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# Practical implications of the resource-based view

## Assessing the predictive power of the VRIO-framework


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**Abstract:** Managers use many decision making tools when developing a firm's strategic direction. Ideally, such tools yield a good solution for an acceptable amount of application effort. This paper presents the results of an experimental research project that compares the effectiveness of a theory-based strategic decision making tool, the *VRIO-framework*, with two alternative decision making heuristics for predicting the stock-market performance of different companies. First, we assess how the predictions of the *VRIO-framework* contrast with decisions based on "gut feeling" using the forecasts derived from a recognition-based decision making tool, the *Recognition Heuristic*. Secondly, the *VRIO-framework's* predictive power is compared to predictions derived from *Analyst Ratings*. Our results suggest that the predictions of the *VRIO-framework* are superior to those of the *Recognition Heuristic* and the *Analyst Ratings*, supporting the practical usefulness of resource-based theory. We conclude that resource analysis is important to strategic decision making and discuss the implications of our findings for future research and management practice.

**Keywords:** VRIO-framework · Resource-based view · Strategy tools · Strategic analysis · Intuition

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## 1 Introduction

Business firm success depends on high-quality strategic decisions that must be made despite time and information constraints. To make high-quality decisions expeditiously, managers often rely on strategy tools as decision making heuristics. Such tools can help boundedly rational managers to achieve good results with acceptable problem-solving efforts (e.g., Clark 1997; Glaister and Falshaw 1999; Jarzabkowski and Kaplan 2008; Knott 2008). Strategy tools are defined as "techniques, tools, methods, models, frameworks, approaches and methodologies which are available to support decision making within strategic management" (Clark 1997, p. 417).[1]

The strategic management literature advocates the use of many strategy tools such as SWOT-analysis or frameworks for industry and value chain analysis. However, the extent to which these different heuristics are effective when applied in strategic decision making processes is a neglected issue. For example, few studies actually compare the relative effectiveness of alternative strategy tools in practical contexts. Such studies are needed, particularly when strategy tools are theory-based and more complex in order to demonstrate and confirm their value and to convince managers that it is worthwhile for them to apply such tools.

This study assesses the relative usefulness of a specific problem solving technique derived from the resource-based view, the *VRIO-framework*. Presently, the *VRIO-framework* is taught very widely in business schools around the world but we have little evidence as to whether it is solid. We test the *VRIO-framework* with regard to its ability to forecast a firm's market performance. Performance forecasts often directly influence the selection of future firm strategies and should be based on reliable tools. The decision making context in our study is the acquisition of equity in other stock corporations. Firms may acquire such stock for short-term speculative or long-term strategic purposes. Before the investment decision is made, however, it is necessary to estimate how the potential investment may perform in the future. To determine the *VRIO's* effectiveness, we compare it with two alternative decision making heuristics. First, we assess how the *VRIO-framework* fares in comparison to decisions based on intuition by using the predictions derived from a simple recognition-based decision making tool, the *Recognition Heuristic* (*RH*). Research on strategic decision making has shown that managers often rely on "gut feeling" or intuition when they select alternatives even if sophisticated decision making tools are available (Dane and Pratt 2007). Since intuition is based on a pattern-recognition process (Klein 2003; Hodgkinson et al. 2009), comparing the *VRIO-framework* to the *RH* considers the interesting question whether a widespread theory-based strategic decision making tool may outperform such recognition or intuition. Second, the *VRIO's* predictions are compared to predictions derived from *Analyst Ratings* (*ARs*). *ARs* are used as a second benchmark because investment banks claim their analysts are experts and they encourage private and business investors not only to take note of their views but also to follow them as they make stock selections (Brenner 1991).

Thus our study contributes to the strategic management literature by providing a systematic empirical assessment of the *VRIO-framework*, a prominent theory-based strategic decision-making tool. The article proceeds as follows: In the next section we revisit the literature that has studied strategic decision making tools to justify our research design.

Thereafter, we present the three decision making tools compared in this study. We then specify our research methods and data and report our results. The article concludes by discussing research and practical implications.

## 2 The study of strategy tools

In strategic analysis and decision making, a large variety of tools are employed with new heuristics continuously being introduced by theoreticians and practitioners (e.g., Webster et al. 1989; Hussey 1997). Classification criteria distinguish tools based, for example, on their methodology, i.e., whether a tool relies on quantitative mathematical computations such as linear programming or qualitative assessments such as SWOT-analysis. They also distinguish tools based on their origin and their time frame. Some tools originated in practice, e.g., portfolio matrices, whereas others have been derived from theory, e.g., Porter's industry analysis. Some tools use historical data, e.g., to estimate experience curve effects, while others focus on present time, e.g., benchmarking, and still others are future oriented forecasting approaches such as scenario analysis or trend extrapolation. Table 1 lists a sample of strategy tools that are used by managers to analyze internal and/or external environmental conditions and developments.

Conceptual work (e.g., Hill and Westbrook 1997; Chesley and Wenger 1999; Jarzabkowski and Wilson 2006; Jarzabkowski and Kaplan 2008; Spee and Jarzabkowski 2009) and empirical research (e.g., Clark 1997; Glaister and Falshaw 1999; Frost 2003; Woods and Joyce 2003; Stenfors et al. 2004; Knott 2008; Rigby and Bilodeau 2010) has examined

**Table 1:** Strategy tools used in practice. (Adapted from Powalla 2010, pp. 27–28)

| |
|---|
| Benchmarking |
| Competitor analysis |
| Core competencies analysis |
| Critical success factors analysis |
| Delphi method |
| Experience curve analysis |
| Gap analysis |
| Historical analogy |
| Life cycle concepts |
| Linear programming |
| PEST analysis |
| PIMS analysis |
| Porter's 5-forces model/industry structure analysis |
| Portfolio matrices |
| Scenario planning |
| Stakeholder analysis |
| Strategic group mapping |
| Strategy workshops |
| SWOT-analysis |
| Trend projection |
| Value chain analysis |
| VRIO-framework/resource analysis |

the role played by strategy tools and their relevance to practice. A review of this literature reveals that three main questions have been studied: Which functions do strategy tools perform? Which contextual factors influence their adoption? How common is the application among managers within strategic decision making?[2]

Regarding *functionality*, strategy tools typically provide structure for gathering and interpreting information in uncertain contexts. The tools support the ordering, selection, and consolidation of relevant information and—in doing so—influence decision makers' perceptions, thoughts, and actions. Furthermore, strategy tools fulfil a communication and coordination function, because they can enable a simplified and focused presentation of complex assumptions and relationships. Just to describe a complex strategic decision making problem typically requires elaborate explanations and multiple pages of text. In contrast, a strategy tool can systematically reduce this effort to one or two easily understood charts that provide a basis for interpersonal communication. Additionally, strategy tools may serve as a source of inspiration because information can be presented and considered from different points of view, so that discussions can lead to new ideas and innovative solutions. Finally, managers sometimes justify their decisions by highlighting how they are in accordance with the results expected by applying one or several strategy tools (Clark 1997, p. 418; Hill and Westbrook 1997, pp. 50–51; Chesley and Wenger 1999, pp. 70–71; Frost 2003, p. 50; Jarzabkowski and Kaplan 2008, pp. 20–25; Knott 2008, pp. 27–29).

