A RESEARCH REPORT FROM SWEDISH INSTITUTE FOR FINANCIAL RESEARCH

Learning by Investing: Evidence from Venture Capital

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NO 53 — MAY 2007

Swedish Institute
for Financial Research

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Sveriges Riksbank funds a position as visiting professor at SIFR.

SIFR also gratefully acknowledges research grants received from Bankforskningsinstitutet, Föreningsbankens Forskningsstiftelse, Jan Wallanders och Tom Hedelius Stiftelse, Riksbankens Jubileumsfond, and Torsten och Ragnar Söderbergs stiftelser.

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April, 2007

Abstract: To understand the investment behavior of venture capital (VC) investors, this paper estimates a dynamic model of learning. Behavior reflecting both learning from past investments (exploitation) and anticipated future learning (exploration) are found to be prevalent, and the model's additional predictions about success rates and investment speeds are confirmed empirically. Learning is important, since it can create informational frictions, and it has potential implications for VCs' investments and organizations. VCs are found to internalize the value of learning, and this may help promote exploration beyond the levels sustained in standard capital markets, which is socially valuable.

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Given their importance for financing high-tech start-ups, venture capitalists (VCs) have substantial impact on innovation and development of new technologies. While a great deal has been written about the relationship between VCs and their portfolio companies,[1] less is known about VCs' decisions to invest in particular companies.[2] An important determinant of investment decisions is the information VCs gain about new technologies and investment opportunities, and this "learning" provides a natural starting point for understanding their investment behavior. This paper presents and estimates a dynamic model of investor learning based on the multi-armed bandit model. In this model investors balance the benefit of exploring new investments to learn about their returns against the opportunity cost of investments with more certain immediate returns, and the model is estimated with data for VCs' investments in U.S. entrepreneurial companies. The results show that VCs both invest in companies where they expect high immediate returns and make explorative investments in companies with lower immediate returns, but where the information gained helps guide future investments. The model generates additional predictions, and these are confirmed empirically. More profitable investments, as measured by the model, are made faster, and VCs that explore more have higher success rates. These findings provide additional supporting evidence for the model. Overall, the primary contribution is to document the presence of learning. The hypothesis that VCs' investments are chosen independently to maximize the return from each

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[1] See, for example, Gorman and Sahlman (1989), Sahlman (1990), Lerner (1995), Gompers and Lerner (1999), Hellmann and Puri (2000), Hellmann and Puri (2002), Kaplan and Strömberg (2004), and Hochberg, Ljungqvist and Lu (2006).
[2] Notable exceptions are Kaplan and Strömberg (2004) and Gompers, Kovner, Lerner and Scharfstein (2005).

individual investment, as assumed in standard models of capital markets, is clearly rejected. An additional contribution is methodological. To demonstrate the presence of learning, the paper develops a novel identification result for the dynamic learning model. This result relies on a statistical *index result* and demonstrates how to empirically distinguish behavior reflecting learning from past experience (exploitation) from behavior reflecting anticipated future learning (exploration). The index result also simplifies the estimation of the model and provides a more transparent empirical approach, which may also be applicable to other situations with learning.

Learning is important since it can create informational frictions. For example, when learning is costly and investors observe signals generated by other investors, a free-riding problem arises (see Bolton and Harris (1999) and Keller, Rady and Cripps (2005)). This problem arises when VCs have an incentive to reduce their own investments in learning, knowing they can free-ride on the information created by other investors, and this may reduce the overall exploration and learning in equilibrium. Learning may also lead to an informational cascading problem.[3] When other VCs' actions are observable, each VC's decision depends both on the privately learned signals and the other investors' publicly observable actions. When the other investors' actions are more informative relative to a VC's private signal, each VC's own action will depend more heavily on the publicly observed actions and less on the investor's own private signal. Hence, less new information is incorporated into the actions and they become less informative, leading to

[3] Devenow and Welch (1996) and in particular Hirshleifer and Teoh (2003) present excellent overviews of the extensive literature about informational herding. More recently, Amador and Weill (2006) present an explicit model of the problem of slowing learning with public and private signals as described here.

less informed decisions. In the limit, when investors base their decisions entirely on publicly observable actions, no new information is incorporated into these actions, and learning stops entirely. Focusing on the period 1995-2000, Goldfarb, Kirsch and Miller (2007) present indirect evidence of such an informational cascade for VC investors.

Both of these frictions reduce the equilibrium level of exploration and learning, and both frictions arise from informational spillovers in markets with learning. However, VC firms are organized as limited partnerships, investing in privately held companies, and being very reluctant to disclose information about their current investments and performance. This reduces informational spillovers, and it may allow VCs to internalize the value of learning, potentially promoting overall exploration and learning beyond the levels that would be sustained in a more transparent capital market. Promoting learning is socially valuable, and it may present an additional source of value created by VCs. Their ability to internalize the value of learning also suggests that VCs are particularly suited for investing in companies with greater potential for learning, such as high-tech companies developing new technologies or new business ideas. Consistent with this, Kortum and Lerner (2000) find that VCs account for as much as 8 to 14% of all U.S. innovative activity.

The empirical learning model is based on the multi-armed bandit model. This model dates back to Robbins (1952), and the name refers to a gambler facing a number of slot machines (one-armed bandits). The gambler is uncertain about the distributions of payouts from these machines, but learns about these distributions while playing. The gambler is concerned about finding the optimal gambling strategy, but the return from each gamble is two-fold. The gambler receives both the immediate payoff of each gamble and an option value of learning, since more information helps improve future gambles. The optimal strategy trades off *exploiting* machines with known payoffs and *exploring* machines with less certain payoffs but a higher value of information.[4] In the words of Berry and Fristedt (1985), "it may be wise to sacrifice some potential early payoff for the prospect of gaining information that will allow for more informed choices later."

Bergemann and Valimaki (2006) present a brief survey of the literature about bandit models. In the theoretical literature, Rothschild (1974) uses the bandit model to model firms' experimentation with prices to learn about uncertain demand. Weitzman (1979) analyzes a model of the optimal sequencing of research projects. In venture capital Bergemann and Hege (1998) and Bergemann and Hege (2005) present models of staged financing based on the bandit model. They address the question of how and for how long a VC should finance an entrepreneur given the potential for learning about the quality of the project. Empirically, Jovanovic (1979) and Miller (1984) estimate bandit models of job turnover in which workers learn about job specific skills. Erdem and Keane (1996), Crawford and Shum (2005) and Hitsch (2006) estimate models of firms' experimentation with prices and products to learn about uncertain demand.[5] Their empirical approaches are based on numerically intensive estimation procedures to solve the dynamic programming problem inherent in the learning model. In contrast, the empirical method

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[4] The terms *exploration* and *exploitation* are introduced by March (1991) in the context of organizational learning.

[5] Starting from Arrow (1962) there is also a substantial literature about learning by doing. In this literature learning is a costless byproduct of an activity and the trade-off between exploration and exploitation does not arise. Recent finance studies of learning-by-doing include Linnainmaa (2006) and Pastor, Taylor and Veronesi (2006).

presented below is numerically simple and transparent, while maintaining the essential features of the problem.

To keep the analysis tractable, it is based on a simple learning model, which presents a somewhat simplified view of VCs' investments. The formal model assumes a stationary environment where investors only learn from their own past investments, projects arrive exogenously, and learning happens immediately. These assumptions are stylized but necessary for the theoretical derivations, and the empirical analysis includes additional controls to assess the robustness of the results. More generally, empirical analyses of entrepreneurial companies face data limitations. These companies, by definition, have short operating and financial histories and little information is systematically observed about them. This means that classifications of companies and investment outcomes are necessarily crude, although common in the literature.

The paper proceeds as follows. The following section presents the theoretical learning model and the important index result. The second section presents the data and the construction of the variables. Section three discusses the econometric implementation of the model, the statistical identification, and the choice of prior beliefs. Section four presents the empirical evidence of learning, and the final section concludes.

I. The Multi-Armed Bandit Model

The learning model presented here is a bandit model with an infinite horizon, geometric discounting, and independent Bernoulli arms.[6] Each period a VC invests in one company in a given industry. The VC is uncertain about the probability of a successful investment in the different industries, but has beliefs about those probabilities. The opportunity cost of investing in a project in a new and uncertain industry is that it prevents an investment in an industry with a more certain return. The outcome of each investment is either success or failure, it is immediately observed, and the VC's beliefs are updated accordingly, using Bayes' rule.

