Predicting Entrepreneurial Performance: Simple Rules versus Expert Judgment

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INTRODUCTION
The use of heuristics as an aid to organizational decision making has become an important discussion in the strategy literature (Bingham and Eisenhardt, 2014; Vuori and Vuori, 2014). Heuristics are claimed to offer a potential for ‘rationality’ that surpasses more traditional, resource- and information-intensive approaches (Bingham and Eisenhardt, 2011), especially when the environment surrounding the organization is dynamic and difficult to predict (Eisenhardt, Furr, and Bingham, 2010). They are typically defined as rules of thumb (or ‘simple rules’) that provide organizational members cognitive shortcuts for decision making (Bingham and Halebian, 2012:152). As such, they are purported to aid in the discovery and capture of better opportunities, particularly when these are abundant and fleeting (Bingham, Eisenhardt, and Furr, 2007).

However, as the relatively novel theoretical perspective that it is (Brown and Eisenhardt, 1997; Eisenhardt and Sull, 2001), the idea of rational heuristics as an antecedent to firm performance has only been supported by a few empirical studies. The goals of this research are to develop a method for studying rational heuristics empirically and conduct an empirical test of the theory. By doing this, we aim at answering whether organizations can effectively craft a set of ‘simple rules’ to aid in the discovery of entrepreneurial opportunities.

To model the way in which rational heuristics are constructed by organizational members, we rely on a machine learning method that outputs an optimal set of parameters that are correlated with a performance outcome of interest at a latter point in time. Therefore, much like the development of individual-level heuristics can be modeled as Bayesian updating (i.e., recurring observations of a match of a given event that precedes a specific occurrence are ‘learned’ to be an event that accurately predicts the occurrence), machine learning goes through several iterations testing potential relationships between a parameter and an outcome, ‘learning’ which parameters are more consistent predictors of the specified outcome.

To construct a test set of rational heuristics we rely on the Start-Up Chile program as an empirical setting. Approximately once every four months Start-Up Chile receives around 1,500 applications of startups that compete for a $40,000 grant and a space in the program. Only 100 startups are accepted each time. Hence, this is a perfect setting to test the use of simple rules, because as an organization, Start-Up Chile needs to discover which are the best opportunities to invest in from a pool of ‘superabundant, heterogeneous and fast moving’ (Bingham & Eisenhardt, 2014:1698) opportunities.

Because the only way to validate whether a rational heuristics approach is an effective method for achieving higher performance is to compare it against an alternative approach, we pit the idiosyncratic set of simple rules identified by our machine-learning model against the traditional way in which Start-Up Chile chooses the startups in which to invest. Consistent with the way most investment groups and public policies evaluate potential investments, Start-Up Chile relies on expert judges to assess each application on its own merits. Therefore, our analytical strategy relies on comparing the power of the judges to predict latter performance, against the power of the simple rules to predict the same performance outcomes.

Our findings support the principle that the development of a set of idiosyncratic simple rules can help organizations make faster, more accurate and more efficient decisions about which opportunities to pursue. Thus, our paper makes an empirical contribution to the theoretical perspective of rational heuristics as organizational dynamic capabilities, as well as to the entrepreneurial opportunity literature regarding organizational-level capabilities for the discovery of high-value opportunities.

THEORETICAL BACKGROUND
The literature on heuristics can be divided into three main programs: ‘heuristics-and-biases’ (Tversky and Kahneman, 1974), ‘fast-and-frugal’ (Gigerenzer, 2008), and ‘rational-heuristics’ (Bingham and Eisenhardt, 2011). As suggested by Bingham and Eisenhardt (2014), these programs differ in their focus of heuristics around the dimensions of idiosyncrasy, emergence and consequences. While the first two programs focus on universal heuristics that typically emerge automatically at the individual level, the third focuses on unique heuristics that emerge from thoughtful reasoning, which can be developed either individually or collectively. Moreover, while the first program focuses on the negative implication of the use of heuristics, the last two programs focus on the positive consequences of their use.

