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Managing Complexity and Unforeseeable Uncertainty in Startup Companies: An Empirical Study

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Novel startup companies often face not only risk, but also unforeseeable uncertainty (the inability to recognize and articulate all relevant variables affecting performance). The literature recognizes that established *risk planning* methods are very powerful when the nature of risks is well understood, but that they are insufficient for managing unforeseeable uncertainty. For this case, two fundamental approaches have been identified: *trial-and-error learning*, or actively searching for information and repeatedly changing the goals and course of action as new information emerges, and *selectionism*, or pursuing several approaches in parallel to see ex post what works best. Based on a sample of 58 startups in Shanghai, we test predictions from prior literature on the circumstances under which selectionism or trial-and-error learning leads to higher performance. We find that the best approach depends on a *combination* of uncertainty and complexity of the startup: risk planning is sufficient when both are low; trial-and-error learning promises the highest potential when unforeseeable uncertainty is high, and selectionism is preferred when both unforeseeable uncertainty and complexity are high, provided that the choice of the best trial can be delayed until its true market performance can be assessed.

Key words: unforeseeable uncertainty; complexity; new ventures; empirical study; selectionism; learning
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1. Introduction

New ventures often do not correctly foresee real market opportunities or the best ways of addressing them, and so are forced to adapt and modify their approach over time (McGrath and MacMillan 1995). A classic quote illustrates this:

> When a new venture does succeed, more often than not it is in a market other than the one it was originally intended to serve, with products and services not quite those with which it had set out, bought in large part by customers it did not even think of when it started, and used for a host of purposes besides the ones for which the products were first designed. (Drucker 1985, p. 189)

This challenge is often reflected in the contracts between venture capital (VC) investors and the entrepreneurs: under high uncertainty, the VC installs control mechanisms that allow it to redefine the venture's actions in response to unexpectedly emerging events (e.g., Kaplan and Strömberg 2003). "The challenge is to recognize and react to the completely unpredictable" (Brokaw 1991, p. 54). Adapting to the unpredictable is difficult—many new ventures fail (Sahlman 1990, deYounge and Pearce 2004).

Thus, the challenge that managers of novel projects must deal with is not only Knightian uncertainty, or the lack of knowledge about probabilities (Knight 1921), but even *unforeseeable uncertainty*, or the inability to recognize and articulate some of the relevant variables themselves and their functional relationships (Schrader et al. 1993).[1]

Of course, not all new ventures are so novel that they must deal with the unpredictable—after the 2001 burst of the dot-com bubble, VC firms retracted and tended to invest in later-stage startup companies with known management teams, technologies, and markets (PriceWaterhouseCooper 2005). When, thus, at least the major influence variables are known, established *planning and project risk management* methods are sufficient, including risk identification, prioritization, mitigation, and prevention, and contingent response (Chapman and Ward 1997, Smith and Merritt 2002, Loch et al. 2006).

However, if a venture does target novel terrain, having methods for responding to unforeseeable uncertainty is important for its success. No amount of planning, however thorough, can foresee all major possible events (Morris and Hough 1987, McGrath and MacMillan 1995, Miller and Lessard 2000, Pich et al. 2002). In other words, if a stage of a business initiative cannot be conceived at the time of the decision and initial investment, planning is not possible (Adner and Levinthal 2004, p. 122).

Prior literature has shown, both conceptually (Pich et al. 2002) and based on empirical observations (Leonard-Barton 1995), that *selectionism* and *trial-and-error learning* are the two basic approaches available to respond to unforeseeable uncertainty. Selectionism refers to trying several candidate solutions and selecting the one that works best ex post, or in other words, generating enough variety that at least some variants will yield desirable results (McGrath 2001, p. 118).[2] Selectionism has been documented in startups (Loch et al. 2006, chap. 6) as well as in large companies, for example, software (e.g., Microsoft, see Beinhocker 1999) and pharmaceutical companies (Girotra et al. 2007).

Trial-and-error learning refers to *actively searching* for new information and *flexibly adjusting* activities and targets to this new information, applying new and original problem solving (not only triggering preset contingency plans) as new information becomes available.[3] This type of flexible adjustment to unforeseen changes has characterized the development of many breakthrough technologies (Chew et al. 1991), for example, Motorola's pager, Corning's fiber optics (Lynn et al. 1996), Apple and HP's personal digital assistants (Leonard-Barton 1995), Sun's Java (Bank 1995), and integrated circuit design (Thomke and Reinertsen 1998). In particular, iteration is common in startup companies (Loch et al. 2008).

It is useful for management to know under what circumstances which approach offers better outcomes. The first difference that might come to mind lies in their *costs*. This aspect is well understood (Loch et al. 2001, Sommer and Loch 2004): selectionism carries the sheer cost of pursuing several solutions, of which only one will be chosen.[4] Trial-and-error learning not only results in direct costs of activities aiming to identify unknown influences (e.g., experimentation or hiring of experts), but also causes a delay that may be unacceptable in the market, or politically in the organization. These costs are foreseeable as resulting from the decision to take the approach, and they are conceptually easy to understand.

A second difference between the two approaches lies in the "solution quality" offered by pursuing multiple solution candidates, or by iterating through multiple large modifications; which approach offers the higher upside? Capturing the upside may dwarf the size of the costs, but comparing the upside is conceptually much less clear than comparing the cost side. To examine this question, we take a complex search theory perspective. New ventures in effect search a performance landscape that is not only complex but also uncertain (Levinthal 1997, Levinthal and Warglien 1999, Anderson 1999, Rivkin 2000).

Previous theoretical modeling work suggests that the answer depends not only on the presence of unforeseeable *uncertainty*, but also on the *complexity* of the venture or project in question (Sommer and Loch 2004). Complexity refers to the number of decision variables a venture has to consider and the number of interactions among these decision variables (Simon 1969, p. 195; Rivkin 2000). The Sommer and Loch (2004) model suggests that traditional planning and risk management are the most efficient when unforeseeable uncertainty and complexity are low. High complexity calls for selectionism, and high unforeseeable uncertainty calls for trial-and-error learning. In the presence of both unforeseeable uncertainty and complexity, the theory does not allow for the prediction of a systematic performance advantage of either approach; however, theory does make the prediction that selectionism is effective *only if* the selection of the parallel trials can be performed after the unforeseen influences have been recognized, in other words, if the parallel trials can be kept alive until a full market test (revealing the real market response) has been carried out.

Although these theoretical comparisons are available, the effectiveness of planning, selectionism, and learning has not been compared empirically (Leonard-Barton 1995, Sommer and Loch 2004). This is the contribution of the current article: Based on a sample of 58 startup companies in Shanghai, China, we find empirical support for the theoretical predictions outlined above. Understanding what drives the choice between planning, selectionism, and learning is important for the management team of a venture because the three approaches must be enabled by different structures and management processes.

2. Theory and Hypotheses

The current study tests predictions from a mathematical model of selectionism and learning developed by Sommer and Loch (2004). We summarize the key elements here and explain the intuition of the resulting hypotheses; the reader is referred to Sommer and Loch (2004) for the mathematical derivations. The model starts by conceptualizing a venture as an *outcome*, represented by a payoff function $\Pi = \Pi(\omega, A)$. For example, think of Π as the valuation of the initial public offer (IPO). The venture's payoff depends on the "state of the world" $\omega \in \Omega$ and a chosen set of actions $A \in \mathcal{A}$ (which represents what the team does over the course of the venture). Π includes both the performance outcome and the costs of the actions.

Ω denotes the set of all possible states of the world relevant to the outcome of a venture, with $\omega = (w_1, \ldots, w_N)$ as a generic element. Each parameter w_i may take any value from its domain D_i. One state ω represents one combination of realizations of all parameters. A state of the world may include management team capabilities, resource costs, competitor moves, market demographics, emergence of other technologies, technology difficulty, or regulatory changes, and myriad additional influences.