Before going through the formal model, two particular features warrant separate discussions. First, the model captures several kinds of learning. The investor may learn about a specific ability to pick more successful companies and add value in individual industries, or the investor may learn about industry conditions more generally. At the industry level, learning may give rise to informational cascading problems, as discussed by Goldfarb, Kirsch and Miller (2007). At a finer level, investors may learn about individual entrepreneurs or technologies within each industry. The investor may then invest in a company developing a particular technology or introducing a new business idea in a particular market segment. If the company is successful, the investor learns about the viability of other applications of this technology or idea for future investments. At this level, learning is closely related to innovation and technological progress in the

[6] See Whittle (1982), Berry and Fristedt (1985), and Gittins (1989) for general discussions of this model.

spirit of Arrow (1969)'s statement that "[t]echnological progress is in the first instance the reduction in uncertainty." Promoting exploration and learning is then equivalent to promoting innovation and technological progress, and at this finer level the free-rider problem may be a more important informational friction. The empirical analysis does not separate learning at the aggregate industry level from learning at finer levels, due to data and tractability issues, which are described below. The analysis is conducted at the industry level, but the results are consistent with learning taking place at finer levels as well. At all levels, learning has implications for the market for entrepreneurial finance, but separating and characterizing learning at various levels is left for future research.

A further assumption is that the investor learns the outcome of an investment and updates the beliefs before making any subsequent investments. In the data, investments are made 48 days apart, on average, and while the assumption that all learning takes place within this period may not be entirely realistic, it is necessary for the theoretical model. In reality, investors learn gradually over the life of a project (see Bergemann and Hege (1998), Bergemann and Hege (2005), and Pastor, Taylor and Veronesi (2006)). Hence, final outcomes are always somewhat anticipated, and the alternative assumption that all the learning takes place at the time of the exit is equally stark. Empirically, the uncertainty about the timing of learning simply introduces noise in the estimates of the investors' beliefs. This noise should make the empirical analysis less likely to find evidence of learning and it leads to perhaps more conservative estimates of the extent of learning in the market.

A. The Formal Model

Each investor faces an infinite sequence of periods, t = 0, 1, … . At each time t, the investor chooses between K arms where each arm represents an industry, denoted i = 1, 2, … , K. An investment in industry i, at time t, is either successful or not, as represented by the random variable $y_i(t) \in \{0,1\}$. The true success probability is denoted $p_i = \Pr[y_i(t) = 1]$. It is constant over time but may vary across arms and investors. The investor is uncertain about p_i but has prior beliefs given by $F_i(0)$. These beliefs are updated after each investment, and the updated beliefs before investing at time t are $F_i(t)$. These updated beliefs depend on the prior beliefs and the entire history of investments and outcomes up to time t. Naturally, the support of the distributions $F_i(0)$ and $F_i(t)$ is the interval from 0 to 1, representing all possible values of p_i.

The investor's strategy specifies the current investment decision as a function of the investment history. At time t the strategy is $s(t):\{1,...,K\}^t \times \{0,1\}^t \rightarrow \{1,...,K\}$, the full strategy is $S = \left\{s(0), s(1), s(2),...\right\}$, and the investor's problem is to choose the strategy that maximizes the total expected return. When δ is the discount rate, the investor's problem can be stated as follows

$$V = \sup_{S} E\left[\sum_{t=0}^{\infty} \delta^t y_{s(t)}(t) \middle| F(0)\right]. \tag{1}$$

Equivalently, the problem can be viewed as a dynamic programming problem, represented by the Bellman equation

$$V\left(F(t)\right) = \max_{s(t)=1,2,\ldots,K} E[y_{s(t)}(t) \mid F(t)] + \delta E[V(F(t+1)) \mid F(t), s(t)] . \tag{2}$$

In this formulation, the state space contains the beliefs about success probabilities in different industries, and these beliefs develop according to the transition rules

$$F_i(t+1) = F_i(t) \; for \;\; s(t) \neq i \tag{3}$$

$$F_i(t+1)(v) = \begin{cases} \dfrac{\int_0^v u f_i(t)(u)du}{\int_0^1 u f_i(t)(u)du} & for \;\; s(t) = i \;\; and \;\; y_i(t) = 1 \\ \dfrac{\int_0^v (1-u) f_i(t)(u)du}{\int_0^1 (1-u) f_i(t)(u)du} & for \;\; s(t) = i \;\; and \;\; y_i(t) = 0 \end{cases} \tag{4}$$

Equation (3) states that the beliefs are unchanged unless an investment is made in an industry, and equation (4) reflects Bayesian updating of the beliefs about p_i after investing in industry *i* and observing either $y_i(t) = 1$ (success) or $y_i(t) = 0$ (failure).

The Bellman formulation illustrates the fundamental trade-off in this model. The first term in equation (2) is the investor's expected immediate return from investing in industry *s*(*t*), and the second term is the continuation value. Without learning, the continuation value would be independent of the current investment, and the optimal investment would simply be the one with the highest expected immediate return. With learning, the information gained from the current investment affects future investments, and the continuation value depends on this information. The continuation value increases for more informative investments, and this creates an additional option value of learning.

B. The Gittins Index

Gittins and Jones (1974) solve a general version of the investor's problem, and formulate the solution in terms of the *Gittins index*. This index can be calculated from the history of investments in each industry separately, and the investor's optimal strategy is to invest in the industry with the highest value of the index. In other words, if $v_i(t)$ is the Gittins index for industry *i*, at time *t*, the *index result* states that the optimal strategy is

$$s(t) = \arg\max_{i=1,\ldots,K} v_i(t)\,. \tag{5}$$

To calculate the index, let τ denote a stopping time for investing in just industry *i*, and Gittins (1979) derives the following expression for the index

$$v_i(t) = \sup_{\tau} \left\{ \frac{E\left[\sum_{s=t}^{\tau} \delta^s y_i(s) \,|\, F_i(t) \right]}{E\left[\sum_{s=t}^{\tau} \delta^s \,|\, F_i(t) \right]} \right\}, \tag{6}$$

where the supremum is taken over stopping times. Solving for the optimal stopping time involves solving a dynamic programming problem, but this problem is more tractable, since it is solved for each arm independently, and the state space contains only the beliefs for this particular arm.

Still, there is no known closed form solution for the index. Gittins and Jones (1979) derive an illustrative approximation for the case where $\delta = 0.75$ and the prior beliefs are Beta distributed.[7] While the Beta distribution is not required for the general index result, it is important for keeping the analysis tractable and is maintained below. With Beta distributed priors, Bayes' rule implies that the updated beliefs are distributed $Beta(a_i, b_i)$ where $a_i \equiv a_{i,0} + r_i$ and $b_i \equiv b_{i,0} + n_i - r_i$. Here, r_i is the number of past successes, and n_i is the total number of past investments in industry *i*. As a_i and b_i increase, the mass of this distribution becomes concentrated at the empirical success rate, given by $\lambda_i \equiv a_i / (a_i + b_i)$, which equals the mean of the $Beta(a_i, b_i)$ distribution. For this case Gittins and Jones (1979) approximate the Gittins index as

$$v(a_i, b_i) \approx \lambda_i + \frac{1}{A(\lambda_i) + B(\lambda_i)(a_i + b_i)}, \tag{7}$$

where $A(\lambda_i)$ and $B(\lambda_i)$ are non-negative tabulated functions.

This approximation provides some insight into the determinants of the option value of learning. The total value of an investment is the value of the Gittins index. In equation (7), the first term in the expression for the index is λ_i, which is the expected immediate return, since, with a binary outcome and the value of success normalized to one, $E[y_i \mid F_i(t)] =$ $\Pr[y_i = 1 \mid F_i(t)] =$ $E[p_i \mid F_i(t)] = \lambda_i$. Clearly, the value the investment is at least this large. The second term is the value of the investment in excess of the immediate return, and this represents the option value of learning. This fraction is always

[7] The *Beta*(*a*,*b*) distribution has density $f(s) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} s^{a-1}(1-s)^{b-1}$ for $a > 0$ and $b > 0$, and its mean is $a/(a+b)$.

positive, and the term ($a_i + b_i$) in the denominator equals $a_{0,i} + b_{0,i} + n_i$. This means that, given λ_i, the option value tends to zero as n_i increases. Intuitively, when the number of investments increases, the beliefs become more informed and concentrated around λ_i, which approaches the true p_i, and the option value of learning vanishes.