Important *contextual factors* that can influence whether and how strategy tools are applied in strategic decision making include the actors, the environment, and the complexity of a tool. With regard to the characteristics of decision makers, it has been shown that an individual's knowledge of and experience with strategy tools as well as his/her position in the firm influence tool choices. For example, if a particular technique has worked well in the past, it is often used again in similar situations. Similarly, managers in more advanced positions are more knowledgeable about tools, have more information on their applicability, and are more likely to use a wider variety of tools than lower-level managers (Woods and Joyce 2003, pp. 187–192; Jarzabkowski and Kaplan 2008, p. 41; Spee and Jarzabkowski 2009, p. 225).

External and internal environmental factors also affect strategy tool adoption. As external environments are highly dynamic, strategy tools are used more often because executives have heavy job demands and work under time constraints and they need to rely on the mental shortcuts decision making heuristics facilitate (Hambrick et al. 2005; Hambrick 2007). Additionally, firm-specific factors such as size, corporate strategy, and ownership structure influence the frequency with which tools are applied. Large firms and firms pursuing growth strategies use strategy tools more frequently than small and medium-sized firms, particularly when the latter are confronted with retrenchment. It has also been shown that owner-controlled firms adopt strategy tools less frequently than management-controlled firms (Frost 2003, pp. 55–60; Woods and Joyce 2003, p. 187; Rigby and Bilodeau 2010, p. 6).

The evidence regarding tool complexity is clear cut: practitioners prefer less to more complex tools. This preference results from management's desire to reach decisions expeditiously and efficiently, i.e., on the basis of decision making aids that are easily understood and flexibly applied (Clark 1997, p. 426; Glaister and Falshaw 1999, p. 115; Spee and Jarzabkowski 2009, p. 225).

With respect to the third question, i.e., the *extent to which strategy tools are applied*, empirical studies suggest that strategy tools have a high diffusion rate among practitioners. However, the number and variety of strategy tools used varies from company to company depending on the contextual factors described in the previous paragraphs. A consistent picture concerning the most popular strategy tools can not be inferred. Only SWOT-analysis is mentioned relatively frequently (Clark 1997; Frost 2003; Rigby and Bilodeau 2010).

Two additional observations result form our review of the literature. First, in spite of the tools' diffusion, few empirical studies systematically analyze the effectiveness of alternative approaches in the same decision making context.[3] This omission is surprising because from a practitioner's point of view, systematic assessments can provide valuable information for choosing between alternative strategy tools. Such assessments might also prevent the diffusion of approaches that are in fact ineffectual or ill-conceived. But also from an academic point of view, systematic assessments are necessary when a tool has been derived from strategic management theory. Rigorous testing of these tools will be instructive as to a theory's practical applicability.

Secondly, despite of the availability of a vast array of strategic decision making tools, many corporate managers still rely more on intuition than on deliberate analysis in making strategic decisions. Intuition comprises "affectively charged judgments that arise through rapid, non-conscious and holistic associations" (Dane and Pratt 2007, p. 33) and intuitive decision making has been defined as a pattern-recognition process: when confronted with a decision problem, individuals subconsciously recognize a familiar pattern and a routine way of responding that makes further analysis unnecessary. It has even been argued that intuition leads not only to faster decisions than reliance on analytical decision making tools but also to more effective decisions (Klein 2001, 2003). The prominence of intuition in strategic decision making may also explain why managers prefer less complex to elaborate tools; the former are easier to remember and thus facilitate intuitive decision making.[4]

Our literature review motivates our study. We wish to contribute to an understanding of strategic decision making tools by providing a systematic empirical evaluation of a prominent theory-based tool. We choose the *VRIO-framework* because (1) it is derived from resource-based theory, a leading paradigm to explain competitive advantage in contemporary strategic management research, (2) it is widely taught in business schools on the basis of case studies, (3) it is increasingly used in the consulting industry to assess firm competitive advantage, and (4) no systematic assessment of the framework's solidity exists. We assess the *VRIO's* effectiveness relative to a recognition-based heuristic that represents decision making based on intuition, the *Recognition Heuristic*. The choice of an intuition-based standard of comparison is motivated by the relative frequency of intuitive decision-making in practice, and by the general lack of systematic empirical research on the effective- and usefulness of strategy tools. Rather than comparing the *VRIO-framework* with other strategy tools, e.g., industry analysis, it is more important to us to contrast the *VRIO* to an intuition-based tool because intuition is the most frequently employed alternative to analytical tools in practical contexts.

The specific decision making context of this study is an investment decision and the prediction of the stock-market performance for different companies. This decision making context may involve different time frames and it may also have high strategic relevance as, for example, the takeover battle between Volkswagen and Porsche demonstrated in 2008 and 2009. Both automobile companies attempted to acquire the other for long-term strategic purposes with Volkswagen the ultimate winner. In addition, several banks and other investors such as the Merckle Group purchased stock during the takeover battle in an attempt to realize short-term speculative gains (Dalan et al. 2009; Miller 2009; Seibel 2009). Given this context, we also consider the effectiveness of the *VRIO-framework* relative to *Analyst Ratings* that are a critical and frequently used benchmark when making stock market decisions.

## 3 The study's decision making tools

### 3.1 The VRIO-framework

The *VRIO-framework* represents a set of questions designed to assess a particular organization in terms of the resource-based view (RBV) (Barney 2007; Barney and Hesterly 2010). According to the RBV, a competitive advantage exists when a firm creates more economic value in its product market than its competitors. Economic value is "the difference between the perceived benefits gained by the purchasers of the good and the economic cost to the enterprise" (Peteraf and Barney 2003, p. 314). The RBV argues further that the emergence of competitive advantage depends on firm-specific resources and capabilities that are not only valuable, but also rare, non-imitable, and non-substitutable; an additional requirement is that in the population of firms being considered, resources and capabilities are distributed heterogeneously and are also immobile between firms (Barney 1991).

Competitive advantage and economic value are complex concepts that are not easy to measure directly. However, in practice and for the purposes of applying the *VRIO-framework*, accounting based performance measures such as return on total assets (ROA) or market based performance measures such as return to shareholders (RTS) are commonly used indicators of economic value (Barney 2007; Grant 2010). In our study, a market based performance indicator is used because of the stock-market decision making context.

The *VRIO-framework* is a systematic approach for assessing firm resources and capabilities. The framework relates RBV theory to a particular firm and asks respondents to answer four questions that assess the firm's resources or capabilities (Barney 2007, p. 140): There is a question on *V*alue ("Do a firm's resources and capabilities enable the firm to respond to environmental threats or opportunities?"), a question on *R*arity ("Is a resource currently controlled by only a small number of competing firms?"), a question on *I*mitability ("Do firms without a resource face a cost disadvantage in obtaining or developing it?"), and a question on *O*rganization ("Are a firm's other policies and procedures organized to support the exploitation of its valuable, rare, and costly-to-imitate resources?").