The established discipline of project planning and risk management (Chapman and Ward 1997, Pich et al. 2002) gives management teams tools to choose a "best" course of action A^*, maximizing the *expected* payoff $\mathrm{E}[\Pi(\omega, A)]$ (or some other risk-adjusted measure). Hedging, buffers, risk mitigation, or contingency plans are tools that are known to maximize the expected payoff in the face of foreseeable uncertainty in the venture. These methods are powerful when all important elements of the state ω have been identified and their ranges and (interacting) influences on the payoff Π are well understood.

In this model, one can now define unforeseeable uncertainty and complexity. *Unforeseeable uncertainty* refers to the presence of influence variables that are relevant to the venture's success, but cannot be recognized by the management team at the outset, and cannot, therefore, be included in initial planning and risk analysis. Unforeseeable uncertainty means that an entire set of influences is unidentified: the team knows only the first n influences $\omega_{\text{known}} = (w_1, \ldots, w_n)$. Thus, performance is also a function of fewer variables $\Pi_{\text{known}}(\omega_{\text{known}}, A_{\text{known}})$. The team is unaware of the $(N-n)$ unforeseen dimensions, the unknown unknowns or "unk unks" in engineering parlance,[5] and therefore not aware of additional actions that would be available if it knew of the additional dimensions. These unforeseen dimensions enter the plan as unconsciously made "default" assumptions: for example, British Telecom (BT) developed a digital display phone with caller identity in the early 1990s, taking hardware development for granted. But customers wanted the *service* of identifying who called; BT dropped the hardware midcourse.

Complexity refers to the number of decision variables in the performance function Π and the interactions among them (Simon 1969, p. 195). An interaction means that the best value of decision variable a_1 depends on the value of decision variable a_2. If there are many decision variables and/or many interactions among them, the performance function is complex.

This model suggests the circumstances under which classic planning and risk management methods, selectionism, or learning offer effective decisions that lead to high performance (value of solutions produced). The performance function $\Pi = \Pi(\omega, A)$ represents a "rugged performance landscape" of myriad combinations of decisions, through which the decision maker (the management team) must search to find a configuration that offers a high value (finding the "optimal" value is usually elusive). Rugged landscapes have been widely used to explain the nature of problem search in strategy and innovation (e.g., Levinthal 1997, Beinhocker 1999, Fleming and Sorenson 2001, Kauffman et al. 2000).

The effect of the *costs* of selectionism and learning is clear: if one approach is very expensive, it becomes less attractive. Thus, the model in Sommer and Loch (2004) focuses on the solution quality (the "upside") of the two approaches while holding the costs constant and comparable. We now describe the intuition of the hypotheses with a simplified example with only two decision dimensions, in which the rugged landscape and the unforeseeable dimension can be graphically represented.

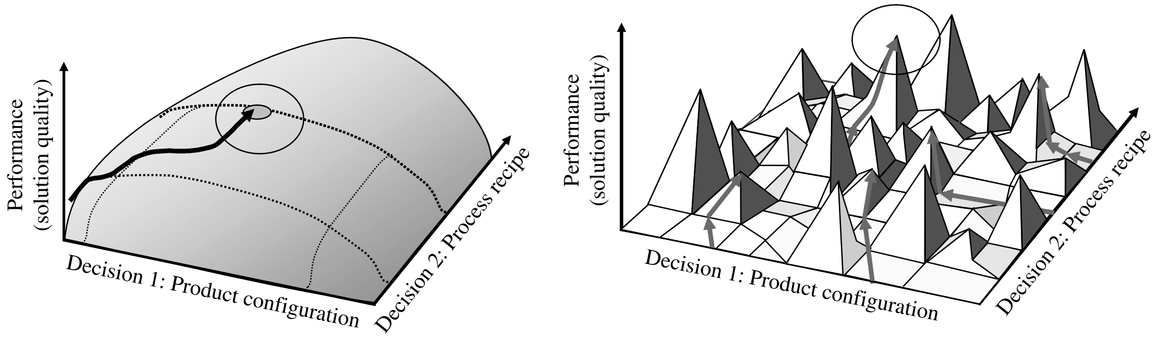
Consider an engineering startup where the management team knows that it will have to adjust the process recipe as well as fine-tune the composition of the final product to suit the process needs of the key reference client. Let us first suppose that there are no unknown unknowns; the team is aware of both the product composition and the process configuration as relevant problem dimensions. There is still risk; the best *values* of the choices themselves are not known at the outset and must be found. Figure 1 represents the team's search for the right product/process configuration in a "performance landscape."

In a simple (noncomplex) performance landscape (left panel of Figure 1), the decision dimensions do not interact: the performance impact of changing dimension 1 remains about the same, no matter what decision 2 is, and vice versa. Such a landscape has few performance peaks (few good design choice combinations). Hence, the team can search incrementally, adjusting product and process configuration iteratively until no further improvement can be found. This incremental search based on an initial solution corresponds to *risk planning*: the team chooses estimated best values at the outset (a "plan") and makes small adjustments in execution to respond to uncertainty in the precise parameter values (risk management). Because both selectionism and learning are costly, and because in a noncomplex situation risk planning finds the optimal (performance maximizing) solution, it is in this case the best strategy. This is consistent with innovation literature, suggesting that extensive planning is appropriate under foreseeable uncertainty (Eisenhardt and Tabrizi 1995, Terwiesch and Loch 1999, Adner and Levinthal 2004).

Hypothesis 1. *For a venture facing only foreseeable uncertainty and low complexity, planning and risk management are associated with a higher venture performance.*

In complex initiatives, in contrast, the decision dimensions interact. This means that in our example, the best product configuration changes with the value of the process recipe, and vice versa, and there are also multiple performance peaks and valleys (right panel of Figure 1). Any incremental search that modifies the decisions in small steps in the "direction of increasing performance"

Figure 1 Planning and Selectionism Under Low Unforeseeable Uncertainty



Notes. Performance landscape: A design parameter configuration is associated with a performance, or "solution quality," measure. In the left panel, the landscape is noncomplex (nonrugged) with a small number of "good" solutions (here: one performance peak). The team can find the best solution by incrementally changing the two design parameters in a series of steps in the direction of increasing performance. In the right panel, the performance landscape is complex or (rugged): It has many "good" solutions (performance peaks), and low and high performance configurations are adjacent. Complexity prevents global search (the peaks are not known); only incremental search (step wise improvements) is possible. However, any incremental search will get "stuck" at a local peak. It is known from systems engineering that higher complexity demands more parallel searches, as shown.

does improve performance, but it is likely to get "stuck" on some inferior local peak. Trial-and-error learning, allowing for radical adjustments if a poor performance peak is reached, is likely to get stuck in another local peak after the adjustment. In this case, having multiple selectionist trials, starting from several solution concepts, and identifying multiple performance peaks of which the best one is chosen ex post, offers, on average, a higher value than learning and adjustment.

The model is consistent with various streams of research. The importance of parallel search for solving complex problems has long been recognized in the search literature (e.g., Fox 1993). Similarly, studies on organizational learning (March 1991, Levinthal and March 1993) and on innovation (Tushman and O'Reilly 1997, McGrath 2001) stress the importance of variety creation for novel innovations. Examples of successful selectionism abound, both involving technical prototyping (e.g., Sobek et al. 1999) and introduction of product variants into the market (Stalk and Webber 1993, Sanderson and Uzumeri 1995). Beinhocker (1999) explicitly links the value of parallel trials to the complexity, or ruggedness, of the search space. In practice, complex projects, such as systems engineering or large-scale simulation problems typically exhibit parallel search (Rivkin 2000, Loch et al. 2001).