Building on the ‘rational-heuristics’ program, the use of heuristics for improving firm performance has been an important topic of discussion in strategy (Vuori and Vuori, 2014; Bingham and Eisenhardt, 2014), especially in relation to markets that have high levels of unpredictability. Studies have argued that managers purposively develop unique, idiosyncratic simple rules to guide firm processes and decisions (Eisenhardt and Sull, 2001), and have found that this approach is positively related to firm performance (Bingham, Eisenhardt and Furr, 2007) because it endows the company with a capability to sustain a competitive advantage in dynamic environments. To this point, computational models have shown that in unpredictable markets, fewer rules (not too many, but certainly some) help firms achieve a sustained competitive position or ‘stay on the edge of chaos’ by
setting just enough structure to reach optimal levels of coordination, flexibility and improvisation (Brown and Eisenhardt, 1997, 1998; Davis, Eisenhardt, and Bingham, 2009). Moreover, recent work has shown that organizations actually develop or ‘learn’ idiosyncratic simple rules as the firm undergoes experiences from trial and error (Bingham and Haleblian, 2012), mirroring the way in which individuals develop universal heuristics through the process of Bayesian updating. That is, past events that seem to frequently antecedent present outcomes are learned and used as predictors for the outcome in the future. Furthermore, more sophisticated managerial strategists develop and refine a portfolio of simple rules that guides firm decision making (Bingham and Eisenhardt, 2011). However, as interesting as this perspective may be, empirical support is still limited to a few case-based studies.

Empirically, the challenge remains to link the theory of rational-heuristics to the discovery and capture of entrepreneurial opportunities in dynamic, high-velocity markets—when opportunities abound and are highly uncertain. While much work has focused on the strategic logics of leverage (Thomke and Kuehmerle, 2002; Tripsas, 1997) and position (Rivkin, 2000; Siggelkow, 2002), less work has focused on the strategic logic of opportunity relative to its importance (Bingham and Eisenhardt, 2008).

Because high-velocity markets are characterized by abundant flows of unpredictable, fast-moving and ambiguous opportunities (Davis, Bingham, and Eisenhardt, 2007), the challenge is to discover the best opportunities among a “haystack” of opportunities. This task is difficult even for experts (Baum and Silverman, 2004) and entrepreneurs (Sørensen and Sorenson, 2003), which sheds light on the limitations of the rationality of choice. Therefore, the setting of new venture funding is a good stage to explore and test the usefulness of rational heuristics on opportunity discovery and capture.

Thus far, empirical work studying the development of simple rules as an independent variable has relied on fieldwork, interviews and case studies, limited to observations of only a few firms (e.g., Bingham et al., 2007). Alternatively, it has relied on modeling rules as a range of restrictions that limit or enable firms to capture opportunities (Davis, Eisenhardt and Bingham, 2009). However, this approach—like most computational models—sacrifices information about the nuances around the development of idiosyncratic simple rules. In contrast, we propose the use of machine learning as a method to model the way in which simple rules are actually developed within the firm. Moreover, this approach allows us to contrast a conventional method for assessing the potential performance of startups that relies on independent expert judges, against an optimal combination of simple rules. This way, we are able to directly and clearly contrast the performance of each method, absent of unobservables and potentially confounding factors.

Machine learning is a method that detects patterns in data and uses those patterns to predict future outcomes, assisting decision making under uncertainty (Murphy, 2012). Thus, in the same way that teams collectively develop and adapt their unique simple rules to direct firm decision making by relying on their observed correlations between past experiences and subsequent outcomes, so does supervised machine learning output rules based on pattern recognition between specific covariates and a response variable. In this case, the data that is input to the machine-learning algorithm antecedes the outcome data in time, which mirrors the Bayesian updating process of individuals’ inference of causality. Furthermore, consistent with how individuals develop fast-and-frugal trees for quick decision making (Gigerenzer, 2008), the chosen machine learning model is the classification and regression tree (Murphy, 2012).

The main test pursued by this study is whether a developed set of simple rules is more effective for discovering entrepreneurial opportunities than alternative methods. By effective, we mean more efficient (in use of resources) and more accurate (in terms of predicting performance).

**RESEARCH SETTING AND METHODS**

To test whether the rational-heuristics approach is more effective than a current evaluation approach used by Start-Up Chile to discover the higher-potential startups, we need to pit each method against each other. To do this, we use Start-Up Chile, a government accelerator that evaluates close to 1,500 startup business plans every four months. Their default evaluation process relies on expert judges who score the business plans based on a series of pre-defined criteria. Each startup application is scored by three independent judges. As a consequence, applicants are ranked from highest to lowest, based on the average scores given by the expert judges assigned to assess them. In principle, if the judging process were accurate in its ability to predict performance outcomes, the ranking based on the judges’ scores would not differ from a ranking based on performance at some latter period. The empirical sample is comprised of 268 startups, all of which participated in Start-Up Chile.

In order to model the rational heuristics approach we developed and implemented into Start-Up Chile’s application process a series of questions that act as simple rules. For example, one question asks *What kind of change caused the emergence of the opportunity?* The answers applicants can chose from are: technological change, market change, market and technology change, and there has been no recent change. The following simple rule is
constructed from this question: If the opportunity emerged as a technology change or a market change, it is predicted that the startup will be high performing. The full list of questions is available upon request from the authors.