Based on such assessments, a decision maker classifies the competitive potential of a firm's resources and capabilities by distinguishing between strengths and weaknesses, the different types of competitive advantage that are attainable, and the associated economic performance. Specifically, resources and capabilities that are not valuable are classified as weaknesses representing a competitive disadvantage associated with below normal performance. If a resource or capability is valuable but not rare exploiting this resource will

**Table 2:** The VRIO-framework. (Adapted from Barney 2007, pp. 150–151; Barney and Clark 2007, p. 70)

| **Is a resource or capability…** | | | | | | |
|---|---|---|---|---|---|---|
| Valuable? | Rare? | Costly to imitate? | Exploited by the organization? | Strength or weakness | Competitive implications | Economic performance |
| No | - | - | No | Weakness | Competitive disadvantage | Below normal |
| Yes | No | - | | Strength | Competitive parity | Normal |
| Yes | Yes | No | | Strength and distinctive competence | Temporary competitive advantage | Above normal |
| Yes | Yes | Yes | Yes | Strength and sustainable distinctive competence | Sustained competitive advantage | Above normal |

enable a firm to generate competitive parity. Such a resource or capability can be thought of as strength although it will lead to normal, i.e., average performance only. Resources or capabilities that are valuable and rare but not costly to imitate are also organizational strengths. However, while above average performance can result from these resources or capabilities, the competitive advantage is nevertheless only temporary because it will be competed away as other firms imitate these resources or capabilities. In contrast, the exploitation of resources and capabilities that are valuable, rare, and costly to imitate can lead to a sustained competitive advantage associated with superior performance for an extended period of time. While the potential for competitive advantage depends on the value, rarity, and imitability of resources and capabilities, it is additionally important that a firm is organized to exploit this potential by implementing supportive structures and systems. The elements and implications of the *VRIO-framework* are shown in Table 2.

Generally speaking, the *VRIO-framework* offers decision makers a structured, theoretically grounded list of criteria to identify the strategic value (and other RBV desiderata) of a firm's resources and capabilities and links these assessments to the sustainability of resource-based competitive advantages and performance implications. In the process of applying this strategy tool, not only is the internal environment analyzed but external environments are also considered. Especially, the question of value underlines the complementary use of internal and external analyses within the *VRIO-framework* because a resource or capability is valuable only if it enables a firm to exploit environmental opportunities or neutralize environmental threats so that either net costs are reduced or the prices firm customers are willing to pay are increased (Barney 2007, pp. 138–140). Despite its clear structure, the tool's practical application is dependent on available information and extensive information processing. In particular, the identification and evaluation of intangible resources and capabilities presents a major challenge (Godfrey and Hill 1995; Levitas and Chi 2002; Dutta et al. 2005). Thus, the *VRIO-framework* can be regarded as a complex strategic management tool in terms of the methodology used to apply it and also in terms of the data required. Currently, as mentioned, the framework's virtues are taught in business schools and it is also increasingly used in the consulting industry to assess firm competitive advantages (e.g., Kubr 2002; O'Riordan 2006; Sheehan 2006; Barney and Hesterly 2010).

## 3.2 The recognition heuristic

Intuition has been studied extensively in psychology and management. It is generally argued that intuition relies on non-conscious pattern-recognition processes (Klein 2001, 2003; Gigerenzer 2008; Hodgkinson et al. 2009; Woiceshyn 2009). Reflecting such a process, the *RH* is a tool that captures intuition and "gut feeling" in decision making. It is a centrepiece of research in modern, interdisciplinary decision making theory (Goldstein and Gigerenzer 1999, 2002). The heuristic involves selecting a subset of objects valued highest on some criterion. Given a choice between two alternatives, one can state: "If one of two objects is recognized and the other is not, then infer that the recognized object has the higher value with respect to the criterion" (Goldstein and Gigerenzer 1999, p. 41). The *RH* can also be generalized for choosing a subset of objects from a larger set by suggesting: "When choosing a subset of objects from a larger set, choose the subset of recognized objects" (Borges et al. 1999, p. 61). Figure 1 summarizes the main features of the *RH*.

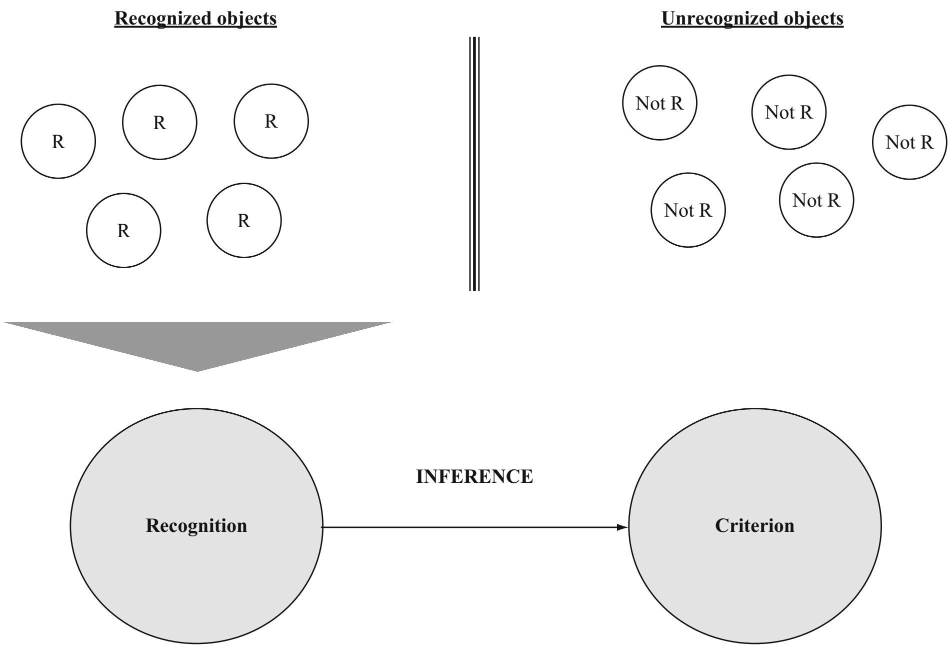


**Fig. 1:** The recognition heuristic. (Adapted from Goldstein and Gigerenzer 1999, p. 39, p. 42)

The *RH* depends on several premises (Powalla et al. 2009): First, people have to possess sufficient cognitive ability to recognize an object they have encountered before, even if they cannot recall specifically when and how they encountered the object. Mere recognition, for example, of a face or a name, is a minimal state of knowledge that is considered integral to human memory capacity, unless this capacity is damaged. Thus recognition is an evolved capacity that is naturally available to most humans (Goldstein and Gigerenzer 1999; Gigerenzer 2008).

