Original Article

The asteroid cometh: Whether IPO 'underpricing' is being exploited by hedge funds

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ABSTRACT **Underperformance of initial public offerings (IPOs) – a minuscule return following initial period of drastic appreciation after their issuance – is one of the remaining mysteries of quantitative finance. The size of the implied underpricing of new issues arguably should attract many a hedge fund to participate. On the contrary, the fraction of hedge funds investing in IPOs is rather small; their longevity is short and their performance decent, but hardly spectacular. In this article, I use a Markov growth-collapse model to explain the phenomenon of the finite growth of an asset, which may exhibit explosive returns punctuated by a rare devastating event. The proposed reason for the fact that hedge funds investing in IPOs never achieve the performance implied by alleged astronomical IPO underpricing is that one especially large and unsuccessful investment can obliterate the bulk of the gains.**

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INTRODUCTION

Ibbotson *et al* suggest that the underpricing of initial public offerings (IPOs) is the most severe case of market efficiency violation.[1] Indeed, in their experiment, the strategy of investment in a random selection of IPOs and sale of the stock in the subsequent month generated a whopping 15 per cent *average* monthly return. Such is the law of the compound percent, that for the 40 years in their sample this strategy should have generated a cash flow that would allow the investor to purchase every security in the NYSE-size exchange every second during the lifetime of the Universe. The enormity of the theoretical gap being supposedly observed by Ibbotson in 1994 seemingly rules out any discussion of the reality of the IPO underpricing phenomenon.

However, a decade later, Loughran and Ritter revisited the question and argued that underpricing exists only in times of stock market bubbles and is negligible otherwise.[2] If true, their empirical consideration would connect IPO underpricing with 'mass madness' or the 'madness of crowds', which visits the markets from time to time and would relegate the studies of IPOs to the field of behavioral finance.[3]

Loughran and Ritter claimed that in the 1980s, the average first-day return on IPOs was 7 per cent.[2] The average first-day return increased to almost 15 per cent during 1990–1998, soared to 65 per cent during the bubble years and fell to the pre-bubble level of 12 per cent in the years 2000–2001. If before the 1990s the median valuation was less than twice annual sales ($72/$38 million), in the 1990s, this coefficient jumped to 2.7 ($122/$46 million) and during the internet bubble the valuation/sales ratio soared to 26 ($387/$15 million), while the absolute sales of the new companies being taken to the market dropped more than threefold.

Since the Ibbotson and Ritter paper, many authors have investigated the reality and magnitude of IPO underpricing and post-IPO underperformance. Extensive references up to 2006 are provided in Gompers and Lerner's book.[4]

DESCRIPTION OF THE SAMPLE

One would suggest that if underpricing of IPOs were real, there would be many hedge funds exploiting this spectacular opportunity. However, a visual inspection of the hedge fund universe tells otherwise. In my early February 2007 sample of hedge funds according to Bloomberg©, I found 1755 entities being described as 'hedge funds'. Of these, only 44 (2.5 per cent) listed investment in IPOs in their self-description. Only about half of the smaller sample was actually functioning at the time of the collection (see Table 1). This contrasted with 1126 funds listing 'emerging companies' or 'emerging markets' as a part of their investment strategy (64.1 per cent of the total). This disparity does not necessarily mean that hedge funds rarely invest in IPO, just that any answer for return anomalies should be searched for in stock bubbles rather than in the IPO performance as such.[5]

Closer inspection revealed an even starker reality: if we select the funds from the previous list according to the following simple rules: (1) the fund should have existed for at least 3 years for a non-active fund and (2) for at least 2 years for the currently active funds, my sample was reduced to 11 funds, which I subjected to further investigation. The funds involved in my sampling procedure are listed in Table 1. I used funds' self-description, which they posted on Bloomberg©. I do not have information on actual holdings of any of these funds, or their performance, below one year granularity. The paucity of public information available should not be considered as a shortcoming because limited liquidity and, hence, infrequent and approximate valuation of holdings is endemic feature of private equity.[6]