C. Discussion of Prior Beliefs, the Index Result, and the State Space

The assumption of Beta distributed priors together with the index result make the state space more tractable and greatly simplify the problem. In principle, the bandit model is a dynamic programming problem, and it could be solved by standard methods, such as iterating the value or policy function (see Judd (1998)). However, these methods are only numerically feasible for problems with fairly small state spaces, and the representation of the investor's beliefs requires a large space.

The benefit of the Beta distribution is that it is closed under Bayesian updating. With Beta distributed prior beliefs and Bernoulli outcomes (a *conjugate pair*), the updated beliefs are also Beta distributed and are fully characterized by the two parameters of this distribution. In contrast, if the prior beliefs could follow any arbitrary distribution, the updated beliefs would also be arbitrary, and the state space would be correspondingly high-dimensional to represent this distribution (in principle, infinite-dimensional). Hence, with six industries, the Beta distribution leads to a twelve-dimensional state space, which is still numerically challenging.

The benefit of the index result is that it separates the dynamic programming problem into separate problems for each industry. Calculating the Gittins index requires solving the problem in equation (6), which is a dynamic programming problem with just a two-dimensional state space, which is quite tractable. For the empirical analysis, this problem is solved for each industry, at the time of each investment, and the resulting Gittins index is used to calculate the option value of learning for each of the investors' potential investments.

The advantages of this empirical approach is that it is simpler and the estimation and identification are more transparent relative to previous empirical studies of learning and experimentation (i.e. Crawford and Shum (2005), Erdem and Keane (1996), and Hitsch (2006)). The approach explicitly separates learning about the immediate return (exploitation) from the value of anticipated future learning (exploration). Further, as shown below, when the outcome of each investment is observed, these two kinds of learning are separately identified, and the model can also recover the investors' prior beliefs. This identification result has not been previously established. In fact, Heckman (1991) shows that when only durations between changes in "arms" are observed (as is common when studying, for example, job-turnover), the model is unidentified and is unable to separate learning from individual heterogeneity. As argued below, when such duration data are supplemented with information about the outcomes of the individual experiments, as is the case here, this identification problem disappears.

One limitation is that the empirical approach relies on the index result, and the index result only formally holds for a narrow class of learning models, which excludes, for example, switching costs (see Banks and Sundaram (1994)) and that the outcome of one arm is informative about the distribution of outcomes of other arms (however, see

Nash (1980)). Still, Duff and Barto (1997) argue that the strategy given by the index result for the Gittins index approximates the optimal strategy for more general Markov decision processes with learning. This should mitigate some concerns about minor misspecification of the model in the presence of switching costs or learning across arms, and it potentially opens for wider applications of this empirical approach.

II. Data Description

A. Sample

The data are provided by Sand Hill Econometrics (SHE) and contain the majority of VC investments in the U.S. in the period 1987 to 2005.[8] SHE combines and extends two commercially available databases, Venture Xpert (formerly Venture Economics) and VentureOne. These two databases are extensively used in the VC literature (i.e. Kaplan and Schoar (2005) and Lerner (1995)), and Gompers and Lerner (1999) and Kaplan, Sensoy and Strömberg (2002) investigate the completeness of the Venture Xpert data and find that they contain most VC investments and that missing investments tend to be the less significant ones.

The sample is constructed as follows. First, the data are restricted to investments made before 2000, since it typically takes VC financed companies three to five years

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[8] It may be a concern that only few companies go public after 2000. For robustness, the model is estimated restricting the sample to end in 2000, 1998, 1996, 1994, and 1992. The main results are robust across these sub periods. The signs and economic magnitudes of the main coefficients (unreported) are largely unchanged, and although the statistical significance is reduced with the smaller sample size, the main coefficients remain statistically significant.

after the initial investment to go public or be acquired, and the information about these outcomes is current as of 2005. It is common for multiple VCs to invest in the same company, and the sample contains these multiple investments by different VCs. Also, VCs typically stage their investments over multiple rounds, but the sample is restricted to each VC's initial investment in a company, since the analysis focuses on learning from individual companies and the effect on subsequent investments in other companies. It would be interesting to refine the analysis to learning at the level of individual rounds, but the need to introduce round level outcome measures would complicate this analysis. Further, VCs that make less than 40 investments in the full sample are excluded, since their short investment histories make it difficult to draw inference about their learning and create convergence problems for the estimation procedure. This reduces the sample from 3,364 to 216 VCs and eliminates 50% of the companies. Not surprisingly, the remaining investors have higher success rates than the eliminated investors. The average success rate for the investors in the final sample is 50%, and the corresponding rate for the eliminated investors is only 39%. The final sample contains 19,166 investments in 6,076 companies by 216 VC firms.

The restriction of the sample to investors making more than 40 investments raises concerns about survivorship bias; however, this is less of a concern when studying learning than for studies of risk and return. When studying risk and return, the problem arises when funds with low returns stop operating or reporting, and funds with larger (typically also more volatile) returns will then be overrepresented in the data, biasing the estimates. This bias does not arise for inference about learning. As explained below, inference about learning is derived from the particular way past investments and their outcomes relate to future investment decisions, and not from more volatile or profitable investments *per se*. If a fund makes random investments and happens to be successful and survive, the investment history will not reflect learning in a mechanical way. When investments are truly random, the estimates of learning are statistically insignificant, regardless of the volatility or relative success of these investments, and the selection of the sample does not cause learning to be statistically significant in a mechanical way. Still, another type of bias arises if the investors left in the sample learn more or differently than the excluded investors. The evidence below shows that investors that explore and learn more also have higher success rates, and if these investors also make more investments, this suggests that sample contains investors that learn more than the average VC investor. In this case, the results should be interpreted as providing evidence of learning for this particular group of investors.

B. Variables

The primary observed variables are the sequence of VCs' investments, their outcomes, and the industry classifications of the companies. These variables are used to construct each VC's investment and learning history, and summary statistics are provided in table I.

**** TABLE I ABOUT HERE ****

Each company is classified as belonging to one of six industries. These are "health / biotechnology," "communications / media," "computer hardware / electronics," "software," "consumer / retail," and "other." The corresponding indicator variables are

Health, *Communications*, *Computers*, *Software*, *Consumer*, and *Other*.[9] The distribution of companies across these industries is presented in panels A and D of table I, and these six major industry classifications are aggregated from 25 minor classifications. This aggregation is necessary to get sufficiently long investment histories within each industry but is necessarily somewhat arbitrary. The intention is to classify companies into industries where experience in one industry in informative about subsequent investments in this industry but not across industries, as assumed in the bandit model.

For each investment, the outcome is given by the binary variable *Success*, and for each investor the variable *Success Rate* measures the performance as the number of past successful investments divided by the total number of past investments. Each investment is classified as successful when the company eventually goes public or is acquired. This classification is consistent with VCs generating most of their returns from a few successful investments, but the measure is obviously a coarse outcome measure. Ideally, success should be measured in dollars or as a percentage return, but these numbers are not generally available in VC data, and the coarser measure is common in the literature. One concern is that companies that are acquired as part of their liquidation are classified as successful investments. To address this concern, Gompers and Lerner (2000) compare different success measures, including counting acquisitions as unsuccessful, and find all of these to be highly correlated. The results here are also largely unchanged when

[9] Since learning may be less pronounced for investments in the “other” category, the model is also estimated while excluding companies in this category. The empirical results (unreported) are unchanged.

classifying acquisitions as unsuccessful investments. In table I, panel B, the average success rate equals 50.3%, ranging from 13.3 to 86.4%.

At the time of each investment, each company is classified as either an early-stage or a late-stage company, where late-stage corresponds to the company having regular revenues. The binary variable *Stage* equals one for late-stage companies, and 28.7% of the investments in the sample are in late-stage companies.

In addition to learning from their own investments, investors may also learn from general public signals and market trends across industries. Although this learning is difficult to formally incorporate in the model, two variables are included to control for these effects. The variable *Industry Investments* contains the total number of VC investments in each industry in each year. It varies from 36 investments in “other” in 1994 to 3,443 investments in “computer hardware / electronics” in 2000, and this variable summarizes broad underlying changes that affect the relative attractiveness of individual industries as reflected in the VCs’ overall concurrent investment patterns. Following Gompers, Kovner, Lerner and Scharfstein (2005), the variable *Industry IPOs* contains the number of VC-backed companies going public in each industry during each year. Industries with more IPOs may represent more profitable investment opportunities, and VCs may be attracted to these opportunities. Gompers, Kovner, Lerner and Scharfstein (2005) find that this variable is an important determinant of VCs’ investments, and the results here confirm this finding.

