商业周期中的投资者行为

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Abstract: Investors often behave in puzzling ways. In this paper, we develop a theory that implies “unusual” investment behaviors in a market equilibrium with heterogeneous investors who formu-late their investment strategies based on their individual assessments of market signals, where mar-ket signals are tacit information and endogenously dependent on the individual assessments. Tacit information requires experience and knowledge to interpret and understand. We find that (1) dif-ferences in investors’ knowledge, experience, risk attitudes and incomes can give rise to unusual investment behaviors under economic rationality; (2) investment behaviors are normal in normal periods, but abnormal in abnormal periods (a reversal of investment behaviors) when a swing mar-ket drives many inexperienced and highly risk-averse investors in and out of the market; (3) a change in the population shares of different types of investors in the market can cause a reversal of investment behaviors among those same types of investors; and (4) empirical evidence supports our theory.

Keywords: Investment Abnormalities, Endogenous Market Signals, Experience, Risk Attitude

JEL Classifications: G14, G19

Introduction

The behaviors of investors can sometimes be quite puzzling indeed. In this paper, we offer a theory to explain some of those puzzling investment behaviors based on economic rationality in-stead of a behavioral approach. The unique feature of our model is that investors rely on market signals to assess the investment environment, but the market signals are conversely endogenously dependent on the investors’ assessment; however, since the market signals are tacit information, the investors’ interpretation of the market signals is dependent on their abilities and different in-vestors have different abilities. We show theoretically and empirically that the unusual investor behaviors can occur in this setting.

Tacit information requires time, effort and experience to learn how to utilize it. For example, swimming takes a lot of practice to master; it cannot be learned by reading swimming materials only. Similarly, for average investors, it would take years of experience to learn to utilize public information. We propose a formulation of expectation under tacit information based on the Bayes-ian approach. The key in our formulation is that the investor's expectation is unbiased, but the variance of this expectation depends on the investor's ability/experience.

Specifically, in a model with a riskfree asset and a risky asset, unusual investment behaviors are when: (1) a less knowledgeable investor invests more in risky assets than a more knowledgeable investor does; (2) a more risk-averse investor invests more in risky assets than a less risk-averse investor does; and (3) a poorer investor invests more in risky assets than a richer investor does. We show that these behavioral "abnormalities" can arise when the population share of those investors who are less knowledgeable, more risk averse or poorer is relatively large. The message we bring is that with endogenous and tacit market signals, the unusual investment behaviors are in fact ra-tional in many circumstances.

We test our theory using data from venture capital (VC) investments. We find strong empirical support for our theory. Specifically, we find normal investment behaviors among different groups of investors in normal periods, but a reversal of investment behaviors (abnormal behaviors) among those same groups of investors in abnormal periods when a swing market drives many inexperi-enced and highly risk-averse investors in and out of the market. We also find that a change in the population shares of different types of investors in the market can cause a reversal of investment behaviors among those same types of investors.

This paper proceeds as follows. Section 2 provides a literature review. Section 3 presents the model. Section 4 offers theoretical analysis. Section 5 provides empirical evidence for our theory. Section 6 concludes this paper with a few remarks.

1. Literature Review

1.1 Reactions to Public Signals

The role of public signals in financial markets has attracted a lot of attention recently. On the announcement effects in financial markets, existing studies have substantially improved our un-derstanding of the price discovery process at work (Ederington and Lee, 1993; Fleming and Remolona, 1999; Andersen et al., 2003, 2007; Ehrmann and Sondermann, 2009). Gropp and Ka-dareja (2006), who study the response of the realized volatility of a commercial bank's stocks to monetary policy shocks, show that the magnitude of this response increases with the time since that commercial bank's release of its annual report. Kandel and Pearson (1995) provide and find support for a model with differential interpretations of public signals by individuals. Ehrmann and Sondermann further (2009) show that whether and how financial markets react to public signals depends on the relative importance of private information. We emphasize differences in the ability of investors to interpret public signals due to differences in their experience and knowledge. We adopt an endogenous market signal whose strength is dependent on the reactions to it. An endog-enous market signal, together with different abilities of investors to interpret it, allows us to explain some unusual investment behaviors in equilibrium.

On the impact of monetary news, by citing Fracasso et al. (2003), Ehrmann and Sondermann (2009) point out that the Bank of England's inflation report is signed off by the Monetary Policy Committee before its release and hence conveys precisely what the policy makers are thinking, making it a vital piece of information for financial market participants. In the interim period be-tween two inflation reports, financial market participants may update their beliefs about the course of the economy and the likely setting of monetary policies. Ehrmann and Sondermann expect these inflation reports, with a greater reliance on the most recent one, to homogenize market participants' views. Indeed, they find that financial market reactions to one inflation report differ from those to another inflation report, with the effects becoming larger over time.

On the reactions of financial markets to public news, existing studies have generally focused on either asset prices (Gürkaynak et al., 2006) or volatility (Gropp and Kadareja, 2006). For exam-ple, by citing a theoretical paper by Scharfstein and Stein (1990) on herd behavior and another by Hong and Stein (1999) on overreaction in asset markets, Gompers et al. (2008) explain that fluc-tuations in VC investment are caused by venture capitalists (VCs)' reactions to public market sig-nals. There are also studies that relate investment fluctuations to herd behavior, information exter-nalities or revelation of information, among which the models of Caplin and Leahy (1994), Chamley and Gale (1994), Demers (1991), and Gale (1996) and Cunningham (2004) have features similar to ours.

Polanyi (1962, 1967) develops the concept of tacit information, of which market signals and public information are examples. Tacit information requires experience, ability and time to under-stand, analyze and digest. Some investors are good at interpreting/making inferences from/utiliz-ing tacit information while others are not, due to differences in their experience and knowledge. In our model, there is a market signal, and because this signal is tacit information, its correct inter-pretation depends on investors' ability. In practice, the number of successful exits (initial public offerings (IPOs) and mergers and acquisitions (M&As)) in an industry is seen by investors as a signal of the potential returns in that industry. More experienced and knowledgeable investors may be better at interpreting public signals. We pay particular attention to the endogeneity of public signals and the relative population sizes of different types of investors. There are two types of in-vestors in our model and they differ in terms of their abilities, risk attitudes or incomes. We discuss and compare the equilibrium solutions against this backdrop.

1.2 Heterogeneity of Investors

Heterogeneity among economic agents has recently been recognized as an important factor in explaining many puzzling economic phenomena. Harrison and Kreps (1978) present an influential theory of speculative behavior. The key to their theory is the assumption of heterogeneous expec-tations. Under this condition, an investor can profit from adopting a speculative strategy on an asset, even if the asset is non-profitable otherwise. Shalen (1993) develops a model in which agents' dispersion of expectations and excess market volatility are correlated. In the work of Harris and Raviv (1993), traders receive common information, but differ in their interpretations of the infor-mation. The older the signal, the more likely the traders are to interpret it differently, causing excess volatility in markets. Wärneryd (1999) indicates that "those who had relatively more invested in risky assets did not think of the investments as being more risky." So it is the different views on risk among investors that give rise to the different investment strategies. We confirm that the heteroge-neity of investors can indeed explain many unusual investment behaviors. While existing studies have typically assumed heterogeneity in agents' beliefs due to the quality of public signals, we in-stead assume heterogeneity in agents' experience and knowledge in the case of tacit public signals. We also consider the differences in risk aversion and income among investors.

There is one strand of literature that attempts to disentangle the role of private information from that of public information in financial markets in order to understand the drivers of market volatility. Empirical tests for the importance of private information in generating market volatility, following the approach of French and Roll (1986), typically rely on identifying differences in vola-tility between trading and non-trading times, while keeping the flow of public signals constant. In particular, changes in institutional settings have been applied as a testing vehicle. Ito and Lin (1992) show that the reduction in market volatility during lunchtime is smaller for the New York Stock Exchange (which does not break for lunch) than for the Tokyo Stock Exchange (which does break for lunch). Ito et al. (1998) further make use of the abolishment of the lunch break in the Tokyo foreign exchange market to arrive at a similar conclusion. Furthermore, Barclay et al. (1990) ana-lyze the volatility before and after the half-day trading on the Tokyo Stock Exchange on Saturdays was abolished and find that "when the Tokyo Stock Exchange is open on Saturday, the weekend variance increases; weekly variance is unaffected." These studies strongly suggest that private in-formation plays a major role in generating market volatility. However, we argue that, rather than private information, the real explanation in these studies is the heterogeneity of opinions. In our view, continuous trading allows traders to synchronize individual opinions, which can be inferred from trading activities, with market conditions. The lunch break simply enlarges the extent of het-erogeneity of opinions among investors, and raises the volatility of stock prices.

Our approach emphasizes the population proportions of different types of investors and the endogeneity of market signals. Differences exist among investors in their risk aversion, income, and ability to assess market signals. We find that these differences can result in unusual behaviors in equilibrium. Although many seemingly irrational behaviors observed in practice have psychological explanations, these behaviors can also be explained by information models under economic ration-ality. More specifically, we consider a model in which each investor i uses a common market signal s to decide how much to invest in a project. To each investor, the project has a random output $\tilde{x}$ following an individual-specific density function $fi(x|s)$. Each investor takes the market signal as given and interprets it in her own way. The market signal is endogenously determined in equilib-rium. A favorable signal attracts investors, which in turn strengthens the signal. If a particular type of investors forms a large proportion of the population, then a favorable signal to them may greatly boost the signal, which may in turn induce them to invest more in risky assets. In a situation (such as a boom period) in which inexperienced investors form a large proportion of the population, then inexperienced investors may invest more in risky assets than experienced investors. This associa-tion between inexperience and investment in risky assets explains many unusual behaviors in our model.

1.3 Herd Behavior

Herding is when people simply follow others instead of making choices based on their own information. But we do not consider it herding when people follow others in making a choice that is in fact rational and sensible. Only when a choice is irrational do we consider it herding. For ex-ample, in a period when many people enter stock markets simply because they see fast rising gains but not the associated rising risks, they are said to be herding. Our model can explain such herd behavior. In our model, since all investors follow a market signal and some exhibit unusual invest-ment behaviors, our solution incorporates herd behavior.

Herd behavior has often been blamed for market crashes, especially in stock and real-estate markets. There are extensive studies on herd behavior. Like our study here, many existing studies have also tried to explain herd behavior using the concept of economic rationality. Scharfstein and Stein (1990) use a principal-agent model, in which the agents are rewarded if they are able to con-vince a principal that they are right. This incentive results in herd behavior in the agents in their model. Flood and Garber (1994) and Abreu and Brunnermeier (2003) present arguments for tra-ditional macro and micro conditions of bubbles. Bikhchandani *et al.* (1992) explain herd behavior based on information availability. Banerjee (1992) shows that "the decision rules that are chosen by optimizing individuals will be characterized by herd behavior; i.e., people will be doing what others are doing rather than using their (own) information." For example, an inexperienced inves-tor would appear irrational if she invests more in risky assets than an experienced investor does. But we show that this behavior is in fact rational in our information model, in which individuals act based on public signals and the public signals in turn rely on the individuals' actions. In our model, an experienced investor understands the market signal well and reacts to it properly; an inexperi-enced investor, however, is unable to make full sense of the market signal and decides instead to follow others to minimize her risks, which may result in other inexperienced investors joining the herd as well. Our message is that *with endogenous market signals and different abilities of indi-viduals to interpret them, herd behavior makes perfect sense*.