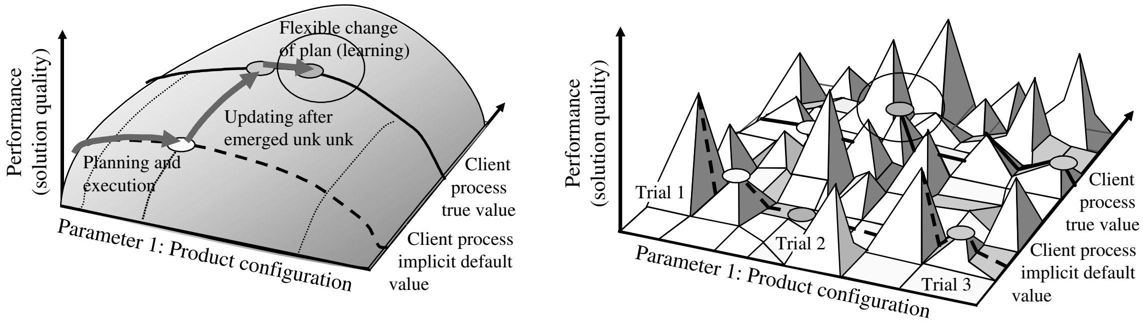
Hypothesis 2. *For a venture facing only foreseeable uncertainty but high complexity, selectionism is associated with higher performance.*

To sum up, we have so far discussed the best search strategy in the absence (or with a low incidence) of unknown unknowns, and have varied complexity. Now, we need to discuss the search strategy when unforeseeable uncertainty is significant.

Returning to our simple illustrative engineering startup example, unforeseeable uncertainty means that one of the two choice dimensions is unknown to the team. Here, we suppose that both the venture team and the client are unaware that the performance of any product configuration depends on the second dimension, the process recipe used by the client. The dimension w_2, the customer's process, is not even considered by the team; without realizing it, the team makes the implicit assumption that the product will perform at the customer's site in the same way that it performs in their own testing lab.[6] This is depicted in Figure 2: the process recipe dimension is an unk unk, and the team makes an implicit assumption about what it is.[7] Thus, the team's conscious project decision happens in the "sublandscape" of the line that corresponds to the default value of the unk unk (the dashed line in Figure 2). In the presence of unk unks, planned risk management is insufficient because it does not offer the flexibility to fundamentally redefine the plan, incorporating a new decision dimension and the adjustments that tend to go with it.

The left panel of Figure 2 represents, again, a low-complexity project where the decision dimensions interact only weakly (for explanation, see Figure 1). Selectionist trials are at least somewhat useful because the best of several attempts tends to be not too far from the best decision. Moreover, in the simple landscape, the best product configuration decision (the known dimension) does not change radically after the unknown dimension has emerged. Thus, selectionism offers useful information, even if the best of the trials must be chosen (for example, for cost reasons) before the process recipe relevance emerges. However, trial-and-error learning offers the best solution value (holding cost constant), better than selectionism. The recognition of and adjustment for the emerging unk unk, and the modification of the product configuration in response to it allows the startup to find not only a rough approximation, but the true best value (shown in the left panel of Figure 2).

Figure 2 Learning and Selectionism Under High Unforeseeable Uncertainty



Notes. Learning allows finding the new optimum after unknown unknowns emerge in simple performance landscapes (left panel). In complex performance landscapes (right panel), learning may get stuck in a low peak after unknown unknowns emerge. Selectionism can identify a good solution if the best trial is identified in the *new* subspace, *after* the unknown unknown has emerged.

The need for iterations and adaptation in unpredictable environments has been recognized repeatedly in the literature (Chew et al. 1991, Lynn et al. 1996). In particular, Eisenhardt and Tabrizi (1995) and Iansiti and MacCormack (1997) find that flexibility and iterative testing cycles are important in environments characterized by "rapidly evolving technologies, changing customer tastes, and sweeping regulatory changes" (Iansiti and MacCormack 1997, p. 108). Similar statements can be found in the literature on dynamic capabilities (Teece et al. 1997, Brown and Eisenhardt 1997). Although this literature focuses on the ability to adjust to a changing environment, rather than the revelation of unknown unknowns, both have the same effect for the venture: As unk unks emerge, the venture's view of the environment changes.

Hypothesis 3. *For a venture facing unforeseeable uncertainty but only low complexity, trial-and-error learning is associated with a higher performance.*

The situation is even more difficult if the performance landscape of the project is complex (right panel of Figure 2). The interaction between the decision parameters renders the solution quality in the subspace that the team is aware of (the dotted line defined by the implicit default value of the process recipe) noninformative about the solution quality in the true subspace (the solid line defined by the true value of the process recipe). Now, the timing of the tests becomes a key issue (as opposed to Hypothesis 2): If the team chooses the best trial (symbolized by the round chips) *before* the unk unk has emerged, this trial may perform very badly later in the true subspace. (Indeed, in Figure 2 the best trial on the dotted line performs worst in the true subspace.) Therefore, selectionism offers little value in a complex project if the choice of the best trial has to be made before unforeseeable uncertainty has been largely resolved.

This problem can be overcome if the product can be "perfectly" tested, that means, tested under fully realistic circumstances, for example, fully functional in the true market. The trials may not capture the highest peak in the true subspace, but, at least, the truly best of the trials that have been developed can be chosen.[8] Indeed, the theoretical results predict that for similar costs, selectionism with full market tests performs as well as trial-and-error learning, which suffers from the problem that any incremental search and adjustment in a complex landscape usually gets stuck on an inferior local performance peak.

Apart from Sommer and Loch (2004), there has been no comparison of selectionism and trial-and-error learning (Leonard-Barton 1995 describes both approaches, but does not compare them). Therefore, the prediction of the relative performance remains inconclusive.

Hypothesis 4. *For a venture facing unforeseeable uncertainty and high complexity, both trial-and-error learning and selectionism, if they are combined with market tests, are associated with a higher performance*; *the comparison between learning and selectionism with perfect tests cannot be predicted from theory.*

To summarize the theory (Figure 3), previous model-based theory of a venture with unknown unknowns suggests that the best choice among the fundamental search strategies of planning, selectionism, and trial-and-error learning is contingent on the environment (complexity and unforeseeable uncertainty) that the venture faces.

Figure 3 Summary of Hypotheses

Unforeseeable uncertainty	**Complexity:** Low	**Complexity:** High
High	**Hypothesis 3:** **Trial-and-error learning** Actively search for unk unks; Flexibility to fundamentally redefine business plan and venture model	**Hypothesis 4:** Selectionism versus learning inconclusive, but selectionism possibly effective only *after* uncertainty resolution
Low	**Hypothesis 1: Planning** Execute plan toward target with risk management	**Hypothesis 2: Selectionism** Parallel trials with ex post selection of the best

This contingency might also offer an explanation as to why the literature on strategic planning could not consistently confirm a benefit of strategic planning (e.g., Shrader et al. 1984, Boyd 1991): Only in stable and noncomplex environments should planning offer a significant benefit.

As discussed before, we have kept the costs of selectionism and learning constant in our discussion. If selectionism becomes more expensive, fewer trials are affordable and their benefit is reduced, shifting the border between Figure 3's Cells 1/3 and 2/4 to the right. If learning becomes more expensive, fewer adjustments, and iterations are affordable, shifting the border between Cells 1 and 3 up.

These predictions, if empirically supported, are useful for the management of the venture in setting up its management processes, *provided that* management can actually estimate the threat from unforeseeable uncertainty and complexity at the outset. This may sound implausible at first—how can one diagnose decision variables at the outset if they are unforeseeable? However, there is evidence that although the influences themselves are unforeseeable, their *presence* can often be diagnosed. Experienced startup managers (and project managers more generally) can ask themselves in which area of the startup they are confident in their knowledge and where there are likely knowledge gaps (Loch et al. 2006, 2008), they can ask themselves for plausibility and contradictions in their plans and assumptions (McGrath and MacMillan 1995), and they can use scenario thinking to broaden their consideration set (Day and Schoemaker 2006). Diagnosing the presence of unforeseeable uncertainty is enough to estimate in which cell of Figure 3 the startup is located and, thus, to apply the lessons of this study.