C. Option Value and Expected Immediate Return

For each investor, at the time of each investment, the expected immediate return and the option value of learning are calculated for each of the industries. Note that these variables depend on the updated beliefs about p_i, but not on its true value, and p_i is not assumed to be constant across investors or industries.

Before calculating the updated beliefs, it is necessary to specify the investors' prior beliefs. These beliefs are taken to be distributed $Beta(a_{i,0}, b_{i,0})$, with $a_{i,0} = 1$ and $b_{i,0} = 19$. This distribution can be interpreted as each investor having previously experienced one success and 19 failures. The particular choice of a_0 and b_0 is discussed in detail below, and the updated beliefs are calculated as follows. For investor j, let $r_{i,j}$ be the number of past successful investment and $n_{i,j}$ be the total number of investments in industry i. These are counted directly in the data. Now, define $a_{i,j} \equiv a_{i,0} + r_{i,j}$ and $b_{i,j} \equiv b_{i,0} + n_{i,j} - r_{i,j}$, and it follows from Bayes' rule that the updated beliefs are distributed $Beta(a_{i,j}, b_{i,j})$.

For each investment, the immediate expected return and the option value of learning are calculated. The immediate expected return is $\lambda_{i,j,t} = a_{i,j,t} / (a_{i,j,t} + b_{i,j,t})$. In table I, panel C, this rate is observed to equal 26.0% on average, varying between 3.2 and 71.7%. For the option value, the discount factor is $\delta = 0.99$, and since the average time between investments is 48 days, this discount factor corresponds to an annual discount rate of 8%. The results are robust to using discount factors $\delta = 0.75$ or $\delta = 0.95$, corresponding to discount rates of 783% and 47%. Of these three choices, $\delta = 0.99$ leads to the smallest coefficient on option value, and it may be considered a conservative choice. The option values are then calculated using a numerical algorithm from Gittins (1989).[10] In table I, the calculated *Option Value* equals 6.2% on average, ranging from 1.9 to 8.2%. As a fraction of the total value of each investment, the option value varies from 3.1 to 53.1% with an average of 25.2%.

III. Specification and Identification of Empirical Model

In the empirical model the investment decision is modeled using a multinomial discrete choice model. The value of an investment in industry *i*, by investor *j*, at time *t*, is specified as

$$v_{i,j,t} = \lambda_{i,j,t}\beta_1 + Option\ Value_{i,j,t}\beta_2 + X'_{i,j,t}\beta_3 + \varepsilon_{i,j,t}\,. \qquad (8)$$

Here $v_{i,j,t}$ is the total value of the investment, $\lambda_{i,j,t}$ is the immediate expected return, and $Option\ Value_{i,j,t}$ is the option value, calculated from the investment history as described above. The variable $X_{i,j,t}$ contains additional controls, and the idiosyncratic shock, given by $\varepsilon_{i,j,t}$, captures investor and investment specific shocks. The investor invests in the industry with the highest value of $v_{i,j,t}$, and the probability that investor *j*, given investment history $hist_j$, invests in industry *i* is denoted $\pi_i(hist_j)$. When $\varepsilon_{i,j,t}$ follows an

[10] A MatLab program for calculation of the index is available from the author.

i.i.d. extreme value distribution, the model is equivalent to the Multinomial Logit model (see McFadden (1973) and McFadden (1974)), and it is well known that

$$\pi_i(hist_j) = \frac{\exp(v_{i,j,t})}{\sum_{i'=1,...K} \exp(v_{i',j,t})}. \tag{9}$$

The likelihood function is the product of these probabilities, and β is estimated directly using maximum likelihood. Note that in this model the scale of the coefficients is not identified, and the coefficients are normalized by fixing the variance of the error term. However, the relative magnitudes of the coefficients are identified.

The coefficient β_1 captures investors' tendency to *exploit*. The model predicts that this coefficient is positive and significant, and a high value of β_1 means that investors are more likely to invest in industries with higher expected immediate returns (i.e. higher λ). The coefficient β_2 captures investors' tendency to *explore*, and the model also predicts that this coefficient is positive. A higher value of β_2 indicates that investors place more weight on the value of information and engage in more explorative behavior. Finally, the learning model predicts that $\beta_1 = \beta_2$, since the expected immediate returns and the value of learning weigh equally in the investors' preferences. Below, this restriction is used to recover the investors' prior beliefs, but first the statistical identification of the model is discussed.

A. Identification of Exploitation and Exploration

With sufficient data, $\pi_i(hist)$ is known for all investment histories, and the identification of explorative and exploitative learning follows from changes in this probability for different investment histories. Consider the three cases of (1) no learning, (2) only exploitative learning, and (3) both exploitative and explorative learning.

Without any learning, an investor's current investment decisions are independent of the past investment history, i.e. $\pi_i(hist) = \pi_i$ for some constants π_i. In this case, the estimated coefficients β_1 and β_2 are not statistically different from zero, and differences in π_i across the industries are captured by industry fixed effects.

With pure exploitative learning, the investment decisions depend only on λ, and not on the option value of learning, i.e. $\pi_i(hist) = \pi_i(\lambda)$ for some function $\pi_i(\lambda)$. This case arises when investors are unable to internalize the future value of learning, and their investments are determined entirely by the immediate returns. In contrast to the case without learning, an investor with successful past investments in an industry is more likely to continue investing in this industry, and the estimate of β_1 is statistically greater than zero. However, the investment decisions are independent of the lengths of the investment histories, and the investor disregards the corresponding difference in the precision of the beliefs and option values of learning. For example, an investor who has made two previous investments in industry *i*, with one being successful, and fifty previous investments in industry *j*, with twenty five successes will be equally likely to invest in these two industries again, since $\lambda_i = \lambda_j = \frac{1}{2}$.

Finally, with both exploitative and explorative learning, for a given λ, investors prefer investments in industries with shorter histories. Consider again an investor with two and fifty past investments in industry *i* and *j*. When $\lambda_i = \lambda_j = 1/2$, an investor who internalizes the value of future learning prefers to invest in the industry with the shorter history, since this industry presents a greater value of learning. For the investor to be indifferent between the industries, the industry with a smaller λ must also have a shorter history, so the additional value of learning compensates for the smaller immediate return. In contrast to the case with pure exploitative learning, the investor is indifferent between an industry with a greater value of λ and a correspondingly longer investment history compared to an industry with a smaller value of λ and a shorter history. In this case, the estimate of β_2 is also statistically greater than zero.

It follows from this argument that to identify exploitative and explorative learning from the observed investment behavior, the model implicitly compares the probabilities of investing in industries with similar magnitudes of λ but with different lengths of the past investment histories. The need to compare each investor's investment decisions across industries with longer and shorter histories means that a fairly long overall investment history is required to make reliable inference about learning. Hence, it is necessary to exclude investors making less than forty investments from the final sample, and it is difficult to refine the analysis to learning with finer industry classifications without more data, since finer classifications means that the histories for each of the individual industries will be relatively shorter.

B. Choice of Prior Beliefs

The identification argument presented above shows that it is possible to separate behavior reflecting exploitative and explorative learning, taking the investors' prior beliefs as given. These prior beliefs are unknown, and they are assumed to follow Beta distributions, parameterized by a_0 and b_0. This distribution is more dispersed and less informed when a_0 and b_0 are smaller. When beliefs are more dispersed, the value of learning is greater, and this creates an inverse relationship between the two parameters and the value of learning.

The prior beliefs can be estimated separately, exploiting a restriction from the learning model. In principle, it is possible to impose this restriction and estimate the parameters jointly with the rest of the model, for example using maximum likelihood estimation; however, it would then be necessary to recalculate the option value repeatedly as part of the estimation procedure, which is numerically difficult. The bandit model generates the restriction that investors place equal weight on λ and *Option Value*, i.e. $\beta_1 = \beta_2$. To impose this restriction, the model in equation (8) is estimated for different choices of a_0 and b_0, and the hypothesis $\beta_1 = \beta_2$ is then tested. The prior beliefs are determined by the smallest values of a_0 and b_0 for which the hypothesis is not rejected.