The “rules” were constructed using existing empirical literature on startup performance. The compliance of these rules by applicants was assessed for each of the startups in each application process. This assessment was executed independently and simultaneously to the public policy’s default evaluation process. This eliminates the potential for confounding between both evaluation approaches.

Construction of simple rules

Individuals and organizations construct rational heuristics through an iterative process of trial and error (Bingham and Eisenhardt, 2011). Through this process, certain outcomes are cognitively associated to prior knowledge and experience, which leads to the creation of cognitive frameworks or prototypes that are correlated to those outcomes (Baron and Ensley, 2006). These cognitive frameworks are updated through iterative cycles where the outcomes are observed. In other words, individuals and organizations adjust their original assumptions about the antecedents of these outcomes based on the perceived correlation between their prediction and the outcome. This new information is then added to the individual’s knowledge base, which serves to update the cognitive framework used to predict future outcomes.

In order to model the process in which organizations develop idiosyncratic simple rules, we use a machine learning method. Specifically, we rely on the construction of decision trees, a supervised learning technique that uses a set of pre-classified observations (the outcomes of interest) as a training sample. By using the training sample, the method constructs the structure of the decision tree that maximizes the ability of a set of initial rules to predict the correct classification of outcomes. Therefore, much like the process used by individuals and organizations to construct simple rules that are correlated with latter performance, the machine learning method is also able to construct simple rules that are correlated with latter performance.

Dependent variable

The performance outcome measure is captured approximately five months after the application evaluation process. Accepted applicants who participate in the Start-Up Chile program are required to participate in a demo-day. This process consists in a showcase of participating startups to a group of expert investors, who identify and select the top 15% of participants. Because these investors are independent from the judges in the original assessment process, the dichotomous measure of winning the demo-day (i.e., being selected among the top 15% of participants) constitutes a valid performance discriminator that is unconfounded with the assessment conducted five months earlier.

Independent variables

The empirical goal is to test and compare the ability of prediction approaches—namely the current reliance on expert judges and the rational-heuristics approaches. To construct a measure that reflects the rational-heuristic approach, we create a dichotomous variable that indicates whether the startup complies with the rules indicated in the decision tree created during the machine learning process. Therefore, from the full sample, there will be a specific quantity “X” of startups that comply with the rules. Obviously, this value X will depend on the types of rules that are used by the decision tree. In other words, one set of rules may be fulfilled by 20% of participants, while another set of rules may be fulfilled by only 10% of participants.

In order to pit this selection criterion against the existing approach, we create a measure for the existing selection criteria that is comparable to the simple rules selection criteria. To be fair with the judges’ prediction when comparing their performance to the decision tree’s performance, we need to extend the number of possible applicants that could make it into the demo-day. Therefore, the measure that equitably reflects the judges’ prediction must be a dichotomous variable that discriminates whether the startup is among the top X ranked of judged participants. That is, the same quantities of participants who fulfill the decision tree rules.

On other words, both approaches have the same quantity of startups that could possibly make it into the demo-day. The decision tree predicts all X participants who comply with the rules, while the judges’ method predicts the top X ranked participants.

Regression model

To test the ability of the judges’ approach to predict latter performance against the rational-heuristics approach, we run two separate logistic regression models. For each model, we test whether there is a significant relationship between the prediction and the outcome. For example, if judges were successful at predicting latter performance, there would be a positive and significant relation between the judges’ prediction of top applicants (the independent variable) and their identification as top participants in the demo-day (the dependent variable). Likewise, if the simple rules decision tree was successful at predicting latter performance there would be a positive and significant relation between participants selected by the simple rules and their identification as top performing in the demo-day.
In-sample and out-sample
One of the challenges of creating sample-based models is the danger of overfitting the data. That is, the model constructed from the data may only be useful for predicting the outcome variables for the specific dataset used to create the model. Therefore, in order to validate that the simple-rules decision tree model is generalizable and useful for other settings, an out-sample analysis must be conducted. We do so using cohort #8 of Start-Up Chile, which has 72 observations.

RESULTS
The simple rules model constructed using the machine learning method relies on the construction of a decision tree that tries to classify observations based on a predefined outcome. In this case, the outcome is whether the startup was selected for the demo-day. The objective function of the decision tree is the maximization of the number of correctly classified observations. Therefore, the machine-learning algorithm identifies the combination and order of simple rules (captured during the application process several months earlier) that maximize the objective function.

Because the sample is unbalanced—only 15% of the participants are selected to participate in the demo-day—the model requires the input of a non-symmetric cost matrix (He and Garcia, 2009). Hence, the model specification penalizes a type I error (not selecting a team that participated in the demo-day) more than a type II error (incorrectly selecting a team that did not participate in the demo-day). Had I not penalized a type I error more than a type II error, the optimization would have resulted in the trivial solution of rejecting all teams—a solution that would correctly classify 85% of observations.