3. Methods and Sample

3.1. Measures

No established measures exist for unforeseeable uncertainty and for the degree to which selectionism and learning are used in a venture. Complexity has been measured in the context of mathematical models, but again, no measure exists that is easy to monitor. Therefore, we had to rely on self-reported qualitative estimates by the senior managers who filled out a questionnaire.[9]

3.1.1. Dependent Variable. We use a self-reported seven-point Likert item for the venture's *success measure*. The question was, "What is your qualitative evaluation of the success of the startup (considering all aspects of performance)?" (from "major failure" to "major success"). We also asked the respondents for various quantitative measures, such as retained earnings, profits, current valuation, and return on investment based on current evaluation. However, these measures were less completely filled out than the qualitative measure, and furthermore, they were not compatible across the various industries of the startups and their life since foundation (different valuation multiples are used across industries). We finally asked for several partial qualitative success measures (on seven-point Likert scales): profitability, liquidity, and return on investment. These measures were significantly correlated with the qualitative measure. Using their average in the regression yielded similar results as the overall success measure, albeit with lower significance levels, which was expected because they are less comparable across firms. The qualitative success measure expresses the venture's perception, which is formed in the context of, and thus accounts for, the venture's age and industry. This becomes apparent in a regression: whereas age has a significant influence on the financial measures, it has none on the qualitative success measure.

3.1.2. Independent Variables. Each of the management approaches of risk planning, selectionism, and learning might be pursued with varying degrees. For example, planning might range from a rough goal definition to a detailed business plan covering all aspects of the startup. Or selectionism might proceed with only few trials or very many. Therefore, we used seven-point Likert items rather than zero-one variables to measure the choice of strategies. First, planning was expressed as the average of three seven-point Likert items: "At the outset, to what extent did you plan: (a) a course of action on how to develop the product/technology, (b) a course of action on how to build a customer base, and (c) for each round of financing?" (from "not at all" to "very detailed").

Second, the use of learning was measured by the question: "You spent a lot of time and resources to discover influence factors not initially known" (a seven-point Likert item from "strongly disagree" to "strongly agree"). Thus, our question focused on active learning of unknown factors rather than flexibility to adjust to these unknowns because in our sample all startups claimed to be very flexible (the question offered insufficient variance).[10]

Third, the selectionism measure is the maximum of three seven-point Likert items: "If you pursued multiple alternatives (sequentially or in parallel), to what extent did you eliminate these alternatives (a) during concept testing, (b) during technical development/implementation, and (c) during market testing of the finished product/technology?" (from "none" to "all"). We used the maximum of the three items rather than the average because unknown unknowns or complexity on the technology side normally require selectionism in an earlier phase than unknown unknowns or complexity on the market side. Thus, selectionism in the earlier and later phases is to some degree complementary—a high degree in both phases does not necessarily provide additional benefits.[11]

As we hypothesize that selectionism in the presence of both unforeseeable uncertainty and complexity is useful only with perfect tests, we measured how trial selection occurred: "Of those alternatives you eliminated, what proportion did you eliminate based on direct feedback from customers, representative of the real target market?" (from <5% to >95%). Incorporating customer feedback results in tests that mirror the true market conditions of the startup more closely, albeit still not perfectly.

3.1.3. Environmental Condition Variables. Unknown unknowns and complexity are hypothesized to influence the effectiveness of the management approach. We measured these concepts again as seven-point Likert items. Unforeseeable uncertainty was represented by the question: "In retrospect, how many factors ended up influencing your startup that were not included in your plan?" (from "very few" to "very many"). Complexity was represented by: "The number of influence factors and interactions among them increase the complexity of a startup project. In retrospect, what was the level of complexity of your startup?" (from "very low" to "very high").

3.1.4. Costs and Controls. We measured the costliness of parallel trials and of learning iterations on a Likert scale (from 1 = very low through 7 = very high). In addition, we tracked and included the age of the venture and the industry (in the grouping shown in Table 1). Furthermore, we collected information about firm size via the number of employees and the registered capital.

To assess the face validity of the above questions, we asked MBA students who were involved in a startup company to evaluate whether the questions captured the intended concepts, and we pretested the questions with seven startup managers who had been approached through different contacts prior to this study. In addition, because some of the concepts are rather complicated, we tested in our follow-up interviews whether the participants had understood the concepts by asking them to give examples. The examples provided evidence that the participants interpreted the questions as had been intended.

Table 1 Industry and Startup Age

Industry	Number	Avg. age	Min. age	Max. age
IT	24	5.92	2	12
Medical instrument	2	7.00	6	8
Biotech/pharma	12	6.92	5	14
Machine/equipment	7	7.86	4	11
Manufacturing	5	7.60	4	11
Materials	4	8.00	3	18
Other	4	5.25	4	6

3.2. Sample

The questionnaire was originally formulated in English and then translated into Chinese by one of the authors. The translation was checked by two members of the Shanghai Venture Capital Association. The Chinese version was then tested for face validity with the help of the CEOs of two startup companies. The chairman of the Shanghai VC Association agreed to help the authors to persuade startups to participate. One hundred and forty startups were approached, mainly by letter (and a few by phone), of which ninety one initially agreed to participate and sixty three finally completed the survey. Of those 63 questionnaires received, one was too poorly filled out to be usable, and the respondent was not available for follow-up interviews. Four additional responses were excluded because of inconsistent answers (e.g., contradictions among various success questions and among complexity or uncertainty questions). Again, they were not available for further follow-up and, therefore, disregarded. Fifty-eight usable responses remained who participated in a follow-up interview. The follow-up allowed us to complete any missing data for the key questions.

The survey was targeted at senior managers who were involved in the startup early on. By targeting senior management (many of the respondents were CEOs, CFOs, and vice presidents), we ensured that they had enough information to judge the startup's overall success (as opposed to market success or technical success alone). By targeting those involved early on in the startup, we ensured that they were knowledgeable about the original plan and about any changes made to it over time. Out of the 58 respondents, 30 were involved in the startup from the beginning, 8 within the first year, and the remaining 20 since the implementation phase. Because our questions related only to implementation rather than to the initial opportunity recognition, the difference in the time of involvement is not relevant to our survey.

The survey was not targeted at a specific industry. Table 1 shows that the companies that responded to the survey covered a number of different industries with the information technology sector representing a large proportion of it (24 of 58). We did not put any restrictions on the companies' age other than that the respondents should feel comfortable to estimate their success at the time of completing the survey. The ventures' average age of approximately 6.64 years reflects the need to wait a few years to be able to do so. However, the actual age varies in all industries (Table 1).[12]

Table 2 shows the descriptive statistics for the variables. All are measured on seven-point Likert scales, with the exception of planning (average of three Likert questions) and selectionism (maximum of three Likert questions). The means and standard deviations are roughly similar across the variables, with the means of the success measures somewhat higher than the rest.

Table 2 Descriptive Statistics and Correlation Table

			Correlation coefficients											
Variables	Mean	Std. dev.	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Unk unks (1)	4.000	0.973	−0.034	−0.392	0.085	0.102	0.000	0.085	0.102	−0.185	−0.261	−0.259	−0.237	−0.102
Complexity (2)	4.845	1.073	1.000	0.118	0.040	−0.044	0.053	0.151	−0.064	−0.012	0.205	0.231	0.076	0.347
Planning (3)	4.736	1.149		1.000	−0.129	−0.136	0.026	0.006	0.019	−0.177	0.266	0.135	0.241	0.125
Learning (4)	3.511	1.476			1.000	0.095	0.257	−0.003	0.105	0.120	0.227	0.197	0.030	−0.054
Cost of learning (5)	4.210	1.210				1.000	0.015	0.235	−0.074	−0.048	0.184	0.168	0.164	−0.004
Selectionism (7)	3.914	0.996					1.000	−0.318	0.241	0.070	0.296	0.196	−0.094	0.124
Cost of selectionism (7)	4.459	1.027						1.000	−0.199	−0.184	−0.073	−0.202	0.054	−0.040
Perfect tests (8)	4.052	1.407							1.000	−0.242	0.397	0.234	0.068	0.294
Age (9)	5.655	2.832								1.000	0.049	0.356	0.178	0.165
Qualitative success (10)	4.948	0.759									1.000	0.641	0.461	0.619
Profitability (11)	4.845	1.461										1.000	0.593	0.545
Liquidity (12)	4.586	1.140											1.000	0.394
ROI (13)	4.677	1.186												1.000

The success measures are, expectedly, biased upward: in addition to the survivor bias (see Endnote 10), participants have a tendency to overstate their success; almost no one calls themselves a "failure." A uniform upward bias is not dangerous because we are looking for success comparisons across the management approaches and cells (Figure 3).