2. The Model

2.1. The Model Setup

Consider a model in which investors invest in two available assets, a riskfree asset and a risky asset. The net return of the riskfree asset is r_0, $r_0 \geq 0$, which is certain and publicly known. The net return of the risky asset $\tilde{r}$ is uncertain and its distribution function is endogenously determined in equilibrium. The investors observe a market signal, from which they form expectati0ns on the re-turn of the risky asset. Their expectations determine their behaviors, which in turn determine the return of the risky asset in equilibrium.

The risky asset has only two possible net returns, a high return rh and a low return rl. Assume rl<r0<rh. The probability of a high return is p, which represents the chance of success. But the investors don't know p; they can only guess at it based on their interpretation of the market signal. To each investor i, p is only a random variable $\tilde{p}$, with an individual-specific density function $fi(p|s)$ conditional on the market signal s. That is, the investors cannot infer p precisely from the market signal and hence are uncertain about the extent of risk associated with investing in the risky asset, although they are fully aware that it is there and they can infer its severity from the market signal. How well an individual can infer p from the market signal depends on that individual's ability, knowledge and experience.

Let s be the share of aggregate investment in the risky asset (the proportion of the aggregate financial endowment invested in the risky asset by the population). The rest goes to the safe asset. Let λi be the population proportion of the group of investors that investor i belongs to based on investor type, αi be the proportion of investor i's financial endowment invested in the risky asset, and Ii be investor i's initial income. Then, I≡$\sum\lambda iIi$ is the aggregate financial endowment, Ir≡$\sum\alpha i\lambda iIi$ is the aggregate investment in the risky asset, and s=Ir/I. The larger the aggregate invest-ment in the risky asset, the more likely the risky asset is to generate a high return. Here, s serves as the unique market signal to all the investors. An investor may decide to invest in the risky asset if s is large enough.

We now provide a formulation/definition of tacit information. Each investor i has certain ex-perience in making inferences from the market signal. She formulates her own conditional density function $fi(p|s)$ of $\tilde{p}$ conditional on her observation of the market signal s. The investors believe that the proportion s of aggregate investment in the risky asset determines the mean $E(\tilde{p})$ of the success probability $\tilde{p}$, specifically, $E(\tilde{p})$=$\phi(s)$ for some function $\phi(\cdot)$. For consistency, we assume that $\phi(s)$ is the true mean. In fact, for tractability, we will simply assume $\phi(s)$=s in this paper and assume that $\tilde{p}$ follows the uniform distribution with a mean of s as shown in the following figure, where τi∈[0,1] represents the investor's experience or knowledge in inferring the chance of suc-cess from the market signal. Interpret τi as how accurate the investor is at inferring p from the mar-ket signal. A smaller τi means a more accurate inference. The level of experience τi represents part of the risk in investment. Hence, differences in experience among investors imply differences in risk.[1] In this formulation of tacit information, an agent forms an expectation of some variable with limited ability. In management studies, accuracy of expectation has been known to be of crucial importance in governance and resource allocation; see, for example, Barney (1986) and Makadok (2003).

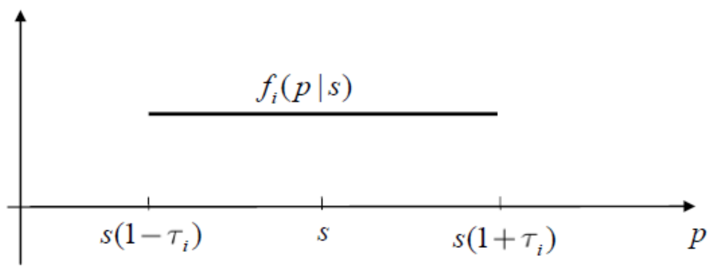

Figure 1. The Distribution of Expectations on the Chance of Success p

There are n types of investors i=1,…,n. An investor's type is defined by a triplet

$\theta_i \equiv (\tau_i, \beta_i, I_i)$, where τ_i is the investor's level of experience, β_i is her level of relative risk aversion, and I_i is her initial income. For our purpose, we will consider only the case with two types of investors (i.e. n=2), where the "good" investors are the ones with more experience, less risk aversion, or a higher income.

2.2. The Investor Problem

$$\max_{0 \le \alpha_i \le 1}$$
$$I_{i1-\beta_i} 2\tau_i s(1-\beta_i) \int [\alpha_i(r(p)-r_0)$$
$$+r_0]_{1-\beta_i} dp_{s(1+\tau_i)s(1-\tau_i)}$$

The random return of the risky asset is $\tilde{r} = \tilde{p} r_h + (1-\tilde{p}) r_l$,

where the probability $\tilde{p}$ of success is a random variable. Given $p \in [0,1]$, denote the mean of return as

$$\bar{r} \equiv r(p) \equiv p r_h + (1-p) r_l. \qquad (1)$$

We have $\tilde{r} = r(\tilde{p})$. Each investor has a total amount I_i to be invested in the risky asset with ex post income $\tilde{x}_i = (1+\tilde{r}) I_i$ and the riskfree asset with ex post income $(1+r_0) I_i$. Let α_i be the share of investor i's investment in the risky asset. Then, the investor's ex post net

$$\max_{0 \le \alpha_i \le 1}$$
$$I_{i1-\beta_i} 2\tau_i s(1-\beta_i) \int [\alpha_i(r(p)-r_0)$$

income is

$\alpha_i I_i [\tilde{p}(1+r_h) + (1-\tilde{p})(1+r_l)] + (1-\alpha_i)(1+r_0) I_i - I_i = \{\alpha_i [\tilde{p} r_h + (1-\tilde{p}) r_l] + (1-\alpha_i) r_0\} I_i = [\alpha_i \tilde{r} + (1-\alpha_i) r_0] I_i = [\alpha_i (\tilde{r} - r_0) + r_0] I_i$.

Then, given the market signal s, the investor's ex ante investment problem is

$$\max_{0 \le \alpha_i \le 1} \int_0^1 u_i\{[\alpha_i(r(p) - r_0) + r_0] I_i\} f_i(p|s) dp. \qquad (2)$$

Finally, for convenience of discussion, we will use the following utility function with constant risk aversion β_i: $u_i(x) = \frac{1}{1-\beta_i} x^{1-\beta_i}$.

Then, the investor's ex ante investment problem becomes

$$\max_{0 \le \alpha_i \le 1} \frac{I_i^{1-\beta_i}}{2\tau_i s(1-\beta_i)} \int_{s(1-\tau_i)}^{s(1+\tau_i)} [\alpha_i(r(p) - r_0) + r_0]^{1-\beta_i} dp. \qquad (3)$$

We can see that each investor's payoff does not depend on what other types of investors there are. Hence, whether or not investor type is private information does not matter and information asym-metry is not a concern.

2.3. The Equilibrium

The first-order condition (FOC) of problem (3) is

$$\left\{[\alpha_i(r(p) - r_0) + r_0]^{2-\beta_i}\right\}_{s(1-\tau_i)}^{s(1+\tau_i)} = r_0 \frac{2-\beta_i}{1-\beta_i} \left\{[\alpha_i(r(p) - r_0) + r_0]^{1-\beta_i}\right\}_{s(1-\tau_i)}^{s(1+\tau_i)}. \qquad (4)$$

We can see from equation (4) that, for those who have invested in the risky asset, only

$\max_{0 \le \alpha_i \le 1}$
$I_{i1-\beta_i} 2\tau_i s(1-\beta_i) \int [\alpha_i(r(p)-r_0)$
$+r_0]_{1-\beta_i} dp_{s(1+\tau_i)s(1-\tau_i)}.$
$\{[\alpha i(r(p)-r0)+r0]2-\beta i\}s(1-\tau$

the expected return $r(p)$ matters. An experienced investor can infer $r(p)$ from the investment share s more ac-curately than an inexperienced one. The range of error defined by the interval $[s(1-\tau),\ s(1+\tau)]$ measures the risk of investing in the risky asset to the investor. Equation (4) implies

$$\{\alpha_i[s(1+\tau_i)(r_h-r_l)+r_l-r_0]+r_0\}^{2-\beta_i}-\{\alpha_i[s(1-\tau_i)(r_h-r_l)+r_l-r_0]+r_0\}^{2-\beta_i}$$
$$=r_0\frac{2-\beta_i}{1-\beta_i}\left(\{\alpha_i[s(1+\tau_i)(r_h-r_l)+r_l-r_0]+r_0\}^{1-\beta_i}-\{\alpha_i[s(1-\tau_i)(r_h-r_l)+r_l-r_0]+r_0\}^{1-\beta_i}\right) \quad (5)$$

Given two types of investors and population proportions $\lambda 1$ and $\lambda 2$, where $\lambda 1+\lambda 2=1$, in equilib-rium, $(\alpha_1\lambda_1 I_1+\alpha_2\lambda_2 I_2)/(\lambda_1 I_1+\lambda_2 I_2)=s$.

Using (5), we identify the following three equations that jointly determine the equilibrium solutions $(\alpha 1*, \alpha 2*, s*)$:

$$\{\alpha_1[s(1+\tau_1)(r_h-r_l)+r_l-r_0]+r_0\}^{2-\beta_1}-\{\alpha_1[s(1-\tau_1)(r_h-r_l)+r_l-r_0]+r_0\}^{2-\beta_1}$$
$$=r_0\frac{2-\beta_1}{1-\beta_1}\left(\{\alpha_1[s(1+\tau_1)(r_h-r_l)+r_l-r_0]+r_0\}^{1-\beta_1}-\{\alpha_1[s(1-\tau_1)(r_h-r_l)+r_l-r_0]+r_0\}^{1-\beta_1}\right)$$
$$\{\alpha_2[s(1+\tau_2)(r_h-r_l)+r_l-r_0]+r_0\}^{2-\beta_2}-\{\alpha_2[s(1-\tau_2)(r_h-r_l)+r_l-r_0]+r_0\}^{2-\beta_2}$$
$$=r_0\frac{2-\beta_2}{1-\beta_2}\left(\{\alpha_2[s(1+\tau_2)(r_h-r_l)+r_l-r_0]+r_0\}^{1-\beta_2}-\{\alpha_2[s(1-\tau_2)(r_h-r_l)+r_l-r_0]+r_0\}^{1-\beta_2}\right)$$

$(\alpha_1\lambda_1 I_1+\alpha_2\lambda_2 I_2)/(\lambda_1 I_1+\lambda_2 I_2)=s$

(6)

There are two solutions to (6). One obvious solution is $\hat{s}=0$, and the other solution is some value $s*$ in (0, 1). (7) consists of the FOCs only. The second-order condition (SOC) rules out $\hat{s}=0$ and ensures $s*$ to be the solution to (3). For all cases in the following analysis, we discuss $s*$; its SOC is verified in each case, but not presented.

3. Theoretical Analysis

In this section, we analyse the equilibrium solutions that are jointly determined by (6). The purpose of doing so is to understand investor behavior and equilibrium in a market where investors rely on an endogenous market signal to make investment decisions. Due to the complexity of the equilibrium conditions, we will rely mainly on graphic illustrations of the solutions to gain under-standing of a few important issues. Our figures are drawn using Mathcad based on (6).

Different types of investors make different choices even if they all receive the same market signal. An endogenous market signal allows us to investigate how the choices of individuals affect the market signal which in turn drives their choices. With two types of investors $\theta i \equiv (\tau_i, \beta_i, I_i)$, i=1 and 2, and population proportions λ_1 and λ_2, where $\lambda_1+\lambda_2=1$, for graphical analysis, we arbi-trarily set benchmark values as follows:

$$r_0=5\%,\quad r_l=1\%,\quad \tau_1=\tau_2=0.5,\quad \beta_1=\beta_2=0.5,\quad \lambda_1=0.5,\quad I_1/I_2=1. \quad (8)$$

In the following figures, r_h is the free variable on the horizontal axis. We alter τ_i, β_i and I_i one by one to see their effects on investment behavior. In each figure, a parameter value is indicated if and only if it is different from its benchmark value in (8).