**** TABLE II ABOUT HERE ****

Table II contains estimates of the model with a_0 = 1 and b_0 varying from 17 to 20. Each row contains estimates of β_1 and β_2, estimated with and without industry fixed effects, and the table also reports the *p*-values for a χ^2 test of the hypothesis $\beta_1 = \beta_2$. It is observed that β_1 is largely constant across the specifications, and b_0 and β_2 are positively related, as expected. Intuitively, given the investment history, a larger value of b_0 makes the initial beliefs more informed and the value of learning declines. Equation (8) must then load more heavily on the option value to explain the history and β_2 increases correspondingly. With industry fixed effects, the hypothesis $\beta_1 = \beta_2$ is not rejected for b_0 equal to 19 and 20. Without industry fixed effects, the hypothesis is not rejected for b_0 equal to 18 or 19. Taken together, a reasonable estimate of the prior beliefs is $a_0 = 1$ and $b_0 = 19$, and these beliefs are maintained below.[11] It is important to note that this procedure does not mechanically make β_1 or β_2 positive or statistically significant. The parameters a_0 and b_0 are chosen to make these two coefficients equal, but they may well be equal at a statistically small or even negative value. In fact, if the investment decisions were not explorative, they would not depend on the option value, β_2 would not vary with the beliefs, and it would not be possible to make the two coefficients equal for any choice of prior beliefs. In this sense, the test of the hypothesis $\beta_1 = \beta_2$ provides a general test of the overall fit of the model, and the model is not rejected.

The prior beliefs imply that the initial value of $\lambda_{i,j,t}$ equals $1/20$ or 5%. This is low compared to the empirical success rate, but it is necessary to capture the persistence in the investments. The specification of $\lambda_{i,j,t}$ reflects the investors' beliefs about the success rate in untried industries. In reality, VCs probably believe that they are

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[11] For the choice of prior to be as uninformative as possible, either a_0 or b_0 must equal 1. The specifications reported in table II have $a_0 = 1$. In unreported estimates of specifications where $b_0 = 1$ and a_0 varies, the two coefficients are not found to be statistically equal.

particularly skilled investors in certain industries and focus their investments here. The initial expected success rate would then be larger for these industries, and to capture this difference in initial beliefs the model is also estimated using each investor's ten initial investments to "burn-in" their beliefs, without including them in the further estimation. This leaves the results (unreported) largely unchanged, although the statistical significance decreases somewhat due to the discarded observations. The model is also estimated with industry fixed effects to capture differences in beliefs across industries. Finally, note that it is natural for λ to be below the empirical rate, even with perfectly rational expectations. The realized rate is calculated from the actual investments, and these are made in the industries where the investors expect the highest returns. In contrast, λ is the expected success rate across all industries, including those industries where the investor does not invest. In other words, if λ were equal to the empirical success rate, the option values of new untried industries would lead the investors to shift to those industries after investing in any industry and realizing the empirical success rate. With this specification, the model would be unable to explain the persistence in their investments.

IV. Empirical Results

Estimates of five different specifications of equation (8) are reported in table III. The first specification is the baseline specification from table II. Across all specifications the coefficients on both $\lambda_{i,j,t}$ and $\textit{Option Value}_{i,j,t}$ are positive and significant. Not surprisingly, investors *exploit* and prefer industries with a higher expected immediate return (i.e. $\beta_1 > 0$), but investors also *explore* and invest in industries with a greater value of learning (i.e. $\beta_2 > 0$).

**** TABLE III ABOUT HERE ****

The additional specifications control for other factors that may affect investment decisions. Although not part of the formal model, investors may learn from other investors and from public market signals. Specifications 2 and 3 include additional controls for the total number of VC-backed IPOs and total number of VC investments during each year in each of the six industries. These general trends appear to have small but positive and significant effects on investment decisions, and this is consistent with Gompers, Kovner, Lerner and Scharfstein (2005) who document that investors follow public market signals. However, including these additional controls does not eliminate the effects of $\lambda_{i,j,t}$ and $\textit{Option Value}_{i,j,t}$, and after controlling for the general trends in the market, the investors still internalize the value of learning from their own investments, as specified by the learning model.

Specification 4 includes the investors' experience in individual industries (*Industry Experience*), calculated as the total number of past investments the VC has made in each industry. This captures other factors, besides learning, that may lead VCs to focus their investments in industries where they have longer investment histories and more experience. One may imagine VCs "entrenching" themselves in an industry, perhaps to enjoy wider access to the deal flow, regardless of the outcomes of their past investments. Alternatively, since industry experience is inversely correlated with option value (a greater experience leaves less scope for learning), this variable may capture misspecifications of the learning process. If these were severe, the multicollinearity arising when including *Industry Experience* would reduce the statistical significance of the estimated coefficients. However, the results in table III show that the coefficients on λ and *Option Value* remain positive and significant when this variable is included, consistent with the model.

Specification 5 is a kitchen-sink regression that includes all regressors. The variable *Previous* is a binary variable that equals one for the industry of the investor's previous investment. This captures additional persistence in investment decisions. For example, if investors only partly update their beliefs between investments, they would be more likely to invest in the same industry again, and the coefficient on *Previous* would be positive (conversely, if they spread their investments across industries before they update their beliefs, it would be negative). Overall, the positive and significant coefficients on *Industry Experience* and *Previous* reveal that there is some element of persistence that is unexplained by the model. The positive and significant coefficients on *Industry IPOs* and *Industry Investments* show that investors follow general trends in the market and public market signals. However, after controlling for all these additional determinants of the investments, the coefficients on λ and *Option Value* remain positive and significant, confirming that learning is a significant determinant of investment decisions.

To investigate further implications of the learning model, table IV reports estimates of a Probit model where the outcome of each investment is a function of the investor and market characteristics. Specification 1 is the baseline specification. The results show that investments with higher λ, higher *Option Value*, and in late-stage companies are more likely to be successful. In the learning model, λ measures the investor's expected immediate success probability. The positive and significant coefficient reported in table IV shows that this measure captures a reasonable amount of the actual success probability, and indicates that the investors' beliefs specified in the model are not unreasonable. The model also predicts that exploratory investments, which are made mainly for their option value, should have lower success rates. In other words, an investment that is attractive because λ + *Option Value* is large should only have a success rate of λ, and *Option Value* should be a weaker predictor of success. Note that this is not a formal prediction of the model. If investors systematically underestimate the value of untried industries, investments with higher *Option Value* will have better realized outcomes. Still, the coefficient on *Option Value* provides a test of the model and the beliefs. Specification 2 includes industry controls and controls for the investor's experience, and the significance of *Option Value* decreases substantially. Finally, specification 3 is a kitchen-sink regression with a number of additional controls for market conditions and investor experience. In this specification the statistical significance of *Option Value* vanishes entirely, but the significance of λ remains largely unchanged, consistent with model.

**** TABLE IV ABOUT HERE ***

A. Investment Strategies and Outcomes

The model has further implications for success rates across investors. It implies that investors that explore and learn to a greater extent should have higher success rates, and to confirm this relationship the model is estimated separately for each investor. For this estimation, the value of an investment in industry *i*, by investor *j*, at time *t* is specified as

$$v_{i,j,t} = \left[\lambda_{i,j,t} + OptionValue_{i,j,t} \right] 1 + OptionValue_{i,j,t}\, \gamma_{j,1} + Industry\, IPOs_{j,t}\, \gamma_{j,2} + \varepsilon_{i,j,t} \ . \quad (10)$$

Here, the bracket contains the immediate return plus the option value, i.e. the Gittins index. The second term is option value in excess of the value in the bracket, and investors with positive $\gamma_{j,1}$ exhibit more explorative investment behavior than predicted by the model. Finally, the coefficient $\gamma_{j,2}$ classifies the investment behavior according to how closely it follows general trends in the market, here measured by *Industry IPOs*.[12] A higher value of $\gamma_{j,2}$ corresponds to an investor that follow these trends to a greater extent.

One slightly unusual feature of this specification is that the scale of the equation is normalized by fixing the "coefficient" for the first term (in the bracket) to equal one. Usually, for discrete choice models, the scale is normalized by fixing the variance of the error term. However, by normalizing the term in the bracket it is possible to estimate the standard deviation of $\varepsilon_{i,j,t}$, and the corresponding coefficient, denoted σ_j, measures the "randomness" or "opportunism" of the investor's behavior. This normalization also makes the estimated coefficients comparable across investors. With the standard normalization, the randomness is captured by the scale of the coefficients, and an investor making more random investments would have smaller coefficients in absolute value. This

[12] The results (unreported) are largely similar when general trends are measured using *Industry Investments*.

would make coefficients difficult to compare across investors, and this alternative normalization eliminates this problem.