Figure 1 shows the machine learning output, i.e., the selected rules inferred from the in-sample, as well as the correctly and incorrectly classified observations. This simple rules model correctly classified 63% of observations. It nominated a total of 92 startups, of which 28 actually made it into the demo-day. In contrast, it rejected 104 startups. This model incorrectly rejected 9 startups that actually did participate in the demo-day (type I error) and incorrectly select 64 startups that did not participate in the demo-day (type II error).

Next we compare the ability of each assessment approach (i.e., the simple rules vs. the expert judges) by running a logistic regression of each performance prediction against the real performance result. As can be seen in Table 1, the simple rules model is better than the judges at predicting latter performance of startups, both for the in-sample as well as the out-sample. The results of the decision tree based prediction (regression models 1 and 3) are statistically significant, while the expert judges’ prediction (regression models 2 and 4) is not statistically significant. Furthermore, the point estimates of the decision tree models are greater than the competing models, suggesting that the former is a stronger and more precise estimation of latter performance.
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DISCUSSION

Prior literature has proposed that management teams must use different strategic logics depending on the characteristics of a firm’s environment (Bingham and Eisenhardt, 2008). Specifically, leverage logic is particularly functional when the firm has control over valuable, rare, inimitable, and non-substitutable resources, which when exploited confer a strategic advantage for the firm (Collis & Montgomery, 2008). In contrast, the positioning logic is useful when resources that may be readily available to multiple competing firms are combined and used in novel, unique ways (Porter, 1996). However, both these logics assume that the competitive environment is relatively stable, and that firms own resources to begin with. Complementing these views, Bingham and Eisenhardt (2008) propose the opportunity logic as a third strategic rationale, which is useful for nascent firms operating in highly dynamic and uncertain environments.

Under the assumptions of this third logic, the literature on strategy and rational heuristics has argued that firms operating in dynamic, uncertain environments will reap the benefits of higher performance through the creation and use of “simple rules” that guide decision making processes. It posits that top management teams who construct a set of rational heuristics are able to capture more opportunities in dynamic environments (Eisenhardt and Sull, 2001), and that higher firm performance ensues when the heuristics are constructed on the basis of prior business experience (Bingham, Eisenhardt and Furr, 2007). Moreover, it finds—through the use of computational modeling—that established companies that use simple rules are more successful at staying at the “edge of chaos”, a sweet spot of organizational structure that enables firms to adapt and survive in dynamic environments. Furthermore, it finds that firms can capture fleeting opportunities using simple rules, and that they can learn them in a specific developmental manner (Bingham and Eisenhardt, 2011).

However, this body of literature has seen few empirical papers supporting the logic that the development of rational heuristics is a capability that can effectively help firms achieve superior performance. By constructing an idiosyncratic set of simple rules and testing their capability to discover entrepreneurial opportunities vis-à-vis alternative methods, we offer empirical support about the performance benefits of using simple rules for decision making in dynamic markets where opportunities are abundant and highly uncertain.

CONCLUSION

Building on novel theoretical and empirical work highlighting the benefits of rational heuristics, we empirically test the use of rational heuristics as a capability for increased firm performance. We modeled the development of simple rules using machine learning algorithms, specifically a classification and regression tree method (Murphy, 2012) which is analogous to the development of fast-and-frugal trees for quick decision making (Gigerenzer, 2008). Similarly to the way individuals and firms construct heuristics, the model begins with a set of rules defined by prior experience. The final set of simple rules is achieved in a developmental manner, through an iterative process of confirmatory feedback loops, much like the way managers develop simple rules (Bingham and Eisenhardt, 2011).

To compare the effectiveness of the rational heuristics approach against a conventional method for choosing new venture investment deals, we pit the resulting combination of simple rules against a judge-based ranking by comparing the ability of both methods to predict future performance of entrepreneurial opportunities. We find that the rational heuristics approach proves significantly better at predicting future performance than the conventional approach, both in precision and magnitude.

This paper contributes to the emerging literature on rational heuristics for strategic performance by providing empirical support for the superiority of rational heuristics in identifying high-potential, nascent opportunities in dynamic and uncertain environments. Moreover, it contributes to the literature on venture capital decision-making by highlighting the limitations and biases of conventional investment selection methods. Furthermore, it contributes to the public policy and entrepreneurship literatures by providing a novel technique to improve entrepreneurship policies’ ability to identify those new ventures with higher performance potential, through which public resources would have deeper impact in economic development, and creation of jobs and wealth.
REFERENCES


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