3.1. Experience

Our first concern is the effect of experience on investment behavior. As shown in the left chart of Figure 2, the investment decisions are sensible in that more knowledgeable and experienced in-vestors invest more in the risky asset. However, the behavior is dependent on the population pro-portions. If knowledgeable investors form a small proportion of the population, the situation is reversed. As shown in the right chart of Figure 2, when the proportion of knowledgeable investors is only 20% (or less), less knowledgeable investors invest more in the risky asset.

Fact 1. *More knowledgeable investors normally invest more in the risky asset than less knowl-edgeable investors. The situation is reversed, however, when the less knowledgeable investors form a large enough proportion of the population.*

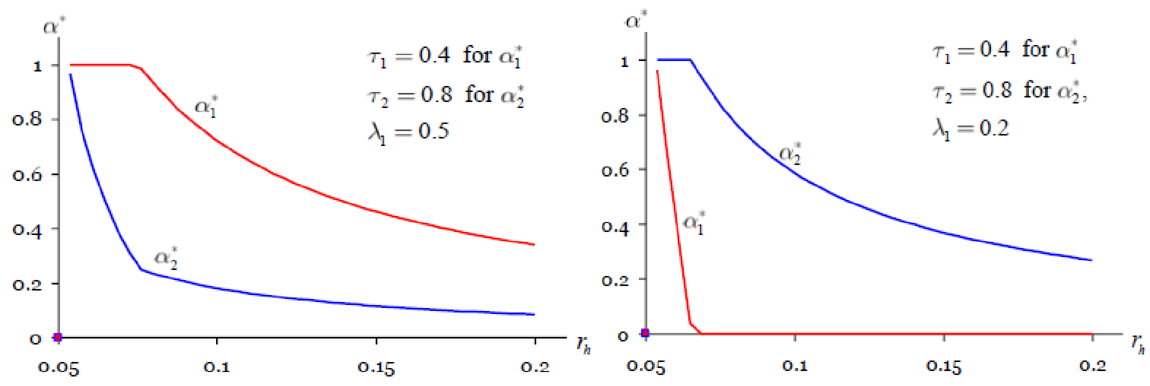

Figure 2. The Effect of Experience

The key point illustrated by Figure 2 is that, when investors are dependent on endogenous market signals and the market signals are dependent on the investors' reactions, the equilibrium choices of investors can differ dramatically depending on the population shares. When knowledge is evenly distributed in a society, we may not observe "irrational" behaviors. Only in a society where knowledge is highly unevenly distributed may "irrational" behaviors be seen. For example, in boom periods less knowledgeable investors may follow others by investing more in risky assets. This herd behavior is unstable and the investment trend could reverse quickly. As the market sentiment changes and investors exit the market, the population share of less knowledgeable investors may change quickly, causing a reversal of investment behavior and a large swing in aggregate investment. This phenomenon is confirmed in our empirical study in the next section.

If we alternatively interpret τ as the level of experience, Fact 1 implies that inexperienced in-vestors may invest more in risky assets than experienced investors. Indeed, there is evidence in the literature supporting this finding. Greenwood and Nagel (2009) find that inexperienced mutual fund managers play a role in the formation of asset price bubbles. Using age as a proxy for a man-ager's experience, they find that young mutual fund managers were more inclined to place overval-ued stocks in their investment portfolios than their older colleagues in the bubble period 1999–2000. Around the peak of this technology bubble, mutual funds overseen by younger managers were more heavily invested in technology stocks than those overseen by older managers. Further-more, young managers, not old ones, exhibit trend-chasing behavior in their technology stock in-vestments. Consistent with Greenwood and Nagel (2009), Wang and Wang (2012) find that the experience of mutual fund managers has a strong negative effect on the likelihood of their overval-uating their chosen stocks in the bubble period. This negative relation does not exist during normal periods. Gonzalez and James (2007) analyze the determinants of banking relations for technology and non-technology firms during 1996–2000. They discover the role of pre-IPO banking relations in post-IPO performance and find that firms with banking relations are older, more profitable or, in the case of technology firms, have lower losses. Hence, inexperienced investors play a role in the formation of asset price bubbles, while experienced investors play a role in reversing it. In our case, the proportion of inexperienced investors in the population matters. In a period when many inex-perienced investors are drawn to the market, these investors may invest more in risky assets, re-sulting in a highly unstable market equilibrium.

Grandstanding is known to occur in the VC industry, where young VCs seek to prove their abil-ity by pushing their portfolio companies to the public market early, which may benefit their future fund raising activities. However, Gompers et al. (2008) show that experienced VCs increase (de-crease) investment by a larger amount than less experienced VCs do in good times (bad times). In other words, experienced VCs are more sensitive to news. This is consistent with our theory. As shown in Figure 2, when τ is smaller (the investor is more experienced), a change in rh has a bigger effect on $\hat{\alpha}\hat{\imath}$; conversely, when τ is larger (the investor is less experienced), a change in rh has a smaller effect on $\hat{\alpha}\hat{\imath}$. Hence, the investment cycle in the VC industry is mostly influenced by experi-enced VCs instead of less experienced VCs. Consistent with Gompers et al. (2008), Wang and Wang (2012) examine how changes in public market signals affected VC investment between 1975 and 1998. They find that when public market signals became favorable, VCs with the most industry experience increased their investment the most, more so than did VC organizations with relatively little industry experience or those with considerable experience but were in other industries. The increase in investment adversely affected the success of these transactions although not to a signif-icant extent. These findings are consistent with the view that VCs rationally respond to investment opportunities indicated as attractive by public market signals. Our theory supports Gompers et al.'s (2008) empirical findings when the various types of investors are evenly distributed. Our theory also supports grandstanding when the various types of investors are unevenly distributed.

Our empirical analysis in the next section extends the work of Gompers et al. (2008) by includ-ing data from not only normal periods but also abnormal periods, especially the high-tech bubble period during 1999–2000. Gompers et al. (2008) discover normal investment behavior in normal periods. We not only confirm their discovery but also make one of our own—that there is a behav-ioral reversal in abnormal periods.

3.2. Risk Aversion

Our second concern is the effect of risk aversion on investment behavior. As shown in the left chart of Figure 3, the investment behavior is sensible in that a more risk-averse investor invests less in the risky asset. However, as shown in the right chart, when the population proportion of less risk-averse investors is small enough (20% or less), the situation is reversed such that a more risk-averse investor invests more in the risky asset.

Fact 2. *More risk-averse investors normally invest less in risky assets than less risk-averse ones. The situation is reversed, however, if the less risk-averse investors form a small enough propor-tion of the population.*

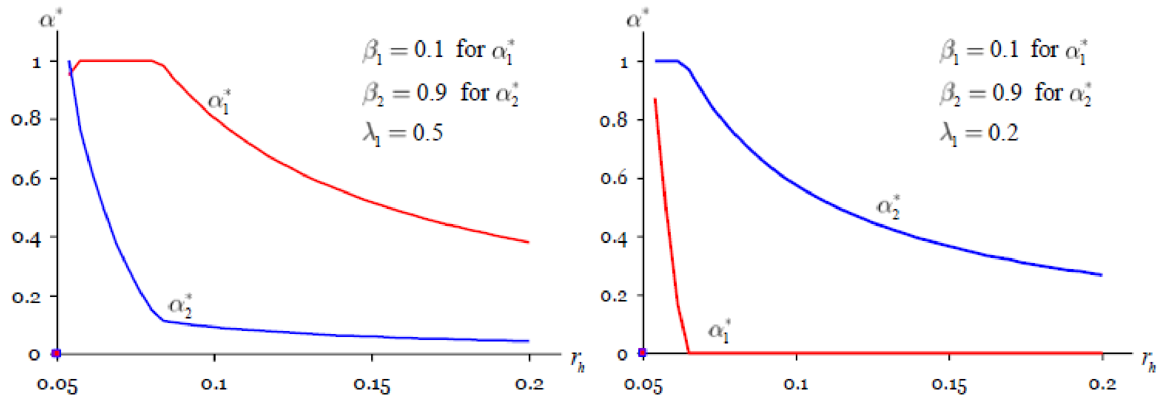

Figure 3. The Effect of Risk Aversion

A market in which more risk-averse investors invest more in risky assets is unstable because these investors are less tolerant of market fluctuations and bad news can easily cause them to flee the market. And as they flee the market, the population proportions change, which may cause a reversal of investment behavior and a large swing in aggregate investment.

There are studies in the literature that show similar investment behavior reversals. Most of these studies are based on information models or psychological observations. According to the well-known Arrow-Pratt theory (Pratt 1964; Arrow, 1971), the more risk averse an investor is, the smaller the share of her wealth that would be invested in risky assets. However, Fu (1993) shows that, if the marginal return on investment decreases (unlike what the Arrow-Pratt theory predicts) with an improvement in the state of nature, then the more risk averse an investor is, the larger the share of her wealth that would be invested in risky assets. Our investors have the same investment behavior as Fu's but we conform to the Arrow-Pratt setting. However, both the Arrow-Pratt theory and Fu's (1993) theory are about the demand for risky assets, while our theory is about investment behavior in equilibrium. In an equilibrium setting, Lintner (1965) shows that "stocks will be held long (short) in optimal portfolios even when risk premiums are negative (positive)." In an information model, Baron (1974) shows that "the opportunity to obtain information regarding the probability distribu-tion of the return on a risky asset, such as a portfolio or a mutual fund, may cause a risk-averse decision maker to accept a single-period actuarially unfair gamble." Also in an information model, Athey (2000) shows that a less risk-averse investor purchases more information under some con-ditions. She suggests that "on the one hand, an agent who is more risk averse might be willing to pay to avoid the uncertainty that comes with an uninformative signal. On the other hand, an agent who is more risk averse may choose a policy that is less responsive to the realizations of signals, and thus may not find it as valuable to purchase better information." The difference between her study and ours is that the signal in her model is exogenous while ours is endogenous. Again in an information model, Roche (2010) shows that if the level of risk aversion is below unity, the equilib-rium asset price exceeds the most optimistic agent's fundamental valuation. When investors are almost risk neutral and the wealth distribution is fairly even, speculation takes place. Roche as-sumes everyone has the same risk aversion, while we allow differences in risk aversion among in-vestors.

3.3. Income Inequality

Our third concern is the effect of income distribution on investment behavior. As shown in the left chart of Figure 4, if the population is more or less evenly distributed, the investment behaviors are sensible in that the high-income investors invest more in the risky asset. However, as shown in the right chart, when the population proportion of high-income investors is small enough (20% or less), the situation is reversed such that a low-income investor invests more in the risky asset than a high-income investor, as is often observed during a bubble period.