SAMPLING PROCEDURE

In my sample, I have only 11 time series of annual returns, and the average length of existence of the fund slightly exceeds 5 years. These data (58 records) are too few to produce

Table 1: The list of sampled funds that used self-description 'investing in IPO' on 01/24/2007

	Funds	*Bloomberg(C) designation*	*Registration*	*Active on 01/24/2007*
1	AIG Greater Taiwan	AIGGRTW TT	Taiwan	No
2	Alpha Trust New Enterprises	ALTEEN GA	Greece	**Yes**
3	BAWAG PSK	BAGPEQF AV	Austria	**Yes**
4	BNP World IPO	6131 2005 JP	Japan	No
5	CJ Vision High Yield IPO	7080 31L1	Korea	No
6	DWS Neuer Markt	DWSNMKD LX	Luxembourg	No
7	FT Multimercado Ipojuca	FMIPOJU BZ	Brazil	**Yes**
8	First Trust IPOX-100 Index Fund	FPX US	USA	**Yes**
9	Hambrecht & Quist IPO Emerging Company Fund	HIPOX US	USA	No
10	Industrialfinans AK Norge	INAKTNG NO	Norway	No
11	Iporanga 30 FI Multimercado	IPORAG 3BZ	Brazil	**Yes**
12	IXIS Constellation	CDCEEIE IX	?	**Yes**
13	JP Morgan Growth Advantage	VHIBX US	USA	**Yes**
14	KTB Double Chance IPO Fund1	4580 KS	Korea	No
15	Meta Markets IPO	IPONX US	USA	No
16	Mirae Asset High Yield Venture Fund	3858 KS	Korea	No
17	New Millenium Investments	MILEN GA	Greece	No
18	Pictet Polish Pre IPO	PICPPII	Luxembourg	No
19	Pre Gold IPO	337501 KS	Korea	No
20	Renaissance IPO Plus Aftermarket Fund	IPOSX	USA	**Yes**
21	Republic Portfolio Selection	REPAIGO GU	?	No
22	Rotschield & Cie. Gestion Elan Introduction IPOX Index (USA)	ROTELINFP	France	No
23	SEI Ace Balanced Fund	5252 KS	Korea	No
24	SEI Prime Bond IPO Fund	4424 KS	Korea	No
25	Seoul Hanil IPO Stock Yield Fund	4206025 KS	Korea	No
26	Tai Fook Asia IPO Segregated	TAIAISP	Cayman Islands	**Yes**
27	Thornton Asia IPO	THOASII OS	?	No
28	TNI Mena Real Estate Fund	TNIMREF UH	UAE	**Yes**
29	TNI UAE Blue Chip Fund	TNIUAEFF UH	UAE	**Yes**
30	Universal-Gontard & Metallbank	GONTIPO GR	Germany	No
31	UOB United Global IPO Fund	UOBGIPO SP	Singapore	**Yes**
32	Van Kampen 498-IPOX-30-2005-3	VKITIDX US	USA	**Yes**
33	Van Kampen 528-IPOX-30-2005-4	VKIPOX US	USA	**Yes**

Table 1 *Continued*

	Funds	*Bloomberg(C) designation*	*Registration*	*Active on 01/24/2007*
34	Van Kampen 543-IPOX-30-2006-1	VKPTWX US	USA	**Yes**
35	Van Kampen 568-IPOX-30-2006-2	VKIPNX US	USA	**Yes**
36	Van Kampen 598-IPOX-30-2006-3	VKIPDX US	USA	**Yes**
37	Van Kampen 608-Focus 15-2006-3	VKNYFX US	USA	**Yes**
38	Van Kampen 610-IPOX-30-2006-4	VKPOTX US	USA	**Yes**
39	Van Kampen 610-Focus 15-2006-4	VKNSEX US	USA	**Yes**
40	Van Kampen 634-IPOX-30-2007-1	VKIPEX US	USA	**Yes**
41	Van Kampen 634-Focus 15-2007-1	VKNYSX US	USA	**Yes**
42	Voyager Select IPO	VOYSIPA BA	Bermuda	No
43	Wilson HTM Special Situations	WHTSPCS AU	Austalia	No
44	WL Asia IPO Ventures II Limited	WLAVIPO VI	Virgin Islands	No

