>
<td>1.620</td>
</tr>
<tr>
<td>i_pro6: process/stage specific goal system</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.54</td>
<td>4.54</td>
<td>1.570</td>
</tr>
<tr>
<td>i_pro7: activities coordinated based on performance- and goal-orientation</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.63</td>
<td>4.64</td>
<td>1.465</td>
</tr>
<tr>
<td>i_pro8: tasks and goals defined clearly and communicated to all involved</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.76</td>
<td>4.76</td>
<td>1.485</td>
</tr>
<tr>
<td><strong>Product Newness</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_deg1: products are novel</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.91</td>
<td>4.91</td>
<td>1.381</td>
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<tr>
<td>i_deg2: products are inventive</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.76</td>
<td>4.76</td>
<td>1.454</td>
</tr>
<tr>
<td>i_deg3: products differ significantly from existing products</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.54</td>
<td>4.54</td>
<td>1.412</td>
</tr>
<tr>
<td>i_deg4: products are exceptional</td>
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<td>1</td>
<td>7</td>
<td>4.33</td>
<td>4.33</td>
<td>1.459</td>
</tr>
<tr>
<td>i_deg5: products are innovative</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.94</td>
<td>4.94</td>
<td>1.334</td>
</tr>
<tr>
<td><strong>Innovation Rate</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_rat1: product offer is continuously updated</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.89</td>
<td>4.90</td>
<td>1.521</td>
</tr>
<tr>
<td>i_rat2: products are subject to permanent innovations</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.97</td>
<td>4.97</td>
<td>1.468</td>
</tr>
<tr>
<td>i_rat3: continuously improve the attributes of the products</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>5.13</td>
<td>5.13</td>
<td>1.315</td>
</tr>
<tr>
<td>i_rat4: every year we launch new products</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.26</td>
<td>4.26</td>
<td>1.761</td>
</tr>
<tr>
<td>i_rat5: products are continuously supplemented with new features</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.63</td>
<td>4.63</td>
<td>1.537</td>
</tr>
<tr>
<td>Item</td>
<td>Description</td>
<td>N</td>
<td>Mean1</td>
<td>Mean2</td>
<td>SD</td>
<td></td>
</tr>
<tr>
<td>------------</td>
<td>----------------------------------------------------------------------------</td>
<td>----</td>
<td>-------</td>
<td>-------</td>
<td>-------</td>
<td></td>
</tr>
<tr>
<td>i_rat6</td>
<td>introduce more novel products than strongest competitors</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.26</td>
<td></td>
</tr>
<tr>
<td>i_rat7</td>
<td>frequently replenish or add novel products</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.49</td>
<td></td>
</tr>
<tr>
<td>i_rat8</td>
<td>introduce many innovative products</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>4.43</td>
<td></td>
</tr>
<tr>
<td>i_rat9</td>
<td>introduce several new products on the market during the next five years</td>
<td>695</td>
<td>1</td>
<td>7</td>
<td>5.58</td>
<td></td>
</tr>
</tbody>
</table>

The formulations of the items are shortened. For complete formulations, see Appendix 2.

a Characteristics of variables after mean imputation of missing values (MV).
b Characteristics of variable before centralization, in preparation for the product term.
### Appendix 4: Structural equation model

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Independent variable</th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
<th>Model D</th>
<th>Model E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Process Alignment</td>
<td>Interactive Use</td>
<td>n/a</td>
<td>0.243***</td>
<td>0.243***</td>
<td>0.243***</td>
<td>0.243***</td>
</tr>
<tr>
<td>Process Alignment</td>
<td>Diagnostic Use</td>
<td>n/a</td>
<td>0.468***</td>
<td>0.471***</td>
<td>0.471***</td>
<td>0.468***</td>
</tr>
<tr>
<td>Process Alignment</td>
<td>Dynamic Tension</td>
<td>n/a</td>
<td>-0.009</td>
<td>n/a</td>
<td>n/a</td>
<td>-0.009</td>
</tr>
<tr>
<td>Innovation Rate</td>
<td>Process Alignment</td>
<td>n/a</td>
<td>0.145***</td>
<td>0.160***</td>
<td>0.144***</td>
<td>0.322***</td>
</tr>
<tr>
<td>Innovation Rate</td>
<td>Interactive Use</td>
<td>n/a</td>
<td>0.256***</td>
<td>0.221***</td>
<td>0.238***</td>
<td>0.222***</td>
</tr>
<tr>
<td>Innovation Rate</td>
<td>Diagnostic Use</td>
<td>n/a</td>
<td>0.182***</td>
<td>0.210***</td>
<td>0.181***</td>
<td>0.331***</td>
</tr>
<tr>
<td>Product Newness</td>
<td>Process Alignment</td>
<td>n/a</td>
<td>0.188***</td>
<td>0.120***</td>
<td>0.078*</td>
<td>0.087*</td>
</tr>
<tr>
<td>Product Newness</td>
<td>Interactive Use</td>
<td>0.163***</td>
<td>0.079</td>
<td>n/a</td>
<td>0.046</td>
<td>n/a</td>
</tr>
<tr>
<td>Innovation Rate</td>
<td>Dynamic Tension</td>
<td>0.083**</td>
<td>0.085**</td>
<td>0.077**</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Product Newness</td>
<td>Dynamic Tension</td>
<td>0.083**</td>
<td>0.085**</td>
<td>0.069*</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