Fact 3. *Wealthier investors normally invest more in risky assets than the less wealthy ones. The situation is reversed, however, when the wealthier investors form a small enough proportion of the population.*

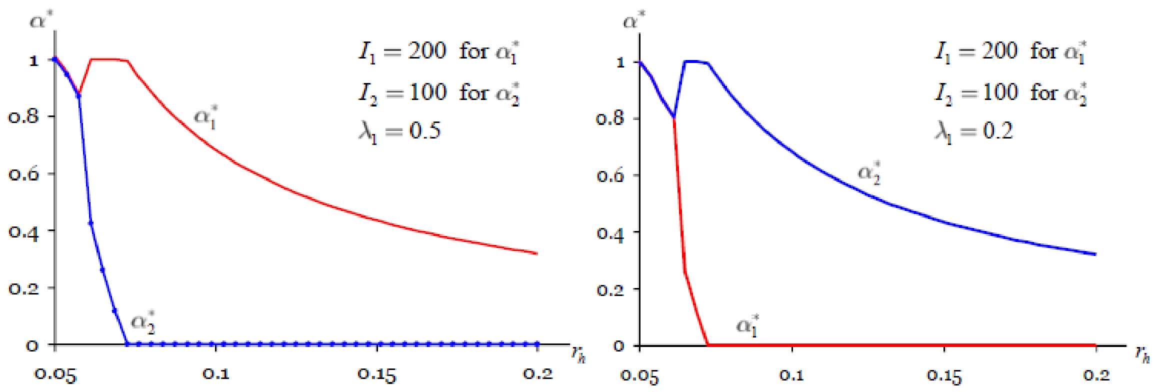

Figure 4. The Effect of Income Inequality

There are both theoretical and empirical studies in support of Fact 3. Kijima and Ohnishi (1993) show that, if an investor has increasing (decreasing) relative risk aversion, she is more conservative (aggressive) if her income is larger. In Roche's (2010) investigation of speculation, the income dis-tribution is also a crucial factor. However, Roche (2010) requires a fairly even income distribution for speculation to take place, while we require an uneven income distribution for the investment reversal to occur. Palme *et al.* (2004) conduct an empirical study on investment behavior in Sweden. They find that "low-income investors take more risk than middle-income earners" even though "workers who qualify for the minimum guarantee generally have low lifetime earnings and would therefore be expected to take less risk in their financial assets."

Heterogeneity of investors is a key factor behind our investment reversals. Heterogeneity has recently become a widely accepted factor in explaining many puzzling behaviors of investors. Hirsheiffer (1975) lays a foundation for speculation to play a role in a general equilibrium model, where speculation derives from the right of short sales, as in an American option, as opposed to holding an asset forever for its fundamental valuation. Feiger (1976) explores the idea of buying and then reselling based on heterogeneous expectations. In the work of Harrison and Kreps (1978), although investors hold the same information, they have heterogeneous subjective expectations about the state transition probabilities. In equilibrium, one agent holds all the shares in one state and sells them to another agent at a price above the most optimistic fundamental value when a switch of state occurs. Morris (1996) introduces learning into Harrison and Kreps' (1978) model. Using the fact that traders can update their beliefs, Morris is able to explain why in some IPOs the share prices are too high with respect to their long-run values. Varian (1989) finds that a large dis-persion of beliefs generates intense trading among agents and can lower or raise the equilibrium asset price depending on the curvature of the agents' utility function. Scheinkman and Xiong (2003) further consider an extension of Harrison and Kreps' (1978) model in which two groups of traders place different weights on signals. The speculative premium or bubble is interpreted as an Ameri-can option to resale the stock. Cao and Ou-Yang (2005) find that the asset price may lie below the lowest fundamental valuation of the agents based on differences in individual agents' interpreta-tions of signals. Roche (2010) recently embeds Harrison and Kreps' (1978) model into a pure ex-change economy and finds that heterogeneous beliefs are needed for speculation to occur.

One recent literature utilizes heterogeneous beliefs and short sale constraints to explain unu-sual investor behavior. Lamont and Stein (2003) investigate the investor behavior of short selling, especially during the high-tech bubble of 1999–2000. They find that short sales move countercy-clically, implying that short sales do not help stabilize stock markets. Their explanation is that ar-bitrageurs are reluctant to bet against aggregate mispricing. This is consistent with our Fact 1 in that experienced or more knowledgeable investors (the arbitrageurs) may invest less in risky assets during run-ups when many inexperienced or less knowledgeable investors are actively placing their bets. Gallmeyer and Hollifield (2008) investigate the effect of short sale constraints on stock prices when traders have heterogeneous beliefs. Short sale constraints may lead to a higher or lower vol-atility in stock prices depending on the optimistic intertemporal elasticity of substitution. Similar studies with short sale constraints and heterogeneous beliefs have been conducted by Lintner (1969), Miller (1977) and Jarrow (1980). Their formulations of heterogeneous beliefs are similar to ours, except that their traders are split between optimistic and pessimistic beliefs while we look at differences in experience, risk aversion and income distribution.

Hong and Stein (2003) present a theory of market crashes based on short sale constraints and differences of opinion among investors. Traders in their model observe a private signal and they are assumed to ignore others' signals even if they can be inferred from the equilibrium solution. Their study follows the literature on rational models with incomplete information. The representa-tive works in this line of research are Grossman (1988), Gennotte and Leland (1990), Jacklin et al. (1992) and Romer (1993). The common theme of these studies is that investors are initially imper-fectly informed about some important variable. But as trading progresses, this information is even-tually revealed by the equilibrium solution, at which time stock prices may change sharply. How-ever, this literature implies symmetric movements of stock prices, i.e., stock prices are equally likely to move upward or downward. In practice, stock prices often move downward sharply but rarely move upward sharply. In contrast, the work of Hong and Stein (2003) implies asymmetric move-ments of stock prices, with larger downward price movements than upward ones. They rely on short sale constraints for this asymmetry result. The private information of relatively bearish investors who are initially sidelined by short sale constraints is more likely to be flushed out in equilibrium when the market is falling.

A stream of studies on responses to volatility can also explain the asymmetric movements of stock prices in response to news. When major good news arrives, investors may expect volatility to rise, which dampens the positive effect of the news; however, when major bad news arrives, inves-tors may again expect volatility to rise, which enhances the negative effect of the news. This is the asymmetric effects of news. The representative works are those by Pindyck (1984), French et al. (1987), and Campbell and Hentschel (1992). However, they require groundbreaking news to ex-plain market crashes. Besides, they assume homogeneous investors and that prevents them from discussing the trading volume. A crucial difference between our work and the literature is that we do not impose short sale constraints. Instead, our work relies on the endogeneity of market signals and differences in risk aversion, income distribution and agents' ability to interpret public signals. In contrast to differences in beliefs and of opinion, our model is based entirely on economic ration-ality.

4. Empirical Evidence

Our theory is applicable to many kinds of investment. With the guidance of our theory, in this section, we conduct an empirical analysis using U.S. VC investment data. As suggested by Gompers et al. (2008), VC investments are highly volatile. And much of this volatility appears to be tied to valuation of public markets. VC performance and fundraising are largely influenced by public mar-ket conditions (Gompers and Lerner, 1998; Jeng and Wells, 2000; Lee and Wahal, 2004; Cochrane, 2005; Kaplan and Schoar, 2005). VCs' value-adding role is also dependent on market conditions (Kortum and Lerner, 2000; Gompers and Lerner, 2002; Cumming and MacIntosh, 2004). Hence, it makes sense to study the investment cycle and investors' reaction to public market signals using VC investment data. Another advantage of using VC investment data is that we have a large sample of it at the investment deal level. Other types of data, such as those for mutual funds and individuals, seldom come with this level of detail.

Our empirical analysis focuses mainly on the impact of VC firms' characteristics including ex-perience and risk aversion on their investment activities and reactions to public market signals in environments that differ in terms of investor distribution.[2] Our theoretical analysis suggests that investment behavior is dependent on the population share. Using a large sample of 137,105 VC firm-industry-year observations constructed from 68,331 VC firm-VC-backed company paired deals, we find that the positive (negative) impact of experience (risk aversion) on investment activ-ity only appears when the population share of inexperienced (more risk-averse) VC firms is modest. The situation is reversed, that is, there is a negative (positive) impact of experience (risk aversion) on investment activity, when the market is dominated by inexperienced (more risk-averse) inves-tors. Further analysis on VC firms' reactions to public market signals suggests that the positive (negative) effects of experience (risk aversion) to good public market signals only occur when the population share of inexperienced (more risk-averse) VC firms is modest.

4.1. Sample, Variables and Research Design

For VC investments, we rely primarily on the ThomsonOne (formerly known as VentureXpert). ThomsonOne is a widely used database in private equity and VC studies. Kaplan et al. (2002) sug-gest that the ThomsonOne database captures around 85% of the financing rounds made by U.S. VCs. This database provides information on both VC firms and their portfolio companies. To ensure data quality, we drop information prior to 1975 and focus on VC investments during 1975–2009.

Our sample construction is similar to Gompers et al. (2008). When an investment is observed for the first time for a portfolio company, we assume that it is the first time a VC firm invests in this portfolio company. This approach results in multiple observations for most portfolio companies since there are typically several VC firms investing in a company. In addition, to ensure that we are capturing genuine VC firms, we limit our sample to firms that invest in more than three portfolio companies. A firm is included in the sample only in the year after its investments exceed a total of three. By applying these selection criteria, we end up with a database of 2,412 unique VC firms investing in a total of 24,010 unique companies between 1975 and 2009, giving 68,331 observations of unique VC firm-portfolio company pairs (or VC deals).

Panel A of Table 1 presents the distributions of the 68,331 VC deals during 1975–2009 by year. The number of observations and the corresponding percentage are listed for every year. Notice the trends of VC investment over time. During the 1970s, the number of VC investment deals was mod-est. But then it grew dramatically after the liberalization of ERISA's "prudent man" rule in 1979, which eased pension fund restrictions on investments in VC. VC investment activities gathered further momentum in the mid-1990s, peaked in the late 1990s, and dropped off considerably following the "bubble burst" of the dot-com era. Notice also a reduction in VC investment after 2007 as a result of the financial crisis in that year.

Following Gompers et al. (2008), we group all investments into nine broad industries based on Venture Economics' classification of industries. The nine broader industries are Internet & Computers, Communications & Electronics, Business & Industrial, Consumer, Energy, Biotechnology & Healthcare, Financial Services, Business Services, and All Others. As suggested by Gompers et al. (2008), such an industry classification scheme groups together businesses having similar technology and management expertise, and reduces the subjectivity associated with classifying firms into narrower industry groups.

Panel B of Table 1 shows the distribution of our deal sample across the nine broad industries. The first two columns give the number of companies (benefiting from VC investment) and the corresponding percentage in each industry. Not surprisingly Internet & Computers is the largest industry with 10,625 companies. Biotechnology & Healthcare (4,104), Communications & Electronics (4,083), and Consumer (1,560) are the next largest industries. The other industries are considerably smaller. We also report the number of observations and the corresponding percentage for each industry. Obviously, there are more observations than there are companies since a company typically benefits from investments from multiple VC firms. Throughout the analysis, we exclude the industry group "All Others", since this represents an agglomeration of unrelated industries in which the responses to market signals would not be relevant.

We aim to explain investment decisions of VCs with different characteristics. Following Gompers et al. (2008), we make use of the annual investment activity of each active VC firm in each industry. The regression sample consists of 137,105 unique VC firm-industry-year paired observations constructed from VC firm-VC-backed company paired deals. For example, a firm that is active during 2000–2005 would contribute 48 observations (6 years × 8 industries). Many of these observations involve industries in which the VC firm did not invest. The investment decisions that we analyze include no investment and the extent of investment by a VC firm.

The dependent variable is industry investment ($INVESTf,c,t$), as measured by the log of one plus the number of investments made by VC firm *f* in industry *c* in year *t*.

We focus on two key characteristics of VC firms: industry experience and risk aversion. Gompers et al. (2008) suggest that industry experience, not overall experience, is a key factor influencing investment decision. Following Gompers et al. (2008), our measure of industry experience ($INDEXPf,c,t$) is the log of one plus the number of investments made by VC firm *f* in industry *c* prior to year *t* minus the log of one plus the average number of investments made by all active VC firms in industry *c* prior to year *t*. This measure adjusts for the positive time trend in experience.