Secondly, the *RH* requires a certain degree of ignorance. It will only work, if some objects—not all—are recognized. For example, in applying the *RH* to a set of corporations, people who recognize the names of all the corporations presented cannot use the *RH* to choose among them in terms of what they recognize and what they don't recognize. In this situation it is not possible to use the results of the *RH* to make distinctions with respect to a specific criterion, e.g., the level of performance or competitive advantage. Conversely, entirely ignorant people who have not heard of any of the corporations also cannot use the *RH*. Thus, a lack of recognition of some but not all objects of interest is essential for deriving a decision by applying the *RH* (Borges et al. 1999; Goldstein and Gigerenzer 1999).

The effectiveness of the *RH* depends on its ecological rationality, i.e., "its ability to exploit the structure of the information in natural environments" (Goldstein and Gigerenzer 2002, p. 76). In other words, the *RH* is likely to be an effective tool for making accurate predictions if recognition (or the lack thereof) in an environment is systematic and not random so that people's recognition of alternatives (e.g., stock corporations) correlates with a given criterion of interest (e.g., stock performance). Such a systematic distribution of unrecognized and recognized objects is typical of many natural environments. An illustrative example is provided by Goldstein and Gigerenzer (1999, p. 43) who asked students from Germany and the United States: Which U.S. city has more inhabitants, San Diego or San Antonio? 62% of the American students chose the correct answer (San Diego). However, 100% of the German students chose correctly. Since many of the German students did not recognize San Antonio but had heard of San Diego, they were able to apply the *RH* and make a correct inference. The American students recognized both cities, and so were not ignorant enough to apply the *RH* effectively. In this example, the *RH* is said to be ecologically rational because there are systematic differences between German and U.S. students regarding their level of knowledge about U.S. cities and the heuristic exploits this systematic difference.

Because it does not require information other than recognition, the *RH* is simpler to use than the *VRIO-framework*. Even complicated decisions such as stock selections can be performed by laypeople that do not posses decision specific expertise other than the ability to distinguish between recognized and unrecognized company names. Gigerenzer and his research group characterize the *RH* as "fast and frugal." While the *RH* can be used consciously, it typically is associated with intuition because recognition is an evolved capability so that decision makers are "genetically prepared" to rely on recognition in many difficult situations (Goldstein and Gigerenzer 1999, p. 54). The simplicity of the heuristic might lead to the expectation that its use causes inaccurate results as compared to more scientific, elaborate decision making tools. However, several empirical tests have shown that the *RH* allows for intelligent inferences despite missing or limited knowledge with regard to, for example, predictions of the size of geographical objects (e.g., Goldstein and Gigerenzer 2002; Pohl 2006), the outcomes of sports events such as soccer championships or Wimbledon (e.g., Serwe and Frings 2006; Pachur and Biele 2007), and even stock performance (Borges et al. 1999).

Ortmann et al. (2008), for example, demonstrated that the *RH* can exploit the systematic distribution of recognition in the stock market environment. They asked 100 randomly selected pedestrians in Berlin to identify the stock companies they recognized from lists of corporations. They then used the recognition data to construct portfolios of high and low recognition stocks. Subsequently, these portfolios were entered in stock-picking contests performed by the German magazines *Capital* and *Stern-Boerse Online*. Surprisingly, the high recognition portfolios not only beat the benchmark portfolios proposed by the magazines, they also outperformed more than 80% of thousands of submitted portfolios. There appears to be a link between name recognition and stock valuation in the sense that well recognized firms often have a history of above-average performance and accordingly a reputation of solidity and trustworthiness (Borges et al. 1999, p. 71). Since some studies have provided only mixed support for the effectiveness of the *RH* in the stock market environment (Boyd 2001; Frings et al. 2003; Andersson and Rakow 2007), further tests are necessary.

Thus, the *RH* is an interesting and challenging benchmark against which to assess the effectiveness of the *VRIO-framework* that has demonstrated its effectiveness in the stock-market environment. For the purposes of our study, the *RH* enables a comparison between an intuition- and a strategic management theory-based tool as recognition is considered a central driver of intuition.

### 3.3 Analyst ratings

Financial analysts are important information intermediaries in capital markets who influence the demand for stocks and thus stock prices (Womack 1996; Jegadeesh et al. 2004). Their role has been extensively studied by the finance and accounting literature, and more recently, it has also led to research in the field of strategic management. Analysts produce earnings forecasts and stock recommendations. They share these expert opinions with the investment community, thus reducing the information asymmetry between firm managers and investors (Healy and Palepu 2001).

Financial analysts develop sophisticated financial trading models to predict a firm's future performance, and they summarize their forecasts and recommendations in research reports (Schipper 1991; Hernsberger and Wiersema 2011; Wiersema and Zhang 2011). Major sources of information that analysts use in developing their forecast models are financial statements that firms are required to disclose at regular intervals and third party reports, e.g., on specific industries. Apart from public information, analysts also collect and process information from private sources, for example, by means of conference calls with firm executives. Conference calls allow executives to explain their strategic actions and thus give analysts the opportunity to consider information in developing their earnings forecast models and stock recommendations that may not be available form other sources (Bowen et al. 2002; Hernsberger and Wiersema 2011).

In issuing stock recommendations, financial analysts typically use a five point system that distinguishes between "buy", "overweight", "hold", "underweight", and "sell" recommendations. Both private and institutional investors use these recommendations to guide their decisions, and empirical evidence shows that *ARs* impact investors' decisions and stock prices significantly (Lys and Sohn 1990; Francis and Soffer 1997; Givoly and Lakonishok 1979).

Research has also demonstrated that, for any given firm, typically, there is considerable variation in analyst forecasts and stock recommendations (Demirakos et al 2004; Hernsberger and Wiersema 2011). This variation can be attributed to two major sources. First, predicting a firm's performance is associated with a great deal of uncertainty, and analysts must make many judgment calls about what information to trust and which variables to include in their forecast models (Rogers and Grant 1997). However, it is difficult to discern how judgment decisions have affected analyst models because analysts consider the specifics of their financial models proprietary knowledge and do not make such information publicly available.

Second, although analysts claim to be "rational" and "objective" in their analyses and conclusions, many are, nevertheless, biased about a stock's future prospects (Healy and Palepu 2001; Wiersema and Zhang 2011). For example, research shows that analysts may exhibit "herding behavior" by following the average, consensus forecast of all security analysts assessing a particular firm's stock rather than following their own information and analyses (Hong et al. 2000; Hong and Kubik 2003). Similarly, they may imitate the recommendations of higher status peers who have displayed high accuracy in their past predictions (Hernsberger and Wiersema 2011). Empirical evidence also demonstrates that analysts are often overoptimistic in their stock recommendations, issuing either more "buy" than "sell" recommendations (Brown et al. 1985) or being generally more optimistic in their ratings of newly added stocks as compared to stocks with previous recommendations (McNichols and O'Brien 1997). The problem of overoptimistic forecasts is reinforced by the fact that many analysts are employed by investment banks and brokerage houses. This situation often leads to a conflict of interest if an analyst's employer is underwriting or seeks to underwrite new securities for a company that, at the same time, is rated by in-house analysts (Lin and McNichols 1998; Dechow et al. 2000). Finally, Zuckerman (2000) has shown that since analysts tend to specialize by industry, they often are biased against diversified firms because it is difficult to assign such a firm to a specific industry.