On a technical note, the model is estimated by first estimating a standard Logit model and then rescaling the coefficients using the value of the first coefficient. The standard error of the first coefficient provides a measure of how precisely the characteristics of the investor's strategy are estimated, and for investors with shorter investment histories the coefficients are estimated less precisely. To adjust, the investors are weighted according to the precision of the estimates of their characteristics, with less weight placed on investors with less precise coefficients. One disadvantage of this method is that a small number of investors have negative estimates of the first coefficient of the model. These are typically investors with short investment histories and imprecisely estimated characteristics. However, these investors will appear to have negative values of σ_j, which is difficult to interpret. Since these investors have low weights, all the results are robust to excluding them as well as replacing σ_j with its absolute value.

In short, the model is estimated separately for each investor and classifies their investment strategies along three dimensions. An investor with a higher value of $\gamma_{j,1}$ places more weight on option value and explores more. A higher value of $\gamma_{j,2}$ reflects an investment strategy that follows overall market trends to a greater extent. Finally, the coefficient σ_j measures the standard deviation of the error term and a higher value corresponds to an investment strategy that is more "random" or "opportunistic." To form meaningful units of these measures, they are rescaled to have a standard deviation equal to one in the sample. Panel B in table I presents both the scaled and raw estimates of these measures.

First, consider the relationship between a VC's performance and investment behavior. Here, performance is measured using *Success Rate*, which is the investor's fraction of successful investments to total investments, and the estimates of the following regression are reported in table V.

$$Success\ Rate_j = \beta_0 + \gamma_{j,1}\beta_1 + \gamma_{j,2}\beta_2 + \sigma_j\beta_3 + \varepsilon_j \qquad (11)$$

A positive estimate of β_1 indicates that investors that explore more by placing more weight on *Option Value* have higher success rates. A positive estimate of β_2 indicates that investors that follow general trends more have higher success rates, and a negative estimate of β_3 indicates that investors that make more random investments have lower success rates.

**** TABLE V ABOUT HERE ***

In the first specification in table V, panel A, investors with higher $\gamma_{j,1}$ have higher success rates, consistent with the model. An investor that explores more discovers more successful investments and realizes a higher success rate. The greater propensity to explore may be a result of more dispersed prior beliefs or a higher discount factor (a δ closer to one), leading to a higher value of learning. Alternatively, the explorative behavior may be a result of suboptimal investment decisions, but even in this case "excess" exploration should lead to a higher success rate. Suboptimal excess exploration still lead the investor to discover more successful investments, but these successes are realized further in the future, lowering their discounted present value. However, *Success Rate* does not adjust for the timing, and more exploration leads to a higher *Success Rate* in this case as well. Next, the coefficient on *Standard Deviation* shows that investors with a higher σ_j have consistently lower success rates, suggesting that investors who deviate more from the learning model or make more "random" or "opportunistic" investments are less successful. The magnitudes of the effects of *Option Value* and *Standard Deviation* are economically meaningful. A one standard deviation increase in exploration (within the sample of investors) is associated with a 2.14 to 2.62% increase in success rate, and a one standard deviation in the "randomness" is associated with a 1.60 to 2.40% drop in success rate. Compared to an average success rate of 50.3% in the sample, these are meaningful economic effects.

In table V, panel A, the second specification also includes $\gamma_{j,2}$, which measures the investors' tendency to follow general trends in the market, here measured by the number of VC-backed IPOs in each industry in each year. The coefficient is positive but insignificant, suggesting that the relationship between investors' performance and their tendency to follow the market is weak. Specification 3 also includes the total number of investments by the investor (*Final Experience*),[13] and the estimated coefficient is positive but insignificant. Kaplan and Schoar (2005) find that more experienced VCs make more

[13] The difference between *Final Experience* and *Total Experience* is that *Final Experience* is calculated once for each investor at the end of the sample. *Total Experience* is calculated at the time of each investment and increases through the sample period.

successful investments, but the evidence here is less conclusive, perhaps due to the right-truncation of the sample, making *Final Experience* a noisy measure. Alternatively, it may be due to the different outcome measures used by Kaplan and Schoar (2005).

The outcomes of the individual investments provide a finer view of the learning process. Panel B in table V reports the coefficients for a Probit model where the outcome of each investment is estimated as a function of the investor's strategy and additional controls. The empirical specification is

$$\Pr(Success_{i,j,t} = 1) = \Phi\left(\beta_0 + \gamma_{1,j}\beta_1 + \gamma_{2,j}\beta_2 + \sigma_j\beta_3 + X'_{i,j,t}\beta_4\right). \tag{12}$$

The first specification shows that investments by more explorative investors are more successful, and investments by more "random" or "opportunistic" investors are less successful. This confirms the above evidence from the investors' success rates, and the economic effects are meaningful here as well. A one standard deviation increase in $\gamma_{1,j}$ corresponds to an increase in the success probability from 1.48 to 3.35%, and a similar increase in σ_j corresponds to a decrease in the success probability of 2.12 to 2.99%. The second specification includes the measure of the investor's tendency to follow the market, but this effect is again small and insignificant. The final specification is a kitchen-sink regression with additional controls and fixed effects. Not surprisingly, investments in companies at the late stage are 15.14% more likely to be successful, and this effect is statistically significant. Further, investments by more experienced investors are marginally more likely to be successful and investments in industries with more VC-backed IPOs are marginally less successful, which is consistent with Kaplan and Schoar

(2005). Overall, the results at the investment level supports the evidence at the investor level, although the sign on $\gamma_{2,j}$ reverses in the last specification.

B. Investment Speed

The model also has implications for the timing of the investments, and the empirical evidence provides additional support for the model. There are several possible hypotheses. Investors may initially make slow explorative investments, and if these investments are successful, accelerate to benefit from their informational advantage. Alternatively, investors may make a string of quick initial explorations, perhaps to capture first-mover advantages, and then continue at a more measured pace. While the model does not explicitly incorporate investment speed, it provides a simple way to investigate this relationship. In the model, speed is determined by the discount factor. The closer δ is to one, the smaller is the discounting, and the higher the speed. As a starting point, assume that increasing the speed requires costly effort. This may reflect the cost of searching for new investments or investing in lower quality companies and working harder to improve them. The investor's problem is now

$$V(F(t)) = \max_{s(t),e} E[y_{s(t)}(t) \mid F(t)] - C(e) + \delta(e) E\left[V(F(t+1)) \mid F(t), s(t)\right]. \qquad (13)$$

Here e is effort, $C(e)$ is an increasing convex cost of faster investing, and $\delta(e)$ is the discount rate, which tends to one as effort increases. This extended model predicts that when the continuation value increases (the last term in equation (13)), the benefit of a higher speed also increases, regardless of whether the continuation value reflects a higher value of learning or a higher immediate return.

This is confirmed empirically. The coefficients of the following OLS regression are reported in table VI.

$$Time_{i,j,t} = \beta_0 + Gittins_{i,j,t}\beta_1 + X'_{i,j,t}\beta_2 + \varepsilon_{i,j,t}\,. \tag{14}$$

Time is the number of days since the investor's previous investment, and a longer time is equivalent to a slower speed. To control for investments that are made simultaneously, the sample is restricted to investments that are made at least fourteen days apart.[14] In this sample, the average of *Time* is 80.8 days with a standard deviation of 126. The variable *Gittins* represents the continuation value, given by the investment's Gittins index.[15]

In the first specification in table VI the coefficient on *Gittins* is -119.85. As predicted, investments with greater values are made faster. Specification 2 includes industry and year controls, along with the investor's total experience. Again, more valuable investments are made faster, and more experienced investors are also found to invest faster, although the magnitude of this effect is smaller.

**** TABLE VI ABOUT HERE ***

In specifications 3 and 4 the option value and the immediate return enter separately. The model predicts that both coefficients should be negative with similar coefficients, but in specification 3 the sign of the coefficient on *Option Value* is positive. However, in

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[14] The regression results are similar when all the investments are included, but the hazard model described below has problems estimating the hazard rates for investments that are very close.

[15] Formally, the continuation value is the Gittins index scaled by a factor, see i.e. Whittle (1982) (p. 214). Notice that a formal solution to this problem would adjust the continuation value to capture the expected future speed and its cost. This problem is not solved here.

specification 4, when including year and industry controls, both coefficients become negative, although their magnitudes are still somewhat different. The larger negative coefficient on *Option Value* suggests that investors make explorative investments faster, perhaps to capture first-mover advantages or for other reasons outside the model.