It is difficult to measure risk aversion accurately. We thus use the realized investment risk to proxy for risk aversion. Investors who are less risk averse are likely to make more risky investments. The seed or early stage investment dummy is often used to indicate VC investment risk (Cochrane, 2005; Kaplan and Schoar, 2005; Nahata et al., 2008). We hence define a variable $RISKAVf,t$ as an inverse proxy for risk aversion, measured by the proportion of investments made in seed or early stage companies for VC firm *f* prior to year *t* minus the average proportion of investments made in seed or early stage companies for all active VC firms prior to year *t*. Similar to *INDEXP*, this measure also adjusts for a possible time trend in risk aversion. Higher values of *RISKAV* represent less risk aversion.

One challenge in identifying empirical evidence to support our theory is the measurement of public market signals. In our theoretical model, the market signal is defined as the aggregate in-vestment in the risky asset, which is not directly measurable empirically. However, we note that the market signal represents investment opportunities or hotness of the market. Hence, we make use of IPO activity to measure the public market signal following Gompers et al. (2008). IPOs are by far the most important means for VC firms to exit an investment (Gompers and Lerner, 2004). Thus, an increase in the number of IPOs in a sector suggests an attractive sector to investors. In addition, an increase in IPO activity may also attract more potential entrepreneurs to the sector, thereby increasing the pool of potential investments and the likelihood of an attractive investment opportunity for VCs.

Pagano et al. (1998) and Ritter and Welch (2002) suggest a strong link be-tween IPO activity and market valuations. Another widely used measure capturing investment opportunities is Tobin-Q, especially in studies of publicly listed companies. But as indicated by Gompers et al. (2008), Tobin-Q may or may not accurately reflect the shifts in public investors' appetite for VC-backed companies both because it uses data on mature public companies and because it relies on an inexact match between SIC codes and Venture Economics codes. Hence, we use the lagged industry Tobin-Q only as an alternative measure of the public market signal in robustness checks and use the lagged industry IPO activity ($IPOS_{c,t-1}$) as measured by the log of one plus the number of VC-backed IPOs in industry *c* in year *t-1* as the primary proxy for the public market signal.

To examine our theoretical implication of the dependence of investment decisions on population share, we employ the following two OLS models in different population share environments:

$$INVEST_{f,c,t} = \beta_0 + \beta_1\, IPOS_{c,t-1} + \beta_2\, INDEXP_{f,c,t} + \beta_3\, RISKAV_{f,t} + Controls_{f,c,t} + \varepsilon_{f,c,t}, \qquad (9)$$

$$INVEST_{f,c,t} = a_0 + a_1\, IPOS_{c,t-1} + a_2\, INDEXP_{f,c,t} + a_3\, RISKAV_{f,t} + a_4\, IPOS_{c,t-1} \times INDEXP_{f,c,t} + a_5\, IPOS_{c,t-1} \times RISKAV_{f,t} + Controls_{f,c,t} + \varepsilon_{f,c,t}. \qquad (10)$$

Model (9) tests the overall impact of VC firms' industry experience and risk aversion on their in-vestment decisions, and model (10) examines the reaction of VC firms with different levels of industry experience and risk aversion to public market signals. We include non-industry experience $NONINDEXP_{f,c,t}$ to control for the influence of experience gained outside industry c prior to year t. The measure of $NONINDEXP_{f,c,t}$ is similar as that of *INDEXP* and is the log of one plus the number of investments made by VC firm *f* outside industry *c* prior to year *t* minus the log of one plus the average number of investments made by all active investors outside industry *c* prior to year *t*. We also control for lagged industry investment (*INVEST_1*), an industry-specific AR(1) term, to control for serial correlations.

We define two industry-year level dummy variables to distinguish among environments based on the population share of inexperienced VC firms and the population share of more risk-averse VC firms, i.e., *INDEXPPOPU* and *RISKPOPU*. The dummy variable $INDEXPPOPU_{c,t}$ indicates whether the population share of inexperienced VC firms in industry *c* in year *t* belongs to the top quartile, where the population share of inexperienced investors is measured by the number of in-vestors who had never invested in industry *c* prior to year *t* divided by the number of active inves-tors in industry *c* in year *t*. Similarly, the dummy variable $RISKPOPU_{c,t}$ indicates whether the pop-ulation share of more risk-averse VC firms in industry *c* in year *t* belongs to the top quartile, where the population share of more risk-averse investors is measured by the number of investors who made less than 18% of their investments in seed or early stage companies prior to year *t* in industry *c* divided by the number of active investors in industry *c* in year *t*.[3] *INDEXPPOPU* equals one when the market is dominated by inexperienced investors, and *RISKPOPU* equals one when the market is dominated by more risk-averse investors.

Panel A of Table 2 presents the summary statistics of the regression variables. Since our sample contains many observations of the industries in which VC firms did not invest, the value of *INVEST* is often zero. The AR(1) term *INVEST_1* is quite similar to *INVEST* in terms of distribution. The mean and median values of *IPOS* are 2.15 and 2.20, respectively. The mean (median) values of *INDEXP*, *NONINDEXP* and *RISKAV* are -0.61, -0.92 and -0.02 (-0.58, -0.96 and -0.03), respec-tively. *INDEXP*, *NONINDEXP* and *RISKAV* are adjusted by time trends. Unreported statistics in-dicate that the average numbers of investments made by VC firm *f* prior to year *t* in industry *c* and outside industry *c* are respectively 6.82 and 36.15. The average proportion of investments made in seed or early stage companies for a VC firm prior to year *t* is 26.1%. The two dummy variables *INDEXPPOPU* and *RISKPOPU* are distributed quite similarly with the mean of 0.25.

Panel B of Table 2 reports the Pearson correlations among the regression variables.

4.2. Regression Analysis

Tables 3 and 4 present our main findings after running the two OLS regressions (9) and (10), respectively. The whole sample consists of 137,105 VC firm-industry-year observations. In all specifications, we include both industry and year fixed effects. The t-statistics in parentheses are based on robust errors allowing for data clustering by VC firms.

In Table 3, the dependent variable is *INVEST* and the independent variables include *INDEXP* and *RISKAV*. Column (1) suggests a strong positive relation between *INDEXP* and investment activity. The coefficient on *INDEXP* has a positive value of 0.046, significant at the 1% level, indicating that a VC firm's investment activity grows as it gains more industry experience. Column (2) repeats Column (1) but controls for *NONINDEXP*. The coefficient on *INDEXP* is still positive and significant at the 1% level. However, the coefficient on *NONINDEXP* is negative and insignificant, justifying our use of industry inexperience rather than overall experience as a key characteristic. Column (3) shows a strong positive relation between *RISKAV* and investment activity, i.e., a strong negative relation between risk aversion and investment activity. Column (4) includes both *INDEXP* and *RISKAV* and suggests consistent results. In economic terms, a one standard deviation increase in *INDEXP* boosts the industry investment by 4.60%, and a one standard deviation increase in *RISKAV* increases the industry investment by 1.76%.

Columns (5)–(8) of Table 3 repeat Column (4) using subsamples classified by the population shares of inexperienced VC firms and more risk-averse VC firms. Columns (5) and (6) suggest that industry experience has a positive impact on investment activity only when the population share of inexperienced VC firms is modest. When the market is dominated by inexperienced investors, however, the situation is reserved experienced investors invest less than inexperienced investors. The coefficient on *INDEXP* has a negative value of -0.03 at the 1% significance level when *INDEXPPOPU* equals 1, and a positive value of 0.06 at the 1% significance level when *INDEXPPOPU* equals 0. Similarly, Columns (7) and (8) suggest that risk aversion has a negative impact on investment activity only when the population share of more risk-averse VC firms is modest. When the market is dominated by more risk-averse investors, the situation is reserved—more risk-averse in-vestors invest more than less risk-averse investors. The coefficient on *RISKAV* has a negative value of -0.053 at the 10% significance level when *RISKPOPU* equals 1, and a positive value of 0.152 at the 1% significance level when *RISKPOPU* equals 0. In economic terms, holding all else constant, a one standard deviation increase in *INDEXP* leads to a reduction in industry investment of 1.87% when *INDEXPPOPU* equals 1, and a one standard deviation increase in *INDEXP* leads to a rise in industry investment of 5.79% when *INDEXPPOPU* equals 0. Further, a one standard deviation in-crease in *RISKAV* leads to a reduction in industry investment of 0.72% when *RISKPOPU* equals 1, and a one standard deviation increase in *INDEXP* leads to a rise in industry investment of 2.32% when *RISKPOPU* equals 0.

Columns (9)–(11) examine the interaction terms $INDEXP$×$INDEXPPOPU$ and $RISKAV$×$RISKPOPU$ using the whole sample. The results are consistent with those in Columns (5)–(8). The advantage of using the interaction terms is that the influence of the population share of inexperi-enced investors and that of the population share of more risk-averse investors are revealed in one regression. The disadvantage, however, is that there might be a multicollinearity problem. The co-efficients on INDEXP×$INDEXPPOPU$ and RISKAV×$RISKPOPU$ are both negative and significant at the 1% level.

The public market signals (*IPOS*) and the lagged industry investment (*INVEST_1*) are strongly positively related to industry investment activity throughout all specifications.

In Table 4, by employing regression model (10), we analyze how VC firms with different char-acteristics respond to changes in public market signals in different environments represented by *INDEXPPOPU* and *RISKPOPU*. Gompers et al. (2008) suggest that VC firms with more industry experience react strongly and positively to public market signals. We extend their analysis by distinguishing among environments with different population shares. Further, their analysis is limited to the sample period of 1975–1998 and examines only one VC firm characteristic, i.e., experience, while we expand the sample period to 1975–2009 to include the highly volatile periods of 1999–2000 and 2008–2009, and examine both experience and risk aversion. Column (1) suggests results consistent with those of Gompers et al. (2008) that VC firms with the most industry experience increase their investments the most when public market signals become more favorable. They react more strongly to strengthened public market signals than do VC firms with relatively little industry experience. The coefficient on INDEXP×$IPOS$ has a positive value of 0.028 at the 1% significance level. In economic terms, a one standard deviation increase in *INDEXP* would boost industry in-vestment by 5.7% when IPO activity changes from low (at the 25th percentile) to high (at the 75th percentile). Column (2) further suggests a negative reaction to public market signals by more risk-averse VC firms. The coefficient on RISKAV×$IPOS$ has a positive value of 0.063 at the 1% signifi-cance level. A one standard deviation increase in *RISKAV* would increase industry investment by 12.83% when IPO activity changes from low (at the 25th percentile) to high (at the 75th percentile). Columns (3)–(4) repeat the regression using subsamples classified by the dummy variable *INDEXPPOPU* indicating the population share of inexperienced investors. The coefficient on INDEXP×$IPOS$ is insignificant when *INDEXPPOPU* equals 1, and is significantly positive when *IN-DEXPOPU* equals 0. This suggests that industry experience plays a positive role in responding to public market signals only when the population share of inexperienced investors is modest. When the market is dominated by inexperienced investors, however, the situation is different—experi-enced investors do not respond more strongly to good market signals than inexperienced investors. Similarly, Columns (5)–(6) repeat the regression using the subsamples classified by the dummy variable *RISKPOPU* indicating the population share of more risk-averse investors. The coefficient on $RISKAV$×$IPOS$ is insignificant when *RISKPOPU* equals 1, and is positively significant at the 1% level when *INDEXPOPU* equals 0. This suggests that risk aversion plays a negative role in respond-ing to public market signals only when the population share of more risk-averse VC firms is modest. When the market is dominated by more risk-averse VC firms, the situation is different—more risk-averse VC firms do not respond more strongly to good market signals than less risk-averse VC firms. Columns (7)–(9) make use of the whole sample and examine the interaction terms INDEXP×IPOS×INDEXPPOPU and $RISKAV$×IPOS×RISKPOPU. The coefficients on these two terms are negative at the 1% significance level, suggesting results consistent with those in Columns (3)–(6).