In spite of the variation in analysts' forecasts and recommendations and in spite of the potential influence of analyst bias, research has shown that, on average, analysts have effective stock picking capabilities and add value to the capital market (Womack 1996; Barber et al. 2001). These abilities have also been confirmed by a series of "dartboard contests" undertaken by the *Wall Street Journal*.[5] Thus, *ARs* are included in this research—they are a typical decision making heuristic applied to the investment decision context of our study. *ARs* are considered the equivalent of expert advice because it is assumed that analysts derive their recommendations from the application of sophisticated financial trading models and in-depth analyses. Thus, while the use of *ARs* in making investment decisions is simple from an investor's point of view, the basis of the ratings may be complex mathematical models derived from financial theories and developed by professional investment analysts (e.g., Womack 1996; Zuckerman 2000; Bradshaw 2004; Cowen et al. 2006; Beunza and Garud 2007).

### 3.4 Comparing the tools

From the above presentation, it is possible to summarize and compare this study's decision making tools in terms of the three main issues addressed by previous research, namely the functionality of tools, the context of their adoption, and the diffusion rate. All three tools can be considered functional with regard to the stock market decision making context of this study. Stock markets are dynamic environments where predicting a firm's operational and market performance is subject to a great deal of ambiguity and uncertainty. The *VRIO-framework* can be considered functional in this setting because of the assumed strong links between resource-based competitive advantages and a firm's economic performance, i.e., resource-based competitive advantages can be expected to predict superior market performance. The *RH* can be regarded as a potentially functional alternative to analytical approaches such as the *VRIO-framework* because executives often are pressed for time, particularly in dynamic environments, and frequently rely on mental shortcuts such as intuitive decision making. Additionally, past research on the effectiveness of the *RH* suggests that a positive link exists between name recognition and stock performance. Similarly, *ARs* are functional in this study's context because a clear link between analysts' stock recommendations and the demand for stocks and stock prices has been established by the finance and accounting literature. In fact, analyst recommendations are probably the premier decision making tool in stock market contexts since one of their major functions is to alleviate information asymmetry problems between firm managers and investors.

In terms of the tools' complexity, a prominent contextual condition affecting tool adoption, it has been shown that practitioners prefer less to more complex tools. Arguably, the *RH* and by implication, intuition, is a "fast and frugal" tool that can be applied easily in practice. The same holds for *ARs*, although they are typically based on complicated forecast models. In contrast, the *VRIO-framework* is complex and requires extensive information processing. Thus, it may be difficult to convince decision makers to employ such a demanding tool.

Finally, in terms of the tools' diffusion rate among practitioners, it is possible to make some educated guesses about their relative prominence.[6] It can be reasonably expected that *ARs* are the most widely consulted benchmark in the stock market decision making context. Intuition based on, for example, name recognition, can also be considered widespread. However, the extent to which intuition complements or substitutes for predictions derived from rational analysis is difficult to assess. Although potentially functional and appropriate in the stock market context, the *VRIO-framework* is likely to be the least frequently applied tool of this study. This can be expected due to the tool's relative complexity and the fact that the framework has only started to be used by individual firms and the consulting industry to assess firm competitive advantage and the prospect of sustained above-average performance.

## 4 Methods

We compare stock-market performance forecasts based on the *VRIO-framework*, the *RH*, and *ARs* with actual stock-market performance for different companies. Thus, the strategic decision making context is one where a firm desires to acquire equity in other stock corporations, and can base its decision on three alternative decision making tools that predict the market performance of these stocks. Specifically, the choice can be made based on 1) an assessment of firm resources and capabilities, 2) firm recognition, and 3) analyst recommendations.

The objects of interest in our study were the companies listed in the HDAX[7] index. Each company of the index was assigned to an industry based on its NACE-code. The six industries containing the highest number of firms were selected as the focus of the study: these industries were 1) chemicals and chemical products, 2) machinery and equipment, 3) radio, television and communication equipment and apparatus, 4) medical, precision and optical instruments, watches and clocks, 5) financial intermediation excluding insurance and pension funds, and 6) computer and related activities. For each of these industries, five companies (for a total of 30 firms) were randomly chosen. Because two corporations were acquired and delisted from the stock exchange during the time interval of our study, the final sample is based on 28 HDAX firms with two industry groups including four corporations only.[8]

We designed the following experimental research design: First, 26 MBA students (12 males, 14 females; average age 24.2 years) participating in a strategy seminar were trained to be experts in applying the *VRIO-framework*. All seminar participants were advanced students and had acquired strategic management knowledge in several courses. The training session took a working day and consisted of a detailed presentation and discussion of the theoretical basis of the *VRIO-framework* and its practical application, as well as several experiential exercises. For example, we used Sheehan's "PaperScape" as a hands-on exercise to demonstrate the role that resources and capabilities can play in the generation of superior performance (Sheehan 2006). Subsequent to their training, the participants were randomly assigned to one of the six industries.[9] Each participant individually and independently analyzed the five (four) firms in his/her industry using the *VRIO-framework* and publicly available information on the firms' resources and capabilities. Publicly available information accessed by the participants included, e.g., quarterly and annual reports, press releases, and press articles. Based on the results of the *VRIO*-analyses the participants predicted the future stock-market performance of each company. Each participant generated five (four) firm assessments and rank ordered these assessments from the firm with the best resource position (highest rank) to the firm with the worst resource position (lowest rank) during a two month period. Based on the distribution presented in footnote 9, 121 individual assessments were completed and rank ordered. After the individual analyses, all the participants assigned to the same industry discussed and harmonized their individual results. The final outcome of these discussions were six industry-specific rankings of the expected stock-market performance of the individual firms over the next six months, ranging from predictions of the best to the worst performing company (variable: VRIO_forecast). These rankings were completed on January 28, 2008.

On the same day (January 28, 2008), a second test was performed and completed. In this test, a group of 247 randomly selected students from a variety of disciplines (laypeople) was asked to identify which of the 30 companies used in the first test they recognized. The 247 participants included 110 male and 137 female volunteers and had an average age of 23.4 years. The vast majority of the participating students (more than 75%) had only very limited knowledge of business related matters. Participants were given a randomized list of the 30 HDAX company names and requested to check the names of the firms they recognized. Participants were paid a fixed amount for their participation in the experiment. After the data collection we ranked the companies in each industry according to their recognition rates from the most to the least recognized firm (variable: RH_forecast). This ranking is based on the *RH's* basic assumption that a firm's recognition rate indicates a firm's likely future market performance, i.e., if the *RH* proves to be effective, firms with higher recognition rates will outperform those with lower rates. On average, the participants recognized 10.3 of the 30 companies, and each company was recognized by 35.4% of the participants.