With the exception of selectionism and cost of selectionism, there are no major correlations between the independent variables, the highest correlations falling just below 26%. The financial success measures are highly correlated with the qualitative measure used in the regressions presented below, indicating that the qualitative measure represents the financial measures, while being adjusted for age and industry effects.

The correlation table also supports some of the arguments made in the previous section: the lack of correlation of complexity with selectionism as well as of unk unks with learning indicates that there is a limited concern with demand effect (response bias) in the answers. The low, and in fact negative, correlation of learning with planning is consistant with learning not being misunderstood as an up-front identification of risk factors.

4. Results

4.1. Statistical Analysis

Our research question is under what circumstances selectionism or learning offer better outcomes for a venture facing unforeseeable uncertainty. As a first "quick and dirty" approach, one might attempt to regress venture success against planning, selectionism, and learning across the entire sample of 58 startups. This attempt yields only limited success: in this regression, planning and selectionism are significant drivers of success at the 5% and 10% levels, respectively, but learning is not significant at all. However, although this model is statistically significant (the F-test is significant at the 1% level), it explains only 15% of the variance (adjusted R^2).

As we have discussed in §2, cost differences between selectionism and learning have a theoretically well understood effect. However, the costs had no measurable effect on success in our sample—they were insignificant in the performance regressions (not shown). Nor did costs reliably predict which approach the startup chose: although the cost of parallel trials is significant at the 1% level in a regression with selectionism as the dependent variable, they explained little of the variation ($R^2 = 13.75\%$, $\Pr > F = 9.2\%$), and the cost of iterations is insignificant in a regression of trial-and-error learning. In the interviews, firms sometimes cited cost as a reason for choosing one approach over the other ("we don't have resources to try several candidates in parallel" or "we can't wait for sequential iterations"), and sometimes other reasons such as, "the parallel candidates just naturally presented themselves, and so we tried them," or "we did not have enough information, so we had no choice than trying something and then modifying as new information came in." Indeed, most firms did not track the costs of selectionism and learning well and needed probing to complete the cost questions. This suggests that the cost differences are simply not measured, or cost difference is indeed often dwarfed by the difference in value potential that the two approaches offer. For these reasons, we leave costs out of the analysis for the remainder of this section. This introduces noise into our analysis, because cost differences do make a difference (although they are imperfectly tracked by the firms).

Holding costs thus constant, our theory predicts that the effectiveness of planning, learning, and selectionism changes *nonlinearly* with unforeseeable uncertainty

Table 3 Variable Means Per Subsample

	High unk unks		Low unk unks	
	High complexity	Low complexity	High complexity	Low complexity
Age	6.630	6.125	7.000	7.375
Unk unks	4.240	4.688	2.714	2.875
Complexity	5.556	3.813	5.714	3.750
Planning	4.840	4.167	5.143	5.167
Learning	3.653	3.438	3.286	3.375
Selectionism	4.074	3.750	3.571	4.000
Perfect tests	3.741	4.438	3.857	4.500
Qualitative success	4.963	4.688	5.143	5.250

and complexity. Thus, the moderation involves structural breaks. The value of each strategy is fundamentally different when unforeseeable uncertainty and complexity are high compared to when they are low. In this situation, a split sample analysis is the standard tool used (Greene 2002). We split the data into observations with low and high unforeseeable uncertainty and low and high complexity. By splitting the sample approximately in the middle, we obtained groups of sufficient size, although the cut at an integer prevented the groups from all being the same size (a split exactly in the middle was impossible), and the cutoff for complexity is not the same as for uncertainty due to the somewhat higher mean of complexity measure. Table 3 shows the means of the variables in each subsample.[13]

Note the consistently larger amount of planning under lower unk unks. This confirms that the firms understood the levels of uncertainty they were facing, and made less detailed plans when these plans were likely to be overthrown by unexpected events. However, the averages for learning and selectionism also confirm the observation that most firms did not understand the solution quality difference between selectionism and learning (the topic of Hypotheses 1–4); the choice between selectionism versus learning was made ad hoc.

Our split sample model can be written as follows, using dummy variables. Denote the dummy variable for low complexity and low unforeseeable uncertainty with D_1 (following the numbering of the hypothesis cells in Figure 3), the dummy for high complexity and low unforeseeable uncertainty with D_2, the dummy for low complexity and high unforeseeable uncertainty with D_3, and the dummy for high complexity and high unforeseeable uncertainty with D_4.

$$\text{success} = \sum_{i=1}^{4} D_i[\alpha_i + \beta_{i1} \text{ planning} + \beta_{i2} \text{ selectionism} + \beta_{i3} \text{ learning}]. \quad (1)$$

This corresponds to four separate regressions, in which each has a separate intercept (the main effect of the dummies). The interaction between each dummy and planning, selectionism, and learning represents the cell-specific (and thus moderated) effectiveness of these management approaches. Because this is a split sample analysis, we are not including the independent variables without the dummies (their "main effects"): we are not interested in the effect of the management approaches over the entire sample because the hypotheses do not predict an effect over the entire sample; rather, the hypotheses focus on when which approach works, that is, in which cells the effects are present.

To test Hypothesis 4, which predicts that selectionism should in Cell 4 (high complexity and high unforeseeable uncertainty) be effective only when combined with perfect tests, we add in a second model the term $[D_4\beta_{44} \sqrt{(\text{selectionism} * \text{perfect tests})}]$. The square root keeps the magnitude of the product the same as the other variables, but all results are robust to this specification (without the square root, the estimate of β_{44} shrinks).

The above model formulation excludes many factors that could potentially play a role for the success of the startup. We could not include all available control variables in the split sample regressions because of the small sample size. However, we included the control variables in the regression on the overall data set and found that neither the age of the companies, nor industry or size (included as a dummy variable for large or small) had a significant impact on success (regression not shown).[14]

For each subsample, we rely on standard ordinary least squares (OLS) regressions.[15] Because Likert items result in interval scales, the use of t-tests and F-tests for significance is acceptable (Ferber 1974, pp. 3–34).[16] Taking the moderating effect of unforeseeable uncertainty and complexity into account by performing the split sample analysis dramatically boosts the statistical power of the regression. The results for the four cells are summarized in Table 4.[17]

Hypothesis 1 addresses low complexity and low unforeseeable uncertainty. It is supported, as planning is significant at the 5% level, although selectionism is not significant. Learning does help, although with a lower coefficient (the effect is only half the size) and lower significance. This can be interpreted as at least some unforeseeable uncertainty being present even in the lower part of the sample, some unknown unknowns, which are sometimes referred to as "residual risk" in the context of project risk management: fundamentally, unforeseeable uncertainty is low, but it is not absent (Loch et al. 2006, chap. 1).