4.3. Robustness Analysis

To make our findings more convincing, we undertake some robustness analyses. We repeat the analyses in Tables 3 and 4 with alternative measurements or samples. Select results are reported in Table 5, which corresponds to Columns (4)–(8) of Table 3 and Columns (2)–(6) of Table 4.

Using dummy variables to indicate industry experience and risk aversion

Panel A of Table 5 shows the results when industry experience and risk aversion are measured using dummy variables rather than continuous variables. $INDEXPDf,c,t$ is a dummy variable indi-cating whether the number of investments made by VC firm *f* in industry *c* prior to year *t* belongs to the top quartile. Similarly, $RISKAVc,t$ is a dummy variable indicating whether the proportion of investments made in seed or early stage companies for VC firm *c* prior to year *t* belongs to the top quartile. We also make similar adjustments to non-industry experience. We find that the same basic results hold.

Using alternative measures of public market signals

Panel B of Table 5 reports results using an alternative measure of public market signals—lagged industry Tobin-Q (*Q*)—that is widely used to measure the valuation of publicly listed companies. Since we cannot observe the Tobin-Q of private companies that constitute the pool of potential VC investment targets, we use an estimate of Tobin-Q for public companies as a proxy following Gom-pers et al. (2008). We first link the SIC codes of public companies to Venture Economics industries on which our data are based, so as to identify the SIC codes of all Venture Economics companies that went public. Each of our eight industries might be associated with multiple SIC codes. Then, we construct Tobin-Q as a weighted average of the industry Tobin-Q of the public companies with those SIC codes, where the weights are the relative fractions of companies that went public within the eight industries. Within each SIC code, Tobin-Q is calculated by equally weighting all public companies. Tobin-Q is calculated as the ratio of the market value of the company to the company's book value of assets, where the market value of the company is measured by the book value of assets plus the market value of equity less the book value of equity. Panel B shows results that are quite similar to those in Tables 3 and 4.

Panel C of Table 5 presents results using a dummy variable rather than a continuous variable to indicate public market signals. $IPOD_{c,t-1}$ indicates whether the number of VC-backed IPOs in industry *c* in year *t-1* belongs to the top quartile. All previous results hold if we use a dummy variable to proxy for public market signals to indicate whether the lagged industry Tobin-Q belongs to the top quartile.

Dropping those observations of VC firms that had not invested in an industry up to year *t*

In the above analyses, we use observations of each active VC firm and industry. But some VC firms may be very unlikely to invest in a particular industry simply because they do not have the capabilities to do so. We therefore eliminate those observations of VC firms that had not invested in an industry up to year *t*. Panel D of Table 5 reports the results. All our findings remain qualitatively unchanged.

Addressing the possibility of capital constraints

To address the possible influence of capital constraints, we limit our sample to VCs with above-median fundraising during the prior ten years. Panel E of Table 5 presents the results. Once again, the basic results remain qualitatively unaltered.

In conclusion, the empirical evidence from VC investments strongly supports our theoretical results. In particular, industry experience has a positive impact on investment activity only when the population share of inexperienced VC firms is modest. When the market is dominated by inexperienced investors, however, the situation is reversed, that is, industry experience becomes negatively related to investment activity. Similarly, risk aversion has a negative impact on investment activity only when the population share of relatively more risk-averse VC firms is modest. When the market is dominated by more risk-averse VC firms, however, the situation is reversed, that is, risk aversion becomes positively related to investment activity. Further analyses on the reactions to public market signals of VC firms with different levels of industry experience and risk aversion suggest that positive (negative) reactions to public market signals with higher level of industry ex-perience (risk aversion) exist only when the population share of inexperienced VC firms (more risk-averse VC firms) is modest.

5. Concluding Remarks

This paper demonstrates the possibility of investment reversals. We show that investment “ir-regularities” can arise in information models, in which investors rely on endogenous market signals with different abilities to interpret the signals. Our explanation of investment reversals is based on economic rationality.

We have also identified strong empirical evidence in support of our theory. Our empirical re-sults demonstrate that (1) opposite investment behaviors are observed in the market during normal and abnormal periods; (2) a change in the population shares of different types of investors in the market can cause a reversal of investment behaviors among those same types of investors.

An uneven population distribution of various types of investors is crucial to our conclusions. Population sizes can deepen or diminish the effect of public news. The over-reactions or under-reactions of a particular type of investors when a behavioral reversal occurs are crucially dependent on the population sizes of different types of investors. A behavioral reversal in our model is caused by an over-reaction of the type of investors that form a large proportion of the overall population coupled with an under-reaction of the type of investors that form a small proportion of the overall population. The intuition of our results is clear. If one investor is considering investing in a risky asset after observing a positive signal, then all investors of the same type would be considering the same. With an endogenous public signal, more investment strengthens the public signal. By this equilibrium process, a positive signal is always boosted by investors of the type that make up a large share of the population but dampened by investors of the type that make up a small share of the population. The end result is a behavioral reversal depending on which type of investors is dominant in the overall population. In sum, since we have an endogenous market signal (the strength of which is dependent on the reactions to it), differences in risk aversion, income distribution and the ability to interpret public signals due to the differences in experience and knowledge among investors can lead to unusual investment behaviors in equilibrium.

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Table 1 Sample Distribution

Panel A: Deal-level sample distribution by year

Year	Obs.	Percentages	Year	Obs.	Percentages
1975	56	0.08	1993	948	1.39
1976	82	0.12	1994	947	1.39
1977	86	0.13	1995	1,521	2.23
1978	200	0.29	1996	2,093	3.06
1979	303	0.44	1997	2,727	3.99
1980	481	0.70	1998	3,606	5.28
1981	988	1.45	1999	5,931	8.68
1982	1151	1.68	2000	8,068	11.81
1983	2,018	2.95	2001	4,056	5.94
1984	1,870	2.74	2002	2,683	3.93
1985	1,484	2.17	2003	2,364	3.46
1986	1,765	2.58	2004	2,681	3.92
1987	1,733	2.54	2005	2,584	3.78
1988	1,605	2.35	2006	2,941	4.30
1989	1,321	1.93	2007	3,108	4.55
1990	1,032	1.51	2008	2,737	4.01
1991	771	1.13	2009	1,270	1.86
1992	1,118	1.64	Total	68,331	100

Panel B: Deal-level sample distribution by industry

Industry	Companies	Percentages	Obs.	Percentages
Internet & Computers	10,625	15.55	31,667	46.34
Biotechnology & Healthcare	4,104	6.01	13,371	19.57
Communications & Electronics	4,083	5.98	13,566	19.85
Consumer	1,560	2.28	2,992	4.38
Business & Industrial	793	1.16	1,789	2.62
Energy	667	0.98	1,354	1.98
Financial Services	572	0.84	967	1.42
Business Services	647	0.95	1,164	1.70
All others	959	1.40	1,461	2.14
Total	24,010	35.14	68,331	100

The unit of observation is a VC firm's initial investment in a portfolio company. Panels A and B show the distribution of the deal sample by year and industry, respectively. There are 24,010 unique companies and 68,331 unique VC firm-VC-backed company paired deals.

Table 2 Summary and Correlations of Variables

Panel A: Summary statistics

	0.25	0.5	0.75	Mean	s.d	Obs.
INVEST	0	0	0	0.21	0.47	137,105
INVEST_1	0	0	0	0.21	0.47	137,105
IPOS	1.10	2.20	3.14	2.15	1.26	137,105
INDEXP	-1.23	-0.58	-0.01	-0.61	0.92	137,105
NONINDEXP	-1.71	-0.96	-0.13	-0.92	1.12	137,105
RISKAV	-0.11	-0.03	0.06	-0.02	0.15	137,105
INDEXPPOPU	0	0	1	0.25	0.43	137,105
RISKPOPU	0	0	1	0.25	0.43	137,105

Panel B: Correlations

(Obs.=137,105)	INVEST	IPOS	INDEXP	RISKAV	INVEST_1	NONINDEXP	INDEXPPOPU
INVEST	1						
IPOS	0.2500	1					
	(0.000)						
INDEXP	0.2112	-0.2385	1				
	(0.000)	(0.000)					
RISKAV	0.0724	0.0327	-0.0278	1			
	(0.000)	(0.000)	(0.000)				
INVEST_1	0.5691	0.2222	0.3396	0.0586	1		
	(0.000)	(0.000)	(0.000)	(0.000)			
NONINDEXP	0.1532	-0.0298	0.5291	0.0025	0.2123	1	
	(0.000)	(0.000)	(0.000)	(0.3563)	(0.000)		
INDEXPPOPU	-0.1704	-0.5865	0.246	-0.0412	-0.1718	0.0293	1
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
RISKPOPU	0.0324	-0.1375	0.12	0.0632	0.0185	0.129	-0.0409
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panels A and B respectively present the summary statistics and correlations among variables. The unit of observation is a VC firm in an industry in a year. There are 137,105 unique VC firm-industry year observations constructed from the deal sample. Sample construction procedures are described in the text.

Table 3 The Overall Impact of Industry Experience and Risk Aversion

VARIABLE	(1) INVEST	(2) INVEST	(3) INVEST	(4) INVEST	(5) INVEST	(6) INVEST	(7) INVEST	(8) INVEST	(9) INVEST	(10) INVEST	(11) INVEST
	Whole	Whole	Whole	Whole	IN-DEX-PPOPU=1	IN-DEX-PPOPU=0	RISK-POPU=1	RISK-POPU=0	Whole	Whole	Whole
Constant	0.114***	0.114***	0.076***	0.117***	0.128***	0.064***	0.216***	0.101***	0.131***	0.113***	0.126***
	(8.22)	(8.28)	(5.68)	(8.50)	(3.34)	(3.58)	(9.75)	(6.39)	(9.63)	(8.07)	(9.08)
IPOS	0.046***	0.046***	0.043***	0.046***	0.016***	0.062***	0.044***	0.050***	0.047***	0.046***	0.048***
	(24.08)	(24.03)	(22.17)	(24.08)	(5.74)	(23.72)	(9.31)	(24.19)	(23.75)	(24.19)	(23.95)
INDEXP	0.046***	0.048***		0.050***	-0.030***	0.060***	0.067***	0.045***	0.065***	0.050***	0.066***
	(9.79)	(14.90)		(15.32)	(-3.39)	(17.88)	(12.57)	(13.77)	(18.79)	(15.46)	(18.92)
RISKAV			0.102***	0.118***	0.059***	0.127***	-0.053*	0.152***	0.111***	0.159***	0.152***
			(7.38)	(8.52)	(5.43)	(7.82)	(-1.92)	(11.37)	(8.39)	(11.29)	(11.15)
*INDEXP*INDEXPPOPU*									-0.111***		-0.111***
									(-12.15)		(-12.15)
*RISKAV*RISKPOPU*										-0.187***	-0.184***
										(-7.46)	(-7.42)
INDEXPPOPU									-0.021***		-0.020***
									(-4.54)		(-4.39)
RISKPOPU										0.007**	0.009***
										(2.24)	(2.91)
INVEST_1	0.488***	0.487***	0.526***	0.484***	0.163***	0.500***	0.336***	0.521***	0.474***	0.483***	0.473***
	(31.42)	(30.93)	(26.74)	(30.64)	(3.05)	(33.19)	(15.98)	(33.55)	(28.68)	(30.56)	(28.62)
NONINDEXP		-0.003		-0.003	0.012**	-0.006	0.021***	-0.008**	-0.002	-0.003	-0.002
		(-0.97)		(-1.00)	(2.53)	(-1.56)	(4.46)	(-2.27)	(-0.50)	(-1.00)	(-0.49)
Fixed Effects:	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	137,105	137,105	137,105	137,105	34,711	102,394	34,065	103,040	137,105	137,105	137,105
R-squared	0.3648	0.3648	0.3604	0.3662	0.0496	0.3843	0.3096	0.3919	0.3708	0.3668	0.3714