**Fit indices for the model**

<table>
<thead>
<tr>
<th></th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
<th>Model D</th>
<th>Model E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-square</td>
<td>0.000</td>
<td>0.000</td>
<td>26.208</td>
<td>0.000</td>
<td>432.086</td>
</tr>
<tr>
<td>p-value</td>
<td>n/a</td>
<td>n/a</td>
<td>0.885</td>
<td>n/a</td>
<td>0.000</td>
</tr>
<tr>
<td>df</td>
<td>0</td>
<td>0</td>
<td>36</td>
<td>0</td>
<td>108</td>
</tr>
<tr>
<td>CMINDF</td>
<td>n/a</td>
<td>n/a</td>
<td>0.728</td>
<td>n/a</td>
<td>4.001</td>
</tr>
<tr>
<td>NFI</td>
<td>n/a</td>
<td>n/a</td>
<td>0.998</td>
<td>n/a</td>
<td>0.965</td>
</tr>
<tr>
<td>CFI</td>
<td>n/a</td>
<td>n/a</td>
<td>1.000</td>
<td>n/a</td>
<td>0.973</td>
</tr>
<tr>
<td>GFI</td>
<td>n/a</td>
<td>n/a</td>
<td>0.998</td>
<td>n/a</td>
<td>0.976</td>
</tr>
<tr>
<td>RMSEA</td>
<td>n/a</td>
<td>n/a</td>
<td>0.000</td>
<td>n/a</td>
<td>0.023</td>
</tr>
</tbody>
</table>

Standardized results.

Models A, B, and D are saturated models (df = 0), which is why common fit indices are not reasonable.

* *significant at the 0.10 level; **significant at the 0.05 level; ***significant at the 0.01 level (two-tailed significance).
### 5.7.5 Appendix 5: Bootstrapping of confidence intervals\(^a\)

<table>
<thead>
<tr>
<th></th>
<th>Diagnostic Use</th>
<th>Interactive Use</th>
<th>Dynamic Tension</th>
<th>Process Alignment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Std. indirect effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Process Alignment</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Product Newness</td>
<td>0.041 → 0.136; 0.000</td>
<td>0.021 → 0.077; 0.000</td>
<td>-0.014 → 0.010; 0.753</td>
<td>n/a</td>
</tr>
<tr>
<td>Innovation Rate</td>
<td>0.026 → 0.117; 0.002</td>
<td>0.014 → 0.067; 0.001</td>
<td>-0.011 → 0.008; 0.729</td>
<td>n/a</td>
</tr>
<tr>
<td><strong>Std. direct effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Process Alignment</td>
<td>0.385 → 0.550; 0.000</td>
<td>0.160 → 0.326; 0.000</td>
<td>-0.069 → 0.054; 0.793</td>
<td>0.000 → 0.000; 0.000</td>
</tr>
<tr>
<td>Product Newness</td>
<td>-0.035 → 0.189; 0.169</td>
<td>0.113 → 0.117; 0.000</td>
<td>0.009 → 0.161; 0.027</td>
<td>0.087 → 0.276; 0.000</td>
</tr>
<tr>
<td>Innovation Rate</td>
<td>0.015 → 0.227; 0.026</td>
<td>0.117 → 0.322; 0.000</td>
<td>0.000 → 0.171; 0.051</td>
<td>0.055 → 0.240; 0.002</td>
</tr>
<tr>
<td><strong>Std. total effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Process Alignment</td>
<td>0.385 → 0.550; 0.000</td>
<td>0.160 → 0.326; 0.000</td>
<td>-0.069 → 0.054; 0.793</td>
<td>0.000 → 0.000; n/a</td>
</tr>
<tr>
<td>Product Newness</td>
<td>0.058 → 0.268; 0.002</td>
<td>0.164 → 0.363; 0.000</td>
<td>0.007 → 0.159; 0.033</td>
<td>0.087 → 0.276; 0.000</td>
</tr>
<tr>
<td>Innovation Rate</td>
<td>0.089 → 0.286; 0.001</td>
<td>0.156 → 0.354; 0.000</td>
<td>-0.004 → 0.170; 0.059</td>
<td>0.055 → 0.240; 0.002</td>
</tr>
</tbody>
</table>

\(^a\) Bootstrapping over 10,000 samples generating a 95%-confidence interval and providing two-tailed significance values:
Lower bound value → higher bound value; \(p\)-value.
If the interval does not embrace zero, the path is significant.
Non-significant paths are highlighted in italics.
5.7.6 Appendix 6: Interaction effects

Panel A: Moderation of diagnostic use on the relationship between interactive use and product newness

Panel B: Moderation of interactive use on the relationship between diagnostic use and product newness

Panel C: Moderation of diagnostic use on the relationship between interactive use and innovation rate

Panel D: Moderation of interactive use on the relationship between diagnostic use and innovation rate
5.7.7 Appendix 7: Analysis of the moderating effect of technological turbulence

This table estimates Model B depicted in Appendix 4 (without the path Dynamic Tension → Process Alignment, as this is shown to be far from significant in Model B) for contexts with different levels of technological turbulence. In the upper section, the standardized coefficients are from a model in which all paths are unconstrained between the groups. In the lower section, chi-square difference tests are reported to permit testing for differences among individual path coefficients instead of for the group of path coefficients.