Third, also on January 28, 2008, we retrieved the performance forecasts based on *ARs* for the 30 HDAX corporations considered. The data were obtained from the website of Cortal-Consors, a subsidiary of the French bank BNP Paribas. For each firm, this website lists the consolidated ratings of different analysts as average recommendations of all analysts following a specific company, and it distinguishes ratings according to the recommendation categories "buy", "overweight", "hold", "underweight", and "sell". In addition, the website lists consolidated data on analysts' expectations regarding each stock's one year price increase potential. The consolidated ratings listed on the Cortal-Consors website are provided by FactSet, a company that specializes in financial analysis products for different professional users such as investment banks or consultants. FactSet collects and consolidates data from several thousand analysts and several thousand corporations. Based on the average recommendations for each company, we ranked the companies from the most to the least recommended firm within our six industries, i.e., the companies with the highest to the lowest expected stock performance (variable: ARs_average recommendations_forecast). In addition to these average recommendations, analysts estimate the potential price increase for the next year for each company. Thus, we used the reported one year price increase potential as an additional indicator of analysts' performance expectations by ranking each company based on the potential price increase from the highest to the lowest within each industry (variable: ARs_1 year price increase potential_forecast).

We then determined the actual stock-market performance for the companies for the next three, six, nine, and twelve months. Although our *VRIO* predictions are based on a time interval of six months, we also considered three, nine and twelve months periods to validate our findings across time.[10] Our performance indicator was the change in a firm's dividend adjusted stock market performance (return to shareholders) in the four time periods and this information was obtained from the Yahoo Finance website. Subsequently, the companies were ranked within industries from the most to the least successfully performing firm (variables: Stock-market performance_3months_real, Stock-market performance_6months_real, Stock-market perfor-mance_9months_real, Stock-market performance_12months_real).

The transformation of all variables into rankings required the use of rank correlation coefficients to analyze our data. Specifically, we use Spearman's rho to determine the strength of the relationships between predicted and actual firm stock-market performance. We use these correlations to evaluate the relative predictive power of the *VRIO-framework*, the *RH*, and the *ARs* respectively. To validate our findings, we carry out supplementary analyses based on 1) individual *VRIO* assessments, 2) an accounting-based performance indicator, and 3) randomly selected rankings. All results are presented in the next section.

## 5 Results

As shown in Table 3, Spearman's rho correlations reveal highly significant positive correlations between the *VRIO-framework* predictions and the companies' actual stock-market performance in three of the four periods ($p < 0.01$): Concerning the central six months' period the coefficient is 0.801, for the nine months' period it is 0.654, and for the twelve months' period 0.479. The *RH* is positively but insignificantly associated with actual stock-market performance in all four periods with correlation coefficients ranging between 0.128 and 0.317. Similarly for the *ARs,* insignificant, positive and negative results are found (third and fourth columns of Table 3). For all four periods, both the forecasts derived from the analysts' average recommendations and the estimated one-year price increase potential are only weakly correlated with actual stock-market performance. The correlation coefficients range between values of − 0.265 and 0.276.

The good predictive performance of the *VRIO-framework* made us wonder whether this result was influenced by the pooling of individual assessments within industries. Therefore, we also calculated correlation coefficients on the basis of all 121 individual assessments. The results are very similar to the industry-specific pooled results, i.e., highly significant positive correlations exist between the individual *VRIO-framework* predictions and the actual stock market performance of firms. Specifically, the individual predictions are correlated with actual six month stock market performance at 0.507 ($p < 0.01$), for nine month performance at 0.472 ($p < 0.01$), and for twelve month performance at 0.354 ($p < 0.05$). These findings suggest that individual *VRIO* assessments also lead to good predictions that, however, are improved by a pooling procedure.[11]

Although our study focuses on predictions of changes in the return to shareholders (*RTS*), we were also wondering whether our results could be validated by using an

**Table 3:** Spearman's rho correlations between VRIO-framework-forecast, RH-forecast, ARs-forecasts and actual stock-market performance in four time intervals

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1 VRIO-framework_forecast | | | | | | | |
| 2 RH_ forecast | 0.197 | | | | | | |
| 3 ARs_average recommendations_ forecast | 0.107 | − 0.232 | | | | | |
| 4 ARs_1 year price increase potential_forecast | − 0.133 | 0.022 | 0.022 | | | | |
| 5 Stock-market performance_ 3months_real | 0.246 | 0.128 | − 0.178 | 0.087 | | | |
| 6 Stock-market performance_ 6months_real | 0.801** | 0.307 | − 0.012 | 0.002 | 0.550** | | |
| 7 Stock-market performance_ 9months_real | 0.654** | 0.317 | 0.276 | − 0.265 | − 0.074 | 0.595** | |
| 8 Stock-market performance_ 12months_real | 0.479** | 0.200 | 0.273 | − 0.156 | − 0.197 | 0.368 | 0.763** |

**$p < 0.01$ (two-tailed)

accounting-based performance indicator. Therefore, we collected separate *EBIT* data (operationalized as *EBIT/Total Assets*) for all firms for each quarter of 2008 and also calculated averages consisting of: the first and second quarter; the first, second, and third quarter; and all quarters of 2008. Using these seven *EBIT*-based performance indicators we then rank-ordered the firms within industries from the best to the least performing company. The correlations with our decision making tools show the same pattern as the results using the *RTS*: All seven *EBIT-VRIO* correlations are positive and six are so at significance levels of $p < 0.05$. As to the *RH*, there are five insignificantly positive and one insignificantly negative correlation, and only one correlation is significant and positive. When considering *AR* forecasts based on average recommendations and on one year price increase potential, 13 of the 14 positive and negative correlations are insignificant and one is significant and positive. Arguably, these results validate the *RTS* findings and suggest that superior resources and capabilities are related to operating and market performance in a similar manner.[12]

We were intrigued by the results of the *Wall Street Journal* "dartboard contests" and wanted to assess how our results compared to randomly created rankings. We computed five random variables by randomly assigning ranks to the firms within each industry of our sample. Our results reveal two interesting patterns. First, the five random variables are independent of our other predictors. Eighteen of the respective (positive and negative) twenty correlations are insignificant, one random variable is significantly and positively correlated ($p < 0.05$) with the *VRIO-framework* predictions, and one other random variable shows a significant correlation (positive at $p < 0.05$) with the analysts' predictions based on the estimated one-year price increase potential. Second, on average, the random variables do not predict stock-market performance. Nineteen of the twenty correlations between our four stock-market performance measures and the five random variables are insignificant. Thus, the predictive efficacy of the random variables is low and the results are similar to those obtained for the *RH* and the two *ARs* variables.[12]

## 6 Discussion and implications

This research offers insights into the effectiveness of resource analysis in strategic decision making. We used a hypothetical yet realistic decision scenario, i.e., the acquisition of equity in stock corporations to test the relative predictive effectiveness of a prominent strategic decision making tool—the *VRIO-framework*—in comparison to two alternative tools, the *RH* and *ARs*. The *VRIO-framework* was clearly the stronger predictor and this has implications for strategy research and practice.