The unit of observation is a VC firm in an industry in a year. The dependent variable is the log of one plus the number of investments made by a VC firm in an industry in a year (*INVEST*). The public market signal is the lagged VC-backed IPO activity (*IPOS*), as measured by the log of one plus the number of VC-backed IPOs in an industry a year before (*IPOS*). *INDEXP* is the difference between the log of one plus the number of investments made by a VC firm in an industry prior to a year and the log of one plus the average number of investments made by all firms in the industry prior to that year. *RISKAV* is the difference between the proportion of investments made in seed or early stage companies for a VC firm prior to a year and the average proportion of investments made in seed or early stage companies for all firms prior to that year. *INDEXPPOPU* is a dummy variable indicating whether the population share of inexperienced investors in an industry in a year belongs to the top quartile of the sample, where the population share of inexperienced investors is measured by the number of investors who had never invested in the industry prior to that year divided by the number of active investors in the industry in that year. *RISKPOPU* is a dummy variable indicating whether the population share of more risk-averse investors in an industry in a year belongs to the top quartile of the sample, where the population share of more risk-averse investors is measured by the number of investors who made less than 18% of their investments in seed or early stage companies prior to that year divided by the number of active investors in the industry in that year. NONINDEXP is the difference between the log of one plus the number of investments made by a VC firm outside an industry prior to a year and the log of one plus the average number of investments made by all firms outside the industry prior to that year. *INVEST_1* is an AR(1) term, where *INVEST_1* lags *INVEST* for one year. Our regressions include industry and year fixed effects. The t-statistics in parentheses are based on robust errors allowing for data clustering by VC firms. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Reactions to Market Signals of VC Firms with Different Levels of Industry Experience and Risk Aversion

VARIABLE	(1) INVEST	(2) INVEST	(3) INVEST	(4) INVEST	(5) INVEST	(6) INVEST	(7) INVEST	(8) INVEST	(9) INVEST
	Whole	Whole	IN-DEX-PPOPU=1	IN-DEX-PPOPU=0	RISKPOPU=1	RISK-POPU=0	Whole	Whole	Whole
Constant	0.094***	0.093***	0.126***	0.043**	0.195***	0.081***	0.088***	0.116***	0.087***
	(7.02)	(6.94)	(3.31)	(2.48)	(9.09)	(5.08)	(6.38)	(8.10)	(6.15)
IPOS	0.065***	0.066***	0.018***	0.077***	0.065***	0.070***	0.066***	0.047***	0.067***
	(24.34)	(24.88)	(6.13)	(24.95)	(13.14)	(24.57)	(23.42)	(23.78)	(23.26)
INDEXP	-0.021***	-0.021***	-0.035***	0.007	-0.047***	-0.018***	0.013***	0.049***	0.013***
	(-4.36)	(-4.34)	(-3.99)	(1.52)	(-6.83)	(-3.61)	(2.97)	(15.17)	(2.79)
RISKAV		-0.026*	0.042***	-0.041*	-0.062**	0.008	0.110***	0.027*	-0.003
		(-1.87)	(2.84)	(-1.71)	(-2.17)	(0.56)	(8.37)	(1.74)	(-0.20)
*INDEXP*IPOS*	0.028***	0.028***	0.006	0.019***	0.054***	0.024***	0.019***		0.019***
	(14.59)	(14.66)	(1.63)	(10.08)	(16.34)	(12.33)	(9.98)		(9.96)
*RISKAV*IPOS*		0.063***	0.020	0.063***	0.003	0.060***		0.056***	0.066***
		(7.94)	(1.39)	(6.30)	(0.16)	(7.32)		(6.54)	(7.57)
*INDEXP*IPOS*INDEXPPOPU*							-0.014***		-0.013***
							(-3.57)		(-3.34)
*RISKAV*IPOS*RISKPOPU*								-0.059***	-0.067***
								(-3.85)	(-4.23)
INDEXPPOPU							0.036***		0.034***
							(7.20)		(6.65)
RISKPOPU							-0.045***		-0.045***
							(-12.82)		(-12.72)
*INDEXPPOPU*IPOS*							-0.064***		-0.067***
							(-7.00)		(-7.08)
*RISKPOPU*IPOS*								-0.003	-0.004
								(-0.70)	(-0.97)
*INDEXP * INDEXPPOPU*								0.006***	0.006***
								(2.96)	(2.59)
RISKAV RISKPOPU*								-0.051	-0.029
								(-1.59)	(-0.88)
INVEST_1	0.476***	0.472***	0.163***	0.495***	0.316***	0.510***	0.468***	0.483***	0.467***
	(29.46)	(29.19)	(3.05)	(32.93)	(15.37)	(31.79)	(28.23)	(30.56)	(28.13)
NONINDEXP	-0.002	-0.002	0.013**	-0.005	0.021***	-0.006*	-0.002	-0.003	-0.001
	(-0.66)	(-0.48)	(2.54)	(-1.33)	(4.30)	(-1.66)	(-0.43)	(-0.80)	(-0.21)
Fixed Effects:	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	137,105	137,105	34,711	102,394	34,065	103,040	137,105	137,105	137,105
R-squared	0.3685	0.3704	0.0498	0.3859	0.3171	0.3953	0.3724	0.3673	0.3736

The unit of observation is a VC firm in an industry in a year. The dependent variable is the log of one plus the number of investments made by a VC firm in an industry in a year (INVEST). The public market signal is the lagged VC-backed IPO activity (IPOS), as measured by the log of one plus the number of VC-backed IPOs in the industry a year before (IPOS). INDEXP is the difference between the log of one plus the number of investments made by a VC firm in an industry prior to a year and the log of one plus the aver-age number of investments made by all the firms in the industry prior to that year. RISKAV is the difference between the proportion of investments made in seed or early stage companies for a VC firm prior to a year and the average proportion of investments made in seed or early stage companies for all firms prior to that year. INDEXPPOPU is a dummy variable indicating whether the population share of inexperienced investors in an industry in a year belongs to the top quartile of the sample, where the population share of inexperienced investors is measured by the number of investors who had never invested in the industry prior to that year divided by the number of active investors in the industry in that year. RISKPOPU is a dummy variable indicating whether the population share of more risk-averse investors in an industry in a year belongs to the top quartile of the sample, where the population share of more risk-averse investors is measured by the number of investors who made less than 18% of their investments in seed or early stage companies prior to that year divided by the number of active investors in the industry in that year. NONINDEXP is the difference between the log of one plus the number of investments made by a VC firm outside an industry prior to a year and the log of one plus the average number of investments made by all the firms outside the industry prior to that year. INVEST_1 is an AR(1) term, where INVEST_1 lags INVEST for one year. Our regressions include industry and year fixed effects. The t-statistics in parentheses are based on robust errors allowing for data clustering by VC firms. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Robustness Tests

Panel A: Using dummy variables rather than continuous variables to indicate experience and risk aversion

VARIABLE	(1) INVEST	(2) INVEST	(3) INVEST	(4) INVEST	(5) INVEST	(6) INVEST	(7) INVEST	(8) INVEST	(9) INVEST	(10) INVEST
	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0
Constant	0.051***	0.126***	-0.020	0.135***	0.032*	0.117***	0.128***	0.058***	0.182***	0.109***
	(3.62)	(3.30)	(-1.01)	(6.17)	(1.95)	(8.42)	(3.34)	(3.29)	(8.44)	(6.55)
IPOS	0.044***	0.016***	0.061***	0.042***	0.050***	0.023***	0.015***	0.043***	0.015***	0.031***
	(22.54)	(5.88)	(23.36)	(8.69)	(23.67)	(10.71)	(4.57)	(15.35)	(2.89)	(13.47)
INDEXPD	0.072***	-0.012***	0.119***	0.081***	0.075***	-0.063***	-0.016***	-0.018**	-0.071***	-0.054***
	(14.40)	(-3.58)	(16.20)	(12.03)	(13.34)	(-11.53)	(-3.46)	(-2.17)	(-8.57)	(-9.45)
RISKAVD	0.031***	0.020***	0.036***	-0.015*	0.044***	-0.014***	0.018***	-0.023***	-0.013	-0.004
	(5.90)	(4.04)	(5.80)	(-1.92)	(8.08)	(-2.81)	(3.03)	(-2.90)	(-1.43)	(-0.67)
*INDEXP*IPOD*						0.071***	0.004	0.056***	0.092***	0.064***
						(15.68)	(0.86)	(11.34)	(15.00)	(13.76)
*RISKAV*IPOD*						0.021***	0.001	0.023***	-0.001	0.021***
						(6.93)	(0.26)	(6.18)	(-0.18)	(6.67)
INVEST_1	0.505***	0.154**	0.517***	0.371***	0.538***	0.485***	0.154**	0.507***	0.345***	0.520***
	(25.89)	(2.56)	(27.87)	(14.01)	(28.76)	(24.09)	(2.56)	(27.01)	(12.96)	(26.77)
NONINDEXPD	-0.002	0.003	-0.009**	0.027***	-0.008**	-0.006*	0.003	-0.011***	0.022***	-0.012***
	(-0.48)	(0.84)	(-2.31)	(4.49)	(-2.38)	(-1.71)	(0.84)	(-2.81)	(3.69)	(-3.41)
Fixed Effects:	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	137,105	34,711	102,394	34,065	103,040	137,105	34,711	102,394	34,065	103,040
R-squared	0.3636	0.0443	0.3833	0.3023	0.3902	0.3700	0.0444	0.3860	0.3111	0.3957

Panel B: Using Q as the proxy for market signals

VARIABLE	(1) INVEST	(2) INVEST	(3) INVEST	(4) INVEST	(5) INVEST	(6) INVEST	(7) INVEST	(8) INVEST	(9) INVEST	(10) INVEST
	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0
Constant	0.107***	0.113***	0.047***	0.155***	0.092***	0.073***	0.112***	0.009	0.099***	0.060***
	(7.78)	(2.90)	(2.59)	(6.61)	(5.84)	(5.32)	(2.86)	(0.47)	(4.24)	(3.86)
Q	0.057***	0.009**	0.067***	0.098***	0.058***	0.081***	0.010**	0.094***	0.152***	0.080***
	(17.08)	(2.32)	(16.30)	(13.83)	(14.55)	(20.27)	(2.32)	(18.80)	(19.08)	(17.14)
INDEXP	0.117***	0.059***	0.126***	-0.051*	0.151***	-0.017***	-0.029***	-0.005	-0.088***	-0.014***
	(8.52)	(5.42)	(7.79)	(-1.88)	(11.38)	(-3.82)	(-3.58)	(-1.00)	(-9.24)	(-2.80)
RISKAV	0.048***	-0.030***	0.059***	0.068***	0.044***	0.005	0.011	0.035	-0.072	0.075***
	(14.88)	(-3.41)	(17.69)	(12.72)	(13.47)	(0.23)	(0.41)	(1.21)	(-1.64)	(2.85)
*INDEXP*IPOD*	0.488***	0.163***	0.503***	0.339***	0.525***	0.035***	-0.001	0.033***	0.105***	0.029***
	(31.15)	(3.05)	(33.55)	(16.17)	(34.14)	(12.88)	(-0.21)	(11.47)	(15.26)	(10.15)
*RISKAV*IPOD*	-0.003	0.013**	-0.006	0.021***	-0.008**	0.062***	0.033*	0.048***	0.010	0.040**
	(-0.98)	(2.54)	(-1.63)	(4.47)	(-2.31)	(3.99)	(1.80)	(2.83)	(0.28)	(2.43)
INVEST_1	0.489***	0.163***	0.504***	0.334***	0.526***	0.485***	0.163***	0.501***	0.315***	0.523***
	(31.24)	(3.05)	(33.66)	(15.95)	(34.29)	(30.94)	(3.05)	(33.60)	(15.59)	(33.87)
NONINDEXP	-0.003	0.013**	-0.006	0.021***	-0.007**	-0.002	0.013**	-0.005	0.022***	-0.007*
	(-0.92)	(2.54)	(-1.60)	(4.47)	(-2.22)	(-0.60)	(2.56)	(-1.31)	(4.41)	(-1.91)
Fixed Effects:	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	137,105	34,711	102,394	34,065	103,040	137,105	34,711	102,394	34,065	103,040
R-squared	0.3650	0.0490	0.3828	0.3113	0.3901	0.3674	0.0491	0.3846	0.3186	0.3919