Hypothesis 2 predicts the importance of selectionism under high complexity and low unk unks. This hypothesis is not supported. Instead of selectionism, planning continues to be significant. This cell has the smallest subsample ($N = 7$). This absence of support might be caused by the small sample.[18] Another possible reason

Table 4 OLS Regressions of Performance Under Four Environmental Conditions

Low complexity		High complexity	
Variable	Parameter estimate	Variable	Parameter estimate
	High unk unks		
H3		H4	
Intercept	3.28**	Intercept	2.06*
Planning	0.16	Planning	0.14
Selectionism	−0.11	Selectionism	0.15
Learning	0.34**	Sel.*perf. test	0.39**
		Learning	0.03
$N = 16$; $\Pr > F = 10\%$; Adj. $R^2 = 24\%$		$N = 27$; $\Pr > F = 4\%$; Adj. $R^2 = 24\%$	
	Low unk unks		
H1		H2	
Intercept	2.70*	Intercept	3.33**
Planning	0.54**	Planning	0.38**
Selectionism	−0.25	Selectionism	−0.08
Learning	0.22*	Learning	0.05
$N = 8$; $\Pr > F = 5\%$; Adj. $R^2 = 72\%$		$N = 7$; $\Pr > F = 4\%$; Adj. $R^2 = 85\%$	

*Significant at the 10% level; **significant at the 5% level.

for the lack of support for this hypothesis has been suggested in discussions with two VCs, who stated that, as a rule of thumb, "if a venture wants to pursue several alternative technical solutions, they signal that they don't know what they're doing, and we won't fund them." On the market side, the VCs expressed more tolerance for parallel trials. This suggests potential differences in the propensity of startup companies and established firms to pursue selectionism; however, it is not supported by the data either—we asked the companies in this subsample whether they were VC funded (three were), and a "VC funding" dummy added to the regression turned out insignificant. Of course, this could again be caused by the small sample. In summary, no conclusion can be drawn at this point. What we are left with is that risk planning remains statistically significant in this cell.

Hypothesis 3 is supported: when the startup faces high unforeseeable uncertainty and low complexity, learning is significant at the 5% level, whereas no other variable is significant. To test Hypothesis 4, we first performed the same regression as in the other three cells, with planning, selectionism, and learning as independent variables (not shown in Table 4). Here, selectionism is significant ($p = 2.7\%$), and none of the other variables is. However, the entire model is not significant (the F test gives a p-value of 11.3%) and the explained variance (adjusted R^2) is only 12.3%. Hypothesis 4 predicts that selectionism is most helpful when combined with perfect tests. We therefore added the interaction term of selectionism and perfect tests, as shown in Cell 4 of Table 4.[19] The interaction term is significant at the 1% level and takes over the explanatory power of the selectionism variable. Thus, Hypothesis 4 is supported.

Note also that learning is not significant, providing an initial answer to whether selectionism with market tests, or rather learning, fares better when complexity and unforeseeable uncertainty combine. The data suggest that whereas selectionism with market tests significantly improves the success of the startup, trial-and-error learning does not seem to do so. We also included the combination of selectionism with trial-and-error learning (the interaction effect) to look for evidence of selectionism and learning being combined. This interaction is also statistically insignificant (regression not shown). However, this lack of significance does not necessarily mean that combining selectionism and learning provides little additional value. In this sample of companies, only few practiced selectionism with emerging adjustment of their parallel trials: only 4 of the 27 companies in the subsample with high uncertainty and high complexity checked a response above 4 on both selectionism and learning.

Finally, an interesting difference across the cells of Table 4 can be observed: the intercepts, corresponding to the main effects of the cell dummies, indicate that it is advantageous for a venture to take on *either* high complexity or a high potential for unknowns, but not both. The intercepts in Cells 2 and 3 are approximately 3.3, whereas they are only 2.06 in Cell 4. Unequal variance t-tests confirm that this difference is statistically significant at the 1% level. This suggests that taking on a combination of both high unforeseeable uncertainty and high complexity might be a difficult challenge that endangers success.

4.2. Qualitative Description of Management Approach and Success

Given the small data set, we supplement the results of the quantitative analysis with a more detailed qualitative comparison. Following the suggestion of Yin (2003, p. 52), we selected two cases from the extremes (highest success, lowest success) for each of the cells of Figure 3 (representing the different conditions we want to analyze). For low unforeseeable uncertainty and high complexity (the lower right cell), such a selection was not possible due to a lack of variance in the success measure (which is related to the lack of statistical results for this cell in §4.1). We therefore selected the two cases based on the chosen strategies (one that used selectionism as hypothesized and one that used planning). This cluster should, therefore, be considered more illustrative than confirmatory.

Each of the companies provided examples of the degree and type of uncertainty and complexities they faced, explained the management approach they chose, and provided an explanation of their own success assessment. Tables 5(a) and 5(b) summarize the eight case descriptions in a systematic manner.

The success reports in Table 5(a) (low unforeseeable uncertainty) reflect the upward bias reported earlier—success is described as "moderate" rather than "low." In indicating complexity, respondents consistently focused on the number of influence factors rather than their interactions (see the case descriptions)—many influence factors interact anyway (not only directly, but also through constraints on shared resources, or reputation), and interactions are harder to describe. At the same time, the responses indicated that the respondents did understand the concept and interpreted it consistently.

The case descriptions corresponding to Hypotheses 1, 3, and 4 provide additional support for the hypotheses by confirming the quantitative findings. The companies that were very successful applied the hypothesized management approach. The corresponding case examples also demonstrate that a lack of success may result from unnecessarily using trial-and-error learning although the environment is foreseeable, amounting to a lack of "doing one's homework" (lower left in Table 5(a), Case 32), but it may also result from failing to respond to high uncertainty, inappropriately sticking to risk planning (lower left of Table 5(b), Case 7). The reasons cited by the companies for choosing the respective management approaches were ad hoc, reaching from cost to "we did not think of alternative solution candidates at the outset." This confirms that companies generally do not possess a good decision framework for choosing selectionism and learning.

In the case descriptions corresponding to Hypothesis 2 (right side of Table 5(a)), the detailed explanation of the success measure for Case 44 revealed that this startup turned out to be not so successful in the main target market, thereby providing anecdotal evidence for the Hypothesis. However, because the cases were chosen

Table 5(a) Illustrative Cases in Low Unforeseeable Uncertainty Environment

Low complexity	High complexity
	High success
ID 47: Chemicals for textile, coating, and additives used in industrial applications. Company emerged out of an R&D lab; they had a major failure when they underestimated the speed of switching from magnetic to optical recording technologies.	ID 36: Ink-jet and laser technology based coding and printing equipment.
Complexity: Now medium. Longstanding expertise in the technologies that are combined in their products.	Complexity: High. Multiple technologies (e.g., ink, laser, encoding, tracing, identification), multiple customer industries, and various materials to print on.
Unk unks: Now low. National and local industrial development guidelines available; deep technology and trend knowledge.	Unk unks: Low. Markets, technologies, and regulations well developed; company has experience.
Predicted management approach: Planning.	Predicted management approach: Selectionism.
Management approach: Risk planning. Ideas come from market research and government policies. Detailed budgets and schedules are based on information from their broad cooperation network (foreign and domestic research institutes and laboratories, government agencies, other companies, potential customers, etc.). After technology development, there is still some further development and modification for large-scale production. But based on their careful plans, there are usually no large modifications in implementation.	Management approach: Selectionism, with some learning. Based on customer requirements, they form several programs aimed at one new product. They select the one with the best performance (in cost and customer feedback), typically at an early stage. After the selection, there are still some modifications in the implementation stage, as new requirements.
Success: High, leader in magnetic powder and calcium carbonate. Capital tripled over last few years.	Success: Good, technology leader, 30% market share in China.
	Low success
ID 32: High-pressure air containers; attempt to export into foreign markets.	ID 44: IT software development and services for retail companies.
Complexity: Low. Established regulated market with entry barriers due to licensing requirements, little competition at home because of entry barriers.	Complexity: High. Tailor-made solutions for large customers with varying interacting business processes; collaboration with external partners.
Unk unks: Low. Relatively stable technology; regulatory requirements are clear in foreign markets as well.	Unk unks: Low. Mature technologies and clear regulatory environment.
Predicted management approach: Planning.	Predicted management approach: Selectionism
Management approach: Trial-and-error learning. The company did not sufficiently prepare itself for foreign market regulations and had to modify products after obtaining the necessary information over time.	Management approach: Planning and execution. Careful requirement assessment in the field, then "professional product planning and design," no parallel trials and little modifications.
Success: Moderate: Good at home, but not successful abroad.	Success: Moderate: Good for smaller domestic customers, but not successful for target market of large foreign retail companies in China, who prefer more competitive foreign IT companies.