### 6.1 Implications for research

Our results lend empirical support to the RBV by highlighting the practical value of the theory-based *VRIO-framework* as a strategic decision making tool. Specifically, our findings suggest that identified competitive advantages and disadvantages based on resources and capabilities are evident in a firm's stock market performance over the following six, nine, and twelve months. These results obtain regardless of whether the individual *VRIO* assessments are pooled or not, and they also are validated by an accounting-based performance measure. Thus, our findings are consistent with empirical resource-based research that has tested the theory directly (Barney and Arikan 2001; Newbert 2007; Crook et al. 2008) and not, as we do in this study, based on the theory's transformation into a decision making tool for practitioners. It is noteworthy that the time periods where the *VRIO* predictions were most accurate (six, nine, and twelve months) were in fact also "bear" markets. Almost all stocks faced declining market performance during these periods because of the worldwide finance industry crisis that affected 2008 markets. However, our results suggest that during this period those firms with superior resources and capabilities sustained lower stock market losses than those with inferior resource endowments. The dominance of "bear" markets in the time period that we chose raises the question, however, as to whether the *VRIO-framework* would be equally effective in "bull" market periods.

In our study, the *RH* is not an effective predictor. While Borges et al. (1999) and Ortmann et al. (2008) could validate the effectiveness of the *RH* in the stock market context, our findings are in line with studies that found no or mixed support only (Boyd 2001; Frings et al. 2003; Andersson and Rakow 2007). On the one hand, our results suggest that further studies are needed to (in)validate the *RH* in stock market environments. On the other hand, an additional research focus results when considering recent insights of cognitive psychology. These insights suggest that simple intuitive decision making that, for example, is solely based on recognition, may not be effective in unstructured and dynamic environments such as stock markets unless it is combined with contextual understanding and analytic information processing. According to these dual-process conceptions of decision making, effective managers combine intuition with rational analysis (Sadler-Smith and Shefy 2004; Hodkinson et al. 2009; Woiceshyn 2009). Thus, more research appears to be promising that blends analytic and intuitive approaches to strategic decision making.

Considering the *ARs*, our results do not support the notion that these recommendations add value to the capital market (Womack 1996; Barber et al. 2001). There are only low and insignificant relationships between the predicted and actual stock-market performance and four of the eight coefficients actually have a negative sign.[13] While these results are surprising, they are not unique. Other empirical studies have suggested that although performance predictions by financial analysts may be based on complex financial trading models, they may nevertheless be biased, e.g., due to analysts making overoptimistic or overconfident assessments of particular stocks that override the results generated by mathematical models, simulations, and objective analysis (e.g., Dreman and Berry 1995; Easterwood and Nutt 1999; Zuckerman 2000; Wallmeier 2005). Apart from studying biases, future research could also explore how analyses of firm resources and capabilities could be incorporated into the models used by analysts. To date, these models are dominated by theory developed in finance rather than in the strategic management field. There are two complementary developments, however, that encourage an integration of theory from the fields of finance, accounting and strategic management. First, the importance of analysts for firm strategic decisions is increasingly recognized in the field of strategic management. Zuckerman 2000, for example, demonstrates that analysts influence a firm's level of diversification, and Wiersema and Zhang (2011) show that they may also affect a board's decision to dismiss an underperforming CEO. Second, analysts' potential impact on firm strategies is now also noticed in the finance and accounting literature. For example, Healy and Palepu (2001) suggest that the business model of financial analysts may be changing because prominent analysts are often viewed as strategy advisors to the firms they are analyzing.

To the best of our knowledge, this study is the first systematic attempt to validate the *VRIO-framework* empirically. Since we contrast the *VRIO-framework* with decision making heuristics that have received much attention in modern cognitive psychology or the finance and accounting literature respectively, our study can serve as a starting point for interdisciplinary research on strategic decision making, as indicated in the above paragraphs. Additionally, the limitations of our study suggest promising avenues of future research.

This study has several limitations and it is important to emphasize first of all that our findings are specific to the time and place studied and, thus, should not be generalized. Different time frames and stock market contexts may possibly generate different results. A further caveat of this study is its bivariate nature that is mandated by a research design consisting of different experiments. Arguably, a more fine-grained understanding of the relationships between decision making tools and firm performance could result if future studies would adopt a multivariate research design, a design that controls for factors other than those represented by the tools considered, but that may impact firm performance, e.g., resource endowments, past performance, firm size etc. Future research can also benefit from comparing the predictive power of other theory-based strategy tools, e.g., industry analysis frameworks, to the *VRIO-framework.* In addition, it would be of interest to analyze the *VRIO-framework's* effectiveness in other decision making contexts, with larger samples, and other participants, e.g., managers or other experts with extensive industry experience rather than MBA students. Finally, our study compares three alternative decision making heuristics without considering control groups because we wanted to directly contrast these tools' effectiveness in a realistic strategic decision making scenario. Future experimental studies could, however, model and consider control groups. For example, *VRIO-framework* predictions could be obtained from executives versus groups of industry experts or MBA students. *RH* framework predictions could be contrasted with predictions from a different heuristic from the fast and frugal research programme in modern cognitive psychology, e.g., the "Take The Best" heuristic (Gigerenzer and Goldstein 1999). For *ARs* several meaningful control groups are suggested by the incidence of analyst bias, e.g., *ARs* of newly added stocks versus *ARs* of stocks with previous coverage (McNichols and O'Brien 1997), or *ARs* of analysts whose employers have an underwriting relationship with the companies rated by the analysts versus *ARs* of independent analysts (Dechow et al. 2000).

### 6.2 Implications for practice

Several practical implications are worth noting. First, the comparison we undertook between three decision making tools clearly points to the value of performing resource analysis prior to making strategic decisions. The RBV has always argued that resource analysis is essential to understanding the competitive potential of a firm's resources and capabilities and developed the *VRIO-framework* to facilitate and assess practice applications. Thus, although there are no "rules for riches" (Barney 2001, p. 52), *VRIO* analysis can be seen as an antecedent to value-enhancing strategic choices. *VRIO* analysis allows managers to assess what types of resources and capabilities are likely to permit temporary or sustained competitive advantages and, thereby, provide guidance in choosing appropriate corporate, business, and functional level strategies. Our study demonstrates that *VRIO* analyses may not only be appropriate for an assessment of a firm's internal resources and capabilities, but may also be a performance enhancing tool when applied to the assessment of other organizations, e.g., acquisition targets.

A second practical implication is that it appears possible to train individuals and groups to apply the *VRIO-framework* effectively. Supporting this idea is the fact that good predictions were obtained from both the individual *VRIO* assessments and those resulting from the industry-specific pooling procedure. Such training can take place in seminars or workshops that apply the procedures developed to transform the RBV into a practical decision making tool.