Finally, the investment speed can be captured by a hazard model. In table VI, specifications 5 and 6 report estimates of a Cox hazard model and the results are consistent with the results from the previous specifications. Note, for the hazard model, coefficients greater than one reflects an increase in the hazard rate, corresponding to a shorter time between the investments (and corresponding to a negative coefficient in the OLS regressions). Again, more valuable investments are made quicker, and this effect is observed for both investments with higher immediate returns and higher option values of learning.

Overall, the evidence confirms that more valuable investments are made faster. It is noteworthy that the option values and expected immediate returns are calculated independently of the timing of the investments, and the results provide independent supporting evidence that the *Option Value* and λ measure meaningful economic aspects of the value of the investments, as perceived by the investors when deciding where and how to invest. The option value of learning plays a significant part in this decision.

V. Summary and Conclusion

This paper demonstrates that VCs learn from past investments and anticipate to learn from future ones. When the distributions of payoffs from investments are uncertain, but the outcomes of the investments are informative about these distributions, the return from each investment is both its immediate return and an option value of learning. To empirically test for the presence of learning, the paper presents and estimates a learning model based on the multi-armed bandit model. It is shown that the *index result* dramatically simplifies the estimation and identification of this model, and the empirical approach based on this result may be applicable for investigating learning in other situations.

The empirical evidence confirms that learning is important, and the two alternative hypotheses, that (1) VCs do not learn, and (2) VCs learn only from past investments and do not internalize the value of future learning are both clearly rejected in the data. VCs exhibit *exploitative* behavior by changing their investments in response to the outcomes of past investments to benefit from higher immediate returns. Further, VCs exhibit *explorative* behavior by directing capital towards new unproven investments and internalizing the option value of the information gained from these investments. The model generates further predictions that are confirmed empirically. In the cross-section, VCs with more exploratory investment strategies have greater success rates, and VCs making more random investments have lower success rates. Further, more valuable investments are made faster. These findings are consistent with the model, and corroborate the economic interpretation of the measures of the immediate return and option value of learning derived under the model.

The presence of learning has potentially important implications for understanding the market for VC financing and the organization of VC firms. A theoretical literature shows that informational frictions arise in markets with learning and informational spillovers. The two main frictions are a free-rider problem and an informational cascading problem. These frictions reduce the investors' incentives to explore, and this reduces the equilibrium level of learning below the first-best levels. However, VCs are private investors in privately held companies. This organizational form reduces informational spillovers and may allow VCs to internalize the value of exploration and promote learning to a greater extent than traditional investors in more transparent capital markets. This ability to allocate capital to more explorative investments may present an additional source of value created by these investors.

One potential refinement of the analysis is to separate learning at the industry level from learning at the finer level of the individual technology or business idea. The analysis is consistent with learning taking place at all of these levels, but an explicit separation of these various kinds of learning would sharpen the understanding of the learning process and its implications for the market. The main challenges are data availability and computational issues. With a finer classification of learning, there would be fewer investments within each category. Since the statistical identification is based on comparisons of investments in categories with similar immediate returns but different lengths of investment histories, longer overall investment histories would be required for sufficient variation in the lengths of the histories across categories. In addition, narrower classifications may also lead investments in one category to be informative about investments in related categories, and the index result may have to adjust for this information structure, making the analysis more numerically challenging.

Finally, Gompers, Kovner, Lerner and Scharfstein (2005) demonstrate that changes in economic fundamentals, as signaled by public market signals, are important determinants of VC's investments. The analysis here suggests that there are two kinds of changes in economic fundamentals that can make new investments attractive. An investment becomes attractive when either its immediate return increases (an upward shift in $F(t)$) or when its option value increases (an increase in the "spread" of $F(t)$). An increase in the immediate return may follow from an improvement of a known product, for example through an investment in a project that reduces its marginal cost. This project would generate an immediate return, but it may have a small option value of learning. In contrast, an investment in a new and unproven technology typically has a low immediate return but a substantial option value, since a successful implementation of the technology would spur further investments in other applications. While standard capital markets are well suited for allocating capital in response to the first kind of change, the analysis suggests that VCs may be better able to internalize the option value of learning and this would make them better suited for allocating capital is response to the second kind of change. Casual empirics suggests that VCs invest primarily in entrepreneurial companies with new technologies and high option values, and formalizing the difference between standard capital markets and institutional investors in their abilities to internalize value and allocate capital in response to various economic changes would help understand their complementary roles in the economy.

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TABLE I: Summary Statistics

PANEL A: Summary Statistics By Company

	Obs.	Mean	Std. Dev.	Min	Max
IPO	6,076	0.170	0.376	0	1
Acquisition	6,076	0.329	0.470	0	1
Success (IPO + Acq)	6,076	0.499	0.500	0	1
Year	6,076	1995.2	4.422	1987	2000
Industry Classifications					
Health	6,076	0.181	0.385	0	1
Commmunications	6,076	0.208	0.406	0	1
Computers	6,076	0.240	0.427	0	1
Software	6,076	0.175	0.380	0	1
Consumer	6,076	0.122	0.327	0	1
Other	6,076	0.074	0.261	0	1

PANEL B: Summary Statistics by Investor

	Obs.	Mean	Std. Dev.	Min	Max
IPO Rate	216	0.204	0.094	0.000	0.523
Acq Rate	216	0.299	0.067	0.106	0.492
Success Rate	216	0.503	0.118	0.133	0.864
Total Experience	216	88.731	64.210	40	577
Classifications of investment strategy:					
Option Value	216	2.762	27.551	-80.801	226.649
Standard Deviation	216	0.292	0.608	-4.213	4.640
Industry IPOs	216	0.002	0.016	-0.172	0.056
Normalized scale:					
Option Value	216	0.100	1.000	-2.933	8.226
Standard Deviation	216	0.480	1.000	-6.933	7.634
Industry IPOs	216	0.115	1.000	-11.040	3.602

PANEL C: Summary Statistics by Investment

	Obs.	Mean	Std. Dev.	Min	Max
Experience	19,166	68.081	73.230	1	577
Stage	19,166	0.287	0.452	0	1
Year	19,166	1995.2	4.542	1987	2000
Success	19,166	0.571	0.495	0	1
Lambda	19,166	0.260	0.153	0.032	0.717
Option Value	19,166	0.062	0.012	0.019	0.082
Gittins Index	19,166	0.323	0.147	0.063	0.745
OptionValue / Gittins Index	19,166	0.252	0.138	0.031	0.531

TABLE I: Summary Statistics (cont.)

Panel D presents the number of VC investments and VC backed IPOs (in parenthesis) for each industry in each year in the sample.

PANEL D: INVESTMENTS (IPOs) PER INDUSTRY PER YEAR

Year	Health	Comm	Comp	Cons	Soft	Other	Total
1987	806	420	1,125	164	359	310	3,184
	(3)	(2)	(4)	(0)	(0)	(2)	(11)
1988	592	237	770	92	327	208	2,226
	(4)	(4)	(5)	(1)	(1)	(4)	(19)
1989	395	148	371	57	189	139	1,299
	(11)	(1)	(7)	(4)	(4)	(5)	(32)
1990	283	101	256	56	196	89	981
	(11)	(4)	(10)	(1)	(6)	(4)	(36)
1991	258	100	164	57	206	54	839
	(45)	(11)	(14)	(2)	(8)	(3)	(83)
1992	372	152	142	44	257	58	1,025
	(59)	(15)	(18)	(11)	(11)	(6)	(120)
1993	357	159	123	74	163	57	933
	(35)	(14)	(36)	(9)	(18)	(15)	(127)
1994	338	176	159	65	189	36	963
	(33)	(13)	(27)	(6)	(16)	(6)	(101)
1995	445	240	191	134	280	86	1,376
	(40)	(17)	(30)	(5)	(33)	(6)	(131)
1996	472	429	291	176	458	93	1,919
	(72)	(35)	(28)	(16)	(43)	(13)	(207)
1997	621	533	391	269	633	124	2,571
	(39)	(18)	(21)	(9)	(17)	(10)	(114)
1998	688	723	426	410	739	231	3,217
	(9)	(23)	(16)	(9)	(11)	(2)	(70)
1999	844	1,938	1,055	1714	1,249	175	6,975
	(14)	(94)	(27)	(53)	(68)	(3)	(259)
2000	961	2,824	3,443	1,388	1,034	359	10,009
	(60)	(44)	(29)	(32)	(48)	(8)	(221)
Total	7,432	8,180	8,907	4,700	6,279	2,019	37,517
	(435)	(295)	(272)	(158)	(284)	(87)	(1,531)