Table 5(b) Illustrative Cases in High Unforeseeable Uncertainty Environment

Low complexity	High complexity
High success	
ID 15: Medical fast diagnosis products.	ID 55: Specialty chemicals for the construction industry.
Complexity: Low-medium. Technology follower to foreign pharma companies; incremental development of middle to high level technologies.	Complexity: High. Multiple markets: households, construction, industrial projects, sports centers; multiple target construction materials (e.g., air, concrete, wood, plastic, metals) cut across markets.
Unk unks: High regulatory uncertainty, e.g., failed market-oriented healthcare reform, now coexistence of old rules with new attempt; unpredictable environment.	Unk unks: High. Developed a household high-performance floor wax which first failed and then became successful for sports centers; regulation changes forced unexpected need to build own direct channel for one segment.
Predicted management approach: Trial-and-error learning.	Predicted management approach: Choice between selectionism (with perfect tests) and learning inconclusive.
Management approach: Trial-and-error learning. The company developed a program over time, modifying it as conditions change.	Management approach: Selectionism, and some learning. They form well resourced teams for most promising product candidates, plus one or two backup projects with small teams in case of failure. Also learning, willingness to adapt products as market needs emerge.
Success: Good, 30% sales growth, and high revenue export successes into EU.	Success: High. Attracted high R&D subsidies, and high VC investment, achieved high growth and profitability.
Low success	
ID 7: Seafood aquiculture equipment, e.g., antistorm deep-water sea cage.	ID 59: Back-end design of IC chips, bridging IC design companies and foundries.
Complexity: Low. Technology follower to Swedish market leader; stable modules.	Complexity: High. Simultaneously working with chip designer, foundry, and customer (e.g., consumer electronics client).
Unk unks: High. Not all dynamics could be foreseen, e.g., difficult differentiation between cultured and "natural" seafood, and between high-end "green" products and lower-end products with chemicals; no differentiation of government subsidies between different producers; uncertainty causes only large seafood producers to buy the equipment.	Unk unks: High. In rapidly moving telecom and consumer electronics markets, requirements and market opportunities may change or disappear over the 6–8 month collaboration cycle. Startup ventures are not always trusted as partners, which increases uncertainty and pressure.
Predicted management approach: Trial-and-error learning.	Predicted management approach: Choice between selectionism (with perfect tests) and learning inconclusive.
Management approach: Planning and execution. Management team did not modify original plan because they thought it was impossible to change constraints; instead, they lowered their expectation of success.	Management approach: Risk planning. Usually, they followed only one route during product development, after careful planning (no backup design).
Success: Low: Management buyout. Failure for investors, as one commented: "They cannot meet our financial return requirement. They are satisfied with a slow development and a small profit."	Success: Low: The company would have required diversified technological knowledge and several competing development programs. As they did not have the capability to do so, they failed and were merged into the technical department of HH-NEC, one of the industrial investors.

based on the strategy rather than the success level (which lacked variance in the survey data), this finding should be interpreted as illustrative rather than confirmatory.

5. Discussion and Conclusion

Novel startup ventures are often not only risky but also face unforeseeable uncertainty (events that cannot possibly be foreseen at the outset) combined with complexity (multiple different, possibly interacting, influences). In this paper, we provide evidence that, under these circumstances, classic planning and risk management methods are not sufficient. The management team must enlarge its range of management methods and consider two additional approaches for the parts of the initiative that are vulnerable to unforeseeable uncertainty: (1) selectionist trials, running several parallel solution attempts, of which only one will be chosen at the end, and (2) trial-and-error learning, where the original plan is possibly completely abandoned and a new plan developed midcourse, as new information emerges. In previous literature, these two approaches have been discussed independently of each other, and the question arises under what circumstances which of the two approaches offers better outcomes.

The current article provides the first empirical comparison of the effectiveness of planning, selectionism, and learning under different environmental conditions in the form of complexity and unforeseeable uncertainty. In doing so, we operationalize constructs from the theory of search on rugged landscapes. The 58 Shanghai-based startup ventures in our sample apply combinations of selectionism and learning as responses to complexity and uncertainty. For example, one chemical company is a leader in polymers and nanotechnologies research and development (R&D) (Case 55 in Table 5(b)). It applies selectionism in the form of lead projects and backup projects: a lead group, with significant resources, pursues the most promising program. However, because of possible unforeseeable factors, an additional one or two smaller teams pursue (a priori less promising) competing programs, which "hedge" in case of weaknesses of the main program. Market feedback is the final yardstick of what program is pursued in the long run.

Other companies apply trial-and-error learning. For example, one medical diagnostics company (Case 15 in Table 5(b)) faces an unpredictably changing regulatory environment and changing practices by hospitals and individual customers. The company maintains close contacts with hospitals and regulatory agencies to actively seek information about emerging regulatory requirements and customer needs.

The data from these companies provide empirical support for the theoretical predictions (based on Sommer and Loch 2004). Our results suggest that, although detailed planning and risk management increase a startup's success significantly if it faces *neither high complexity nor high unforeseeable uncertainty*, a detailed plan is less critical if the startup enters very new terrain on the market or technology side, and faces high unforeseeable uncertainty. If *unforeseeable uncertainty is high, but complexity only moderate*, our results suggest that, in addition to making a detailed plan, the startup should focus on learning and identifying unknown factors, because only trial-and-error learning significantly impacts the startup's success.

Our data do not support the hypothesis that high complexity requires selectionism when unforeseeable uncertainty is low; rather, diligent planning seems to continue to drive venture success more effectively, even when complexity is high (but unknown unknowns low). Because this case had the smallest subsample, this result is the least reliable, and other explanations (such as a VC bias against selectionism) are not supported by the data either. More research is needed to examine the case of high complexity with low uncertainty.

The empirical results also provide an answer to the question of whether selectionism in which the parallel trials are continued all the way into the market (and thus, the feedback is true feedback that incorporates all unknown influences), or rather trial-and-error learning, fares better *under a combination of high complexity and high unforeseeable uncertainty* (the case where previous theory does not offer a differentiation). Selectionism with full market feedback significantly improves the success of the startups, whereas learning does not seem to do so. Although this conclusion needs to be confirmed using a larger data set and in different cultural settings, it does provide initial evidence that the benefits of selectionism might outweigh those of learning if market feedback on the final product is available.

This research has important implications for management. First, our results imply that management should ask two important sets of questions at the outset, when they set up a novel strategic initiative: (a) Does the organization have comprehensive knowledge about the venture's success factors, or are they emerging? In other words, are there significant knowledge gaps? Unforeseeable influences cannot, by definition, be analyzed beforehand, but their presence can be diagnosed (Loch et al. 2008). The parts of the initiative that are vulnerable to unforeseen influences should be managed separately from the rest of the initiative. (b) How high is the complexity? In other words, what is the number of important influence factors and how many are likely to interact and cause ripple effects among different decisions? Interactions make it hard for management to assess the full impact of its decisions.

Our results give the management team guidance as to what management approach to choose, planning, selectionism, and/or learning, depending on the presence of unforeseeable uncertainty and complexity. Previous evidence (e.g., Loch et al. 2008) suggests that the possible presence of unknown unknows can be diagnosed at the outset (although not the individual unk unk, by definition). Figure 4 summarizes the resulting choice as suggested by our statistical analysis. Making this choice explicit at the outset is important because management systems must be put in place in order to execute effectively. The appropriate management systems must differ depending on the chosen management approach (planning, selectionism, or learning), to identify the right decisions and to not unfairly punish or reward people for outcomes that are imposed on them by the circumstances.

Our results also highlight the tradeoffs that the venture management team faces in setting its innovation ambition: too much uncertainty and complexity is too hard to handle. There is a need to *choose* how many battles one dares to fight.