<table>
<thead>
<tr>
<th>Partition variable</th>
<th>Total sample</th>
<th>Technological turbulence$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Low Mn=3.30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$n=695$</td>
</tr>
<tr>
<td>Process Alignment ← Interactive Use</td>
<td>0.243***</td>
<td>0.243***</td>
</tr>
<tr>
<td>Process Alignment ← Diagnostic Use</td>
<td>0.471***</td>
<td>0.467***</td>
</tr>
<tr>
<td>Process Alignment ← Dynamic Tension</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Innovation Rate ← Process Alignment</td>
<td>0.145***</td>
<td>0.138*</td>
</tr>
<tr>
<td>Product Newness ← Process Alignment</td>
<td>0.182***</td>
<td>0.045</td>
</tr>
<tr>
<td>Innovation Rate ← Interactive Use</td>
<td>0.221***</td>
<td>0.100</td>
</tr>
<tr>
<td>Product Newness ← Interactive Use</td>
<td>0.218***</td>
<td>0.169**</td>
</tr>
<tr>
<td>Innovation Rate ← Diagnostic Use</td>
<td>0.120**</td>
<td>0.129</td>
</tr>
<tr>
<td>Product Newness ← Diagnostic Use</td>
<td>0.079</td>
<td>0.222**</td>
</tr>
<tr>
<td>Innovation Rate ← Dynamic Tension</td>
<td>0.085**</td>
<td>0.058</td>
</tr>
<tr>
<td>Product Newness ← Dynamic Tension</td>
<td>0.085**</td>
<td>0.092</td>
</tr>
</tbody>
</table>

**Model comparison statistics**

<table>
<thead>
<tr>
<th></th>
<th>χ² restricted (unrestricted)</th>
<th>χ² difference tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.081)</td>
<td>19.564 (0.161)</td>
</tr>
<tr>
<td>DF restricted</td>
<td>(1)</td>
<td>19.403**</td>
</tr>
<tr>
<td>CMINDF restricted</td>
<td>(0.081)</td>
<td>12 (2)</td>
</tr>
<tr>
<td>CFI restricted</td>
<td>(1.000)</td>
<td>1.630 (0.080)</td>
</tr>
<tr>
<td>RMSEA restricted</td>
<td>(0.000)</td>
<td>0.990 (1.000)</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>0.752 (0.975)</td>
</tr>
</tbody>
</table>

**Individual (specific) χ² difference tests**

<table>
<thead>
<tr>
<th></th>
<th>p-value</th>
<th>p-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product Newness ← Process Alignment</td>
<td>0.045</td>
<td>0.253***</td>
<td></td>
</tr>
<tr>
<td>Innovation Rate ← Interactive Use</td>
<td>0.100</td>
<td>0.358***</td>
<td></td>
</tr>
<tr>
<td>Product Newness ← Diagnostic Use</td>
<td>0.222**</td>
<td>-0.091</td>
<td></td>
</tr>
</tbody>
</table>

Standardized results.

* significant at the 0.10 level; ** significant at the 0.05 level; *** significant at the 0.01 level (two-tailed significance).

$^a$ The total sample (mean 4.565; median 4.750) was split according to lowest and highest tertile of the construct Technological Turbulence.
5.8 References


Curriculum Vitae

Benedikt Müller-Stewens

Personal Data
Date & Place of Birth 04.07.1988 in Munich, Germany
Nationality German / Swiss

Education
09/2013 – 10/2016 Doctoral Studies in Management (PMA) (equiv.: Ph.D.), University of St. Gallen, St. Gallen, Switzerland
08/2012 – 08/2013 Master in Strategic Management (M.Sc.), Erasmus University, Rotterdam, the Netherlands
09/2011 – 08.2013 Master in Accounting and Finance (M.A. HSG), University of St. Gallen, Switzerland
09.2007 – 08.2010 Bachelor of Business Administration (B.A. HSG), University of St. Gallen, Switzerland
08/2001 – 07/2007 Matura, Gymnasium Untere Waid, Mörschwil, Switzerland

Publications


Scholarships
12/2015 – 10/2016 Project “The Role of Controls in Innovation: An Examination of Diagnostic Use, Interactive Use, and Dynamic Tension” funded by the Basic Research Fund (GFF) of the University of St. Gallen, Switzerland