Third, the failure of the *RH* to generate useful predictions raises questions about the value of simple intuitive judgments. Arguably, intuition will always play an important role in decision making. In complex decision contexts, however, reliance on an intuitive tool such as simple recognition does not seem to be sufficient. The best way to benefit from gut feelings may often be to treat an intuitive judgment as a best first guess that will then be challenged and altered by reason and feedback from multiple sources including formal analysis. The literature on intuitive decision making often argues that managers can build confidence in their intuition only if they link it to the conscious, i.e., rational analysis. Several authors have offered practical guidelines, for example, suggesting how to develop an intuitive capability that is moderated by reason (e.g., Pondy 1983; Klein 2001, 2003; Sadler-Smith and Shefy 2004).

The last managerial implication relates to the stock market context of our research. Although much work of analysts is based on sophisticated forecast models, *ARs* actually turned out to be the least accurate predictions of the three alternatives. This result may be due to the time period and stock market context studied. However, since many have cautioned that *ARs* can be biased, investors can benefit from challenging the advice analysts provide. Obviously, one important question suggested by this study that could be asked of analysts is whether they can back up their investment advice with a systematic evaluation of firm resources and capabilities.

## Endnotes

1 Note that we use the terms 'strategy tools', 'decision making tools' and 'decision making heuristics' interchangeably. "A heuristic (heuristic rule, heuristic method) is a rule of thumb, (. . . ), trick, simplification, or any other kind of device which drastically limits search for solutions in large problem spaces. Heuristics do not guarantee optimal solutions; in fact, they do not guarantee any solution at all; all that can be said for a useful heuristic is that it offers solutions which are good enough most of the time" (Feigenbaum and Feldman 1963, p. 6). Thus, while the term 'heuristic' is broadly defined and applicable to all decision making situations, the term 'strategy tools' refers to a subset of heuristics used in strategic decision making.

2 We used a thorough process to identify relevant research on strategy tools. After identifying the broad spectrum of strategy tools based on summarizing reviews (e.g., Webster et al. 1989; Hussey 1997; Simon and Ganthen v.d. 2002; Asum and Kerth 2008), we entered the following

keywords into the electronic data bases Google Scholar and Business Source Premier (EBSCO): strategy tools/techniques, strategic tools/techniques, strategic management tools/techniques, strategic planning tools/techniques, strategic decision making tools/techniques, management tools/techniques, tools/techniques for strategic analysis. This procedure identified approximately 80 non-redundant publications. Upon inspection, 30 publications were identified as relevant because they performed in depth analyses of one or several strategy tools. The earliest publication considered was published in 1981, the latest in 2010.

3 There are two exceptions to this finding. The first concerns quantitative forecasting methods such as moving averages, exponential smoothing or linear regression techniques. Several researchers attempted to evaluate and compare the effectiveness of different forecasting tools by comparing the accuracy of forecasts in areas such as technological change, stock market prices, corporate sales, and firm performance (Makridakis and Hibon 1979; Hogarth and Makridakis 1981; Makridakis and Winkler 1983; Schnaars 1989; Makridakis 1990). The results are sobering. On the one hand, the accuracy record of different forecasting methods conflict and so provide little help when academics and practitioners must choose between alternative methods. On the other hand, and regardless of the forecasting technique, as planning time horizons are longer than a year (short-term), forecasts become exceedingly inaccurate. These results are independent of a tool's level of methodological sophistication, i.e., methodologically complex tools do not provide more accurate forecasts than simpler approaches.The second exception relates to research on strategy workshops that discuss and develop a firm's long-term strategic direction (e.g., Mezias et al. 2001; Hodgkinson et al. 2006; Healy et al. 2010). Such workshops use various strategy tools with SWOT analysis being the most common. However, little is known about whether using such tools leads to superior decisions. Only scenario analysis has been shown to improve the strategic understanding of workshop participants. Arguably, further studies that consider the effectiveness of more recent theory-based strategy tools are important.

4 Note that both intuition and the more formal heuristics proposed in the strategic management literature do not always result in high-quality decisions (Wright and Goodwin 2002; Woiceshyn 2009). Researchers in cognitive psychology adopting the "heuristics and biases" perspective developed by Tversky and Kahneman (1974, 1981) have demonstrated how intuition and other heuristics can be associated with systematic biases. Such biases can be detrimental to strategic decision making, particularly in novel, unstructured situations (e.g., Barnes 1984; Schwenk 1984; Schwenk 1985; Zajac and Bazerman 1991; Krabuanrat and Phelps 1998; Hodgkinson 2001; Hodgkinson and Clarke 2007; Hodgkinson et al. 2009).

5 Based on Malkiel's (1973) random walk hypothesis, the *Wall Street Journal* created the "dartboard contests" in 1988. The underlying theme of Malkiel's hypothesis is that financial analysts are not likely to select better performing portfolios than blindfolded monkeys or individuals throwing darts at a newspaper's financial pages. In the contest, *Wall Street Journal* employees created random portfolios by throwing darts at a stock table while financial analysts selected portfolios based on their expert assessments. After 100 dartboard contests, the *Wall Street Journal* summarized the results in 1998 (Unger 2009). The financial analysts won 61 of the 100 contests and their portfolios' average gain was 10.8% versus 4.5% for the random portfolios. The *Wall Street Journal* discontinued the contests in 2002 without declaring a winner, presumably because the financial analysts' portfolios were superior over a short period of time only and showed less impressive gains against the random portfolios after the respective contests ended.

6 As discussed in Sect. 2, the actual use of different strategy tools varies form company to company depending on different contextual conditions with no consistent pattern emerging from the literature. Thus it is not possible to establish exact diffusion rates, only plausible ranks based on an understanding of the tools of this study.

7 The HDAX index includes stocks of the 110 most highly capitalized German corporations traded on the Frankfurt Stock Exchange.

8 The two corporations acquired and delisted from the stock exchange during the time interval for which we considered the actual stock market performance of corporations are EPCOS and techem. For details concerning the firms included in this study, compare Powalla (2010, p. 105).

9 This procedure led to the following distribution: four students per industry were assigned to three industries with five companies each and to one industry with four companies. Four students were assigned to one industry encompassing five companies and to one industry with four companies.

10 How long does it take for a resource-based competitive advantage or disadvantage to affect a firm's market performance? This question cannot be answered unambiguously (Barney 1995, p. 51; Barney 2007, p. 139; Barney and Clark 2007, p. 53). We used a core interval of six months, because during this period of time, some stability of firm resources and capabilities can be assumed. In addition, the competitive implications of a firm's resources and capabilities should have become publicly known through media coverage and statements of financial analysts and other industry experts during a six months period. It has also been shown that forecasts beyond twelve months are generally inaccurate (Makridakis 1990; Hayward 2002). Thus, to assess the stability of our results, we considered performance developments of three, nine and twelve months in addition to our core interval of six months.

11 The potential effectiveness of pooling in performance forecasts has been demonstrated by Makridakis and Winkler (1983) who found that averaging the results of different quantitative forecasting techniques improved forecasts. Results concerning the individual assessments are available from the authors.

12 The results of these analyses are available from the authors.

13 However, to the extent that our random variables can replicate the *Wall Street Journal's* "dartboard contests", the financial analysts are also not outperformed by random predictions or portfolios because our random variables display a pattern of correlations with market performance that is very similar to our *ARs* variables.

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