Figure 4 Summary of Managerial Implications

		Complexity: Low	Complexity: High
Unforeseeable uncertainty	High	**Learning** • Actively search for unk unks • Flexibility to fundamentally redefine business plan and venture model	**Selectionism** Selectionism effective *if* choice of best trial can be deferred until unk unks have emerged (true market response is known) *Success potential limited by difficulty of challenge*
	Low	**Planning** Plan, risk identification, and risk management	**Planning** • Plan, risk identification, and risk management • Selectionism? (inconclusive)

We have conducted this study with the entire startup company as the unit of analysis, and discussed selectionism and learning separately, as if they were always used as mutually exclusive alternatives. However, a sophisticated application of planning, selectionism, and learning can be done at the level of subprojects, or major areas of the startup (Loch et al. 2008), and moreover, selectionism and learning can (and often are) combined within the same startup project.[20] For example, the technology may be highly uncertain (unforeseeable in its performance) *and* complex, the market mature and foreseeable, and the regulatory environment fraught with unforeseeable uncertainty but not very complex. This would imply that the technology development area should use selectionism with late final selection after customer tests. The market approach, in contrast, should be done with a traditional disciplined planning approach, and regulatory management should be done flexibly with the ability to change the business plan to adjust to unexpected regulations.

The results from this relatively small sample will need replication based on a larger sample. Also, our study suffers from a survivor bias: the ventures that were willing to participate were all still alive; strictly speaking, our results imply lessons only for the use of selectionism and learning in *surviving* ventures. Although there is no reason to believe that the search dynamics in complex problems are different in ventures that fail, it might still be useful to attempt targeting managers of failed ventures (this is, of course, difficult because managers do not like to talk about their failures).

After a tentative support for the fundamental predictions from the theory in this first study, additional questions can be examined in future work. For example, what are the relative costs of selectionism and learning (which are not tracked by the companies) and benefits across different parts of the venture?

Although this study has focused on startup ventures, existing evidence suggests that the lessons of managing highly novel projects or new business developments carry over to established companies: many studies have found examples of selectionism and trial-and-error learning in established companies; indeed, several of the examples in our introduction come from large companies.

Our research has provided evidence that management teams who follow these guidelines are better able to create value from novel ventures. No management method can get around the fact that whenever an organization attempts a novel initiative, it is rolling dice. However, intelligently using selectionism and learning helps you to load the dice.

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Endnotes

[1]Schrader et al. (1993) refer to this as "ambiguity." We do not follow this terminology because its use is not consistent across literatures relevant to this paper. In the decision sciences, ambiguity refers to situations with known variables, but unknown probability distributions (Camerer and Weber 1992). The term "unforeseeable uncertainty" implies that some variables themselves are unknown. Economists refer to this concept as "unawareness" (Modica and Rustichini 1999, Dekel et al. 1998) or as "unforeseen contingencies" (Dekel et al. 2001).

[2]Selectionism is sometimes equated with "parallel trials" in the strict temporal sense that the trials happen at the same time. Temporal prallelism is not required, selectionism requires logical parallelism in the sense that in generating variety, the trials do not influence one another and are not influenced by new information midcourse, but that they are selected ex post only. The trials may well happen sequentially in time.

[3]Although learning takes place also under selectionism, trial-and-error learning proposes to actively search for unknown variables in order to bring about their discovery, as early as possible.

[4]Selectionism is often applied not to the entire venture, but to subproblems of the venture. For example, several novel system component candidates are pursued, or several customer segments, alternative channel structures, or multiple potential partners, the best of which is chosen after relative success has been observed.

[5]Wideman (1992); the term has been widely used in aerospace, electrical, and nuclear power project management.

[6]This simple example is, of course, unrealistic in the sense that experienced teams carry out tests at the customer site; this simple situation symbolizes realistic cases where the venture cannot anticipate, not to mention test, all possible problems.

[7]To give another example, a German internet startup "assumed" implicitly that German customers behave the same way as U.S. customers regarding price auctions. Performance in the "known" subspace thus reflects the performance they expect to achieve given U.S. customer behavior, although the true performance, given German customer behavior, might be different and much lower than the performance they thought they achieved.

[8]In fact, even with market tests, the unforeseeable uncertainty might not be completely resolved. Although market tests reveal the true performance of the different trials, they might not reveal the unk unks. In that case, the team would not be able to make minor adjustments at the end, and some selectionist trials would not land on a performance peak at all. We do not show this case in the theoretical discussion.

[9]A possible response bias seems uncorrelated with our variables. The responses showed that the respondents were not aware of a possible contingent effect of selectionism and learning on performance: companies facing high complexity did not use selectionism more extensively, nor did companies facing high unforeseeable uncertainty use a significantly higher extent of learning. This was confirmed by the follow-up interviews and by the lack of correlation between complexity and selectionism or unk unks and learning, as shown in Table 2.

[10]We verified in the follow-up interviews that this question was not misunderstood as risk management and identification of risk factors during the planning phase. Its lack of correlation

with planning (see Table 2, next section) also confirms that the respondents did understand the question as intended.

[11]For robustness, we also tested the sum of the three Likert items, which produced the same significance levels of the individual variables, but slightly lower F-test significance in Cells 2 and 3, possibly due to multicollinearity, which causes selectionism and learning, with their opposing influences, to cancel each other out (Duchan 1969). The maximum is highly correlated with the average (86%), but less correlated with learning, reducing multicollinearity. We also asked an alternative question: "You pursued several, mutually exclusive alternatives (technologies, products, customer segments, business model, etc.) and chose those that performed best." However, the follow-up interviews revealed that several respondents had misunderstood this question as pursuing alternative businesses within the company rather than applying selectionism to parts of the venture.

[12]The need to wait for the availability of reliable success measures makes a survivor bias unavoidable: managers from failed and discontinued startups are unwilling to participate (only one firm in our sample was in the process of closing down its operations).

[13]Ideally, one would exclude the middle third of the data, which is impractical here because of the restricted sample size; but the simple split should make our analysis more conservative rather than less reliable.

[14]We also tested whether the control variables explain the chosen management approach to exclude possible endogeneity effects. An endogeneity effect of firm size (driving both a larger degree of selectionism/learning and firm success) could be excluded. Only the dummy variable for biotech/pharma had a significant positive impact on the choice of selectionism, which is indicative of that industry's practice to run multiple trials. Adding this one variable to the split sample regression did not produce a significant impact on success for any of the clusters, nor did it affect the significance of the other variables.

[15]Running the model described in Equation (1) as a whole would, in all standard statistical packages, enforce the assumption that the variances are the same across the four cells. As this is not satisfied, running the overall model would introduce biases in the estimates and distort the significance levels.

[16]Although Likert questions usually violate the normality assumption of residuals required by t-tests, the robustness of the t-statistic ensures that this violation does not have an effect as long as the distribution is approximately mound shaped (Mendenhall et al. 1993, p. 369). For the entire sample, as well as for all cells but Cell 1 (low unforeseeable uncertainty and low complexity, which contains only eight data points), the residuals are mound shaped. Because the normality assumption can be problematic for small samples, we also performed a bootstrap analysis, which confirmed the results of the t-tests.

[17]The sample sizes in the lower cells are only eight and seven, respectively, which makes the OLS regression excessively sensitive to single outliers. To ensure robustness of the results, we applied a bootstrap analysis and a median regression (least absolute deviation estimator) and obtained virtually identical results in both cells. In addition, we examined scatter plots of the main relationships of interest (based on residual regressions), which allow identifying outliers, and found no grave outliers. These additional results give reasonable confidence that the results shown in the figure are robust. Details can be obtained from the authors upon request.

[18]Both the explanation that complexity was not high enough and that there was not enough variance in selectionism can be excluded from the sample.

[19]The variable *perfect tests* only makes sense in combination with selectionism and if unforeseeable uncertainty is high. (If all variables are known, prototype testing and market testing should provide the same results.) For completeness, we nevertheless tested the main effect of *perfect tests*, and it was not significant, while adding collinearity to the model.

[20]We did not find any evidence for the advantage of a combination of selectionism and learning in our sample. However, due to the small number of such combinations in our sample, this needs to be further examined.

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