TABLE II: Choice of Prior

The table reports estimates of a Multinomial Logit model where investors' industry choice is the endogenous variable. The possible choices are Health, Communications, Computers, Consumer Goods, Software, and Other. The model is estimated with four different choices of prior beliefs, given by $a_0 = 1$ and b_0, and with and without industry fixed effects. The coefficients β_1 and β_2 are the coefficients on λ and *Option Value* respectively, and the number in the column χ^2 is the p-value of a χ^2 test of β_1 and β_2 being equal. A small value means that this hypothesis is rejected. Observations are weighted according to the precision of the estimate of *Option Value* (see text for details). Robust standard errors with clustering at the company level are in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

b_0	β_1		β_2		Industry Controls	χ^2 test	
17	4.597	***	2.326	**	No	0.02	**
	(0.099)		(0.959)				
	3.752	***	-0.803		Yes	0.00	***
	(0.102)		(0.993)				
18	4.692	***	4.407	***	No	0.77	
	(0.101)		(0.996)				
	3.850	***	0.860		Yes	0.00	***
	(0.104)		(1.035)				
19	4.766	***	6.455	***	No	0.10	
	(0.102)		(1.033)				
	3.929	***	2.501	**	Yes	0.18	
	(0.105)		(1.077)				
20	4.822	***	8.525	***	No	0.00	***
	(0.103)		(1.069)				
	3.994	***	4.170	***	Yes	0.87	
	(0.106)		(1.117)				

TABLE III: Aggregate Investment Decisions

The table reports estimates of a Multinomial Logit model (McFadden choice model) where investors' industry choice is the endogenous variable. The possible choices are Health, Communications, Computers, Consumer Goods, Software, and Other. *Lambda* and *Option Value* are investors' expected immediate return and option value of investing. *Industry Investments* is total number of investments in each industry per year across all investors in the data. *Industry Experience* is the past number of investments by the investor in the industry. *Previous* is a binary variable that equals one for the industry of the investor's previous investment. Observations are weighted according to the precision of the estimate of *Option Value* (see text for details). Robust standard errors with clustering at the company level are in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	1		2		3		4		5	
Lambda	4.7657	***	4.2445	***	4.3202	***	3.3410	***	2.4023	***
	(0.1019)		(0.1075)		(0.1106)		(0.1611)		(1.1627)	
Option Value	6.4545	***	5.3043	***	3.0443	***	17.2952	***	8.5117	***
	(1.0329)		(1.0486)		(1.0823)		(1.3323)		(1.3787)	
Industry IPOs			0.0085	***					0.0030	***
			(0.0007)						(0.0008)	
Industry Investments					0.0007	***			0.0006	***
					(0.0000)				(0.0000)	
Industry Experience							0.0228	***	0.0166	***
							(0.0020)		(0.0020)	
Previous									0.2978	***
									(0.0184)	
Industry Controls	No		No		No		No		Yes	
Observations	19,166		19,166		19,166		19,166		19,166	

TABLE IV: Investment Outcomes

The table reports marginal effect from estimates of a Probit model where the outcome (success or failure) of each investment is the endogenous variable. *Lambda* and *Option Value* are investors' expected immediate return and option value of investing. *Industry Investments* is total number of investments in each industry per year across all investors in the data. *Industry IPOs* is the number of companies in the same industry going public in the year of the investment. *Industry Experience* is the past number of investments by the investor in the industry and *Total Experience* is total number of the investor's past investments across all industries. In the third specification, investors initial ten investments are discarded from burn-in. Robust standard errors with clustering at the company level are in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	1		2		3	
Lambda	0.3631	***	0.3544	***	0.6668	***
	(0.0368)		(0.0541)		(0.0772)	
Option Value	3.1726	***	1.0309	*	0.5607	
	(0.3975)		(0.5772)		(0.6615)	
Stage	0.1656	***	0.1601	***	0.1726	***
	(0.0141)		(0.0142)		(0.0147)	
Industry Experience			-0.0032	***	-0.0037	***
			(0.0008)		(0.0098)	
Total Experience			0.0004	***	0.0008	***
			(0.0001)		(0.0002)	
Industry IPOs					-0.0004	
					(0.0004)	
Industry Investments					0.0000	
					(0.0000)	
log(Industry Experience +1)					-0.0363	**
					(0.0159)	
log(Total Experience +1)					-0.0397	***
					(0.0159)	
Year Controls	Yes		Yes		Yes	
Industry Controls	No		Yes		Yes	
Observations	19,166		19,166		17,006	

TABLE V: Investment Strategies and Outcomes

Panel A shows estimated coefficients for an OLS regression. An observation is an investor and the endogenous variable is the investor's success rate. Panel B presents marginal effects estimated from a Probit model. Each observation is an investment in a company and the endogenous variable is the outcome. *Option Value*, *Standard Error*, and *Industry IPOs* characterize the investor's investment strategy in terms of its dependence on option value, its standard error, and on the number of VC backed IPOs in the industry in the same year. These coefficients are normalized to have standard error equal one (see text for details). *Total Experience* measures the number of previous investments by the investor at the time of each investment. *Final Experience* is the investor's experience at the end of the sample. *Stage* is an indicator variable that equals one for investments in late-stage companies. Observations are weighted according to the precision of the estimates (see text for details). Robust standard errors with clustering at the company level are in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

PANEL A: Success Rate of Venture Capital Firms

	1			2			3		
	Coef.	Std. Err.		Coef.	Std. Err.		Coef.	Std. Err.	
Classification of Strategy									
Option Value	0.0214	(.0027)	***	0.0234	(.0087)	***	0.0262	(.0089)	***
Standard Deviation	-0.0160	(.0022)	***	-0.0212	(.0071)	***	-0.0240	(.0080)	***
Industry IPOs				0.0085	(.0112)		0.0086	(.0117)	
Final Experience							0.0001	(.0001)	
Constant	0.5432	(.0044)	***	0.5441	(.0094)	***	0.5285	(.0126)	***
Observations	216			216			216		

PANEL B: Success of Individual Investments

	1			2			3		
	dF/dX	Std. Err.		dF/dX	Std. Err.		dF/dX	Std. Err.	
Classification of Strategy									
Option Value	0.0335	(.0058)	***	0.0148	(.0060)	***	0.0154	(.0060)	***
Standard Deviation	-0.0299	(.0062)	***	-0.0242	(.0075)	***	-0.0212	(.0076)	***
Industry IPOs				0.0029	(.0094)		-0.0013	(.0095)	
Stage							0.1514	(.0157)	***
Total Experience							0.0001	(.0001)	
Industry IPOs							-0.0002	(.0005)	
Year Controls	No			Yes			Yes		
Industry Controls	No			No			Yes		
Observations	19,166			19,166			19,166		

TABLE VI: Investment Speed

The table reports estimated coefficients from four OLS regressions and two Cox Hazard models. An observation is an investment, and the time since the previous investment (measured in days) is the endogenous variable. Each investor's initial investment and investments made less than 14 days apart are excluded. *Gittins* is the Gittins index of the investment, *Option Value* is the option value, and *Lambda* is the expected immediate return. *Total Experience* is the investor's experience, measured as the total number of past investments. Standard errors clustered at the company level are reported in parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	OLS								Cox Hazard			
	1		2		3		4		5		6	
Gittins	-119.85	***	-119.54	***					3.88	***		
	(9.00)		(13.06)						(0.28)			
Option Value					385.70	***	-822.23	***			34.23	***
					(118.47)		(149.28)				(36.86)	
Lambda					-108.55	***	-116.93	***			2.35	***
					(10.30)		(12.87)				(0.26)	
Total Experience			-0.35	***			-0.45	***			1.01	***
			(0.03)				(0.04)				(0.00)	
Constant	118.12	***	128.80	***	82.75	***	174.50	***				
	(3.68)		(5.84)		(9.90)		(12.47)					
Industry Controls	No		Yes		No		Yes		No		Yes	
Year Controls	No		Yes		No		Yes		No		Yes	
Observations	10,881		10,881		10,881		10,881		10,881		10,881	

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