Panel C: Using a dummy variable rather than a continuous variable to indicate market signals

VARIABLES	(1) INVEST	(2) INVEST	(3) INVEST	(4) INVEST	(5) INVEST	(6) INVEST	(7) INVEST	(8) INVEST	(9) INVEST	(10) INVEST
	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0
Constant	0.141***	0.127***	0.082***	0.263***	0.111***	0.120***	0.127***	0.062***	0.249***	0.089***
	(10.20)	(3.32)	(4.48)	(12.19)	(7.02)	(8.58)	(3.32)	(3.33)	(11.38)	(5.62)
IPOD	0.047***	-0.018	0.044***	0.023***	0.062***	0.107***	-0.021	0.085***	0.088***	0.125***
	(13.08)	(-0.53)	(12.19)	(2.91)	(14.76)	(18.45)	(-0.63)	(16.47)	(8.80)	(18.91)
INDEXP	0.049***	-0.030***	0.059***	0.066***	0.045***	0.013***	-0.030***	0.031***	0.033***	0.007*
	(15.07)	(-3.40)	(17.87)	(12.37)	(13.69)	(3.42)	(-3.38)	(9.48)	(6.55)	(1.86)
RISKAV	0.117***	0.059***	0.126***	-0.053*	0.151***	0.074***	0.059***	0.089***	-0.053**	0.106***
	(8.49)	(5.42)	(7.77)	(-1.92)	(11.35)	(7.10)	(5.41)	(6.29)	(-2.40)	(9.96)
*INDEXP*IPOD*						0.074***	-0.063	0.050***	0.108***	0.070***
						(16.94)	(-0.80)	(14.56)	(13.77)	(14.78)
*RISKAV*IPOD*						0.090***	-0.111	0.064***	-0.009	0.086***
						(5.41)	(-0.48)	(3.93)	(-0.22)	(5.24)
INVEST_1	0.487***	0.163***	0.502***	0.338***	0.525***	0.476***	0.163***	0.497***	0.317***	0.515***
	(31.06)	(3.05)	(33.46)	(16.10)	(34.08)	(29.65)	(3.05)	(32.96)	(15.28)	(32.38)
NONINDEXP	-0.003	0.013**	-0.006	0.021***	-0.008**	-0.001	0.012**	-0.005	0.022***	-0.005
	(-0.97)	(2.54)	(-1.62)	(4.49)	(-2.30)	(-0.27)	(2.54)	(-1.20)	(4.38)	(-1.50)
Fixed Effects:	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	137,105	34,711	102,394	34,065	103,040	137,105	34,711	102,394	34,065	103,040
R-squared	0.3643	0.0489	0.3819	0.3084	0.3897	0.3689	0.0489	0.3838	0.3156	0.3940

Panel D: Dropping those observations of VC firms that had not invested in an industry prior to a year

VARIABLES	(1) INVEST	(2) INVEST	(3) INVEST	(4) INVEST	(5) INVEST	(6) INVEST	(7) INVEST	(8) INVEST	(9) INVEST	(10) INVEST
	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0
Constant	0.715***	0.931***	0.629***	0.823***	0.699***	0.697***	0.930***	0.618***	0.791***	0.700***
	(31.04)	(8.82)	(18.40)	(22.03)	(19.23)	(28.61)	(8.86)	(18.59)	(18.47)	(19.02)
IPOD	0.049***	0.015***	0.066***	0.039***	0.054***	0.071***	0.016***	0.081***	0.052***	0.072***
	(22.55)	(4.90)	(22.69)	(5.75)	(23.69)	(23.05)	(4.96)	(23.97)	(7.29)	(23.64)
INDEXP	0.038***	-0.091***	0.050***	0.032***	0.036***	-0.022	0.091***	-0.044	-0.048	0.011
	(8.60)	(-5.16)	(11.78)	(3.52)	(8.91)	(-1.21)	(4.38)	(-1.52)	(-0.93)	(0.62)
RISKAV	0.160***	0.113***	0.168***	-0.072*	0.189***	-0.048***	-0.096***	-0.006	-0.177***	-0.029***
	(8.94)	(6.57)	(8.51)	(-1.68)	(11.03)	(-6.37)	(-5.42)	(-0.99)	(-11.27)	(-4.31)
*INDEXP*IPOD*						0.033***	0.005	0.020***	0.093***	0.025***
						(13.14)	(0.98)	(8.90)	(16.35)	(10.42)
*RISKAV*IPOD*						0.077***	0.024	0.079***	-0.010	0.074***
						(7.86)	(1.26)	(6.29)	(-0.40)	(7.54)
INVEST_1	0.473***	0.127**	0.490***	0.291***	0.518***	0.461***	0.127**	0.484***	0.269***	0.508***
	(28.55)	(2.00)	(31.12)	(12.78)	(32.47)	(26.88)	(2.00)	(30.83)	(11.90)	(30.72)
NONINDEXP	-0.006	0.016**	-0.009**	0.021***	-0.010**	-0.004	0.016**	-0.009*	0.021***	-0.008*
	(-1.53)	(2.30)	(-2.14)	(3.00)	(-2.50)	(-1.01)	(2.31)	(-1.93)	(2.74)	(-1.94)
Fixed Effects:	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	117,097	26,870	90,227	25,142	91,955	117,097	26,870	90,227	25,142	91,955
R-squared	0.3592	0.1118	0.3767	0.2956	0.3853	0.3640	0.1119	0.3784	0.3096	0.3886

Panel E: Addressing the possibility of capital constraints

VARIABLES	(1) INVEST	(2) INVEST	(3) INVEST	(4) INVEST	(5) INVEST	(6) INVEST	(7) INVEST	(8) INVEST	(9) INVEST	(10) INVEST
	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0	Whole	IN-DEX-PPOPU=1	INEX-PPOPU=0	RISKPOPU=1	RISKPOPU=0
Constant	0.208***	0.192***	0.132***	0.333***	0.185***	0.192***	0.190***	0.119***	0.319***	0.171***
	(9.56)	(3.53)	(4.74)	(10.43)	(7.01)	(8.99)	(3.50)	(4.38)	(10.28)	(6.33)
IPOD	0.062***	0.022***	0.082***	0.049***	0.069***	0.081***	0.023***	0.096***	0.067***	0.087***
	(23.69)	(5.28)	(21.82)	(7.69)	(23.10)	(27.16)	(5.36)	(23.13)	(10.47)	(26.24)
INDEXP	0.077***	-0.025***	0.093***	0.084***	0.073***	-0.012***	-0.031***	0.029***	-0.033***	-0.008*
	(19.21)	(-4.83)	(21.05)	(12.74)	(17.20)	(-2.85)	(-4.82)	(4.50)	(-3.74)	(-1.76)
RISKAV	0.128***	0.024*	0.145***	-0.048	0.168***	-0.016	0.034*	-0.008	-0.062	0.023
	(6.75)	(1.72)	(6.27)	(-1.32)	(8.23)	(-0.81)	(1.69)	(-0.23)	(-1.57)	(1.06)
*INDEXP*IPOD*						0.036***	0.006	0.023***	0.056***	0.032***
						(17.93)	(1.16)	(9.59)	(12.46)	(15.50)
*RISKAV*IPOD*						0.062***	-0.012	0.058***	0.001	0.060***
						(5.51)	(-0.60)	(3.86)	(0.05)	(5.11)
INVEST_1	0.429***	0.097***	0.441***	0.290***	0.466***	0.414***	0.097***	0.435***	0.271***	0.451***
	(43.55)	(8.80)	(43.38)	(17.51)	(44.49)	(44.18)	(8.78)	(43.49)	(17.25)	(44.29)
NONINDEXP	-0.021***	-0.000	-0.026***	-0.002	-0.024***	-0.019***	0.000	-0.026***	-0.002	-0.022***
	(-5.89)	(-0.01)	(-5.87)	(-0.42)	(-6.57)	(-5.19)	(0.01)	(-5.69)	(-0.35)	(-5.86)
Fixed Effects:	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year
Observations	73,148	20,133	53,015	20,158	52,990	73,148	20,133	53,015	20,158	52,990
R-squared	0.3940	0.0320	0.4022	0.3429	0.4190	0.3991	0.0321	0.4039	0.3495	0.4235

The regressions here are similar to those reported in Tables 3 and 4. See those two tables for the definition of the sample and variables. In Panel A, we use dummy variables *INDEXPD* and *RISKAV* rather than continuous variables to measure industry experience and risk aversion. *INDEXPD* is a dummy variable indicating whether the number of investments made by a VC firm in an industry prior to a year belongs to the top quartile. Similarly, *RISKAVD* is a dummy variable indicating whether the proportion of investments made in seed or early stage companies for a VC firm prior to a year belongs to the top quartile. The control variable *NONINDEXPD* is measured similarly. In Panel B, we use a dummy variable *IPOD* rather than the continuous variable *IPOS* to measure public market signals. *IPOD* is a dummy variable indicating whether the number of VC-backed IPOs in the industry one year before belongs to the top quartile. In Panel C, we use the lagged industry Tobin-Q (*Q*) rather than the lagged IPO activity (*IPOS*) to measure public market signals. *Q* is measured by the mean value of Tobin Q in an industry one year before. The construction of this variable is described in detail in the text. In Panel D, the sample is varied to include only those VC firms that had invested in an industry prior to a year. In Panel E, the sample is varied to include only those VC firms with above-median fundraising during the past ten years. Our regressions include industry and year fixed effects. The t-statistics in parentheses are based on robust errors allowing for data clustering by VC firms. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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[1] We here follow the Bayesian approach and represent imperfect information by uncertainty. The Bayesian approach imposes restrictions on beliefs. Our requirement of unbiased beliefs is a weak version of Bayesian consistency. Without this, our model can offer more “unusual” investor behaviors.

[2] Since VC firms’ returns are not made public, we do not have qualified data to analyze the influence of VCs’ income as prior theoretical analyses have done. We can only focus on experience and risk aversion in our empirical analysis.

[3] Our results are not very sensitive to the definitions of inexperienced and more risk-averse VC firms. We obtain similar results if we define inexperienced VC firms as those “having only one investment”, and more risk-averse VC firms as those who made less than 16% or 20% of their investments in seed or early stage companies.