No controls on whether this accurately represented reality and which per cent of each fund's holdings was invested in IPO were applied.

reliable statistics. Yet, better data are hard to achieve because, at least in the past, most hedge funds existed for a relatively short period of time and revalued their holdings from time to time. So, we must cheat.

As a statistical cheating device, I use an all-familiar resampling technique[7,8] in the following form. I strike out one portfolio and reshuffle the remaining 10 funds preserving the annual ordering of returns, 512 times.[7,8] Each of the 11 reshuffled portfolios has a length of about 2000 records, corresponding to 2000 fund-years. As the returns of each of the 11 original funds are absent from one of the portfolios, the parameter estimates, if consistent across portfolios, must not contain bias related to a particular holding or investment strategy of the management. On the contrary, if the estimates widely diverge, this would suggest the problems with the original sample.

If one redacts negative returns from these portfolios, the compound growth would be $p \approx e^{150} \approx 10^{65}$ for 512 fund replications. These are truly cosmic numbers. They can explain why, initially, there was widespread belief that chasing 'hot' IPOs could bring one fabulous wealth. In fact, because each portfolio exists only for a few years and the repetition of performance requires a rollover of assets into another hedge fund, following this strategy is impossible in practice.

THE FUNDAMENTALS OF GROWTH-COLLAPSE MODELS

Growth-collapse and closely related decay-surge models were introduced, for instance, in Bak,[9] Rozman *et al*[10] and Carlson *et al*,[11] to explain a number of natural phenomena such as sandpiles and other systems exhibiting self-organized criticality, as well as stick-slip interfacial friction and earthquakes. The stochastic specification of the model we use in the current article is due to Eliezer and Klafter.[12,13] The dynamics of the model between catastrophic events is the same geometric random walk as is used in the Black–Scholes model. However, the return on the asset may be a nonlinear function $F(X)$ of the current endowment. Moreover, during a rare catastrophic event, the portfolio loses a random portion $(1-M)$, $0<M<1$ of its current worth:

$$\begin{cases} X_{t+\Delta t} = X_t + F(X_t)\Delta t + \xi_t X_t \sqrt{\Delta t}, \\ \qquad\qquad \Pr = 1 - r\,(X_t)\Delta t \\ X_{t+\Delta t} = M \times X_t \quad \Pr = r\,(X_t)\Delta t \end{cases} \tag{1}$$

The probability of adverse events is distributed according to a distribution with variable intensity $r(X)$. For simplicity, I assume that this intensity obeys the Poisson distribution. The fraction of the portfolio that remains after the collapse is distributed according to its own random distribution, which we model as beta:

$$p(M) \propto \beta(\gamma_1, \gamma_2) \tag{2}$$

A particular functional form of the distribution of collapses is not essential and is used only for the convenience of simulation.

CONSTRUCTION OF MLE FOR ESTIMATION

The model described by equations (1), (2) is a nonlinear problem with jumps. We simplify it by estimating the continuous part from the Markovian MLE:

$$L(\vec{\theta}) = \prod_{n=2}^{N} p_\theta(X_n, X_{n-1}) \tag{3}$$

where

$$p_\theta(X_n, X_{n-1}) = \frac{1}{\sqrt{2\pi\sigma^2 \times X_{n-1}}} \exp\left(-\frac{(X_n - X_{n-1} - F_\theta(X_{n-1}))^2}{2\sigma^2 X_{n-1}^2} \right)$$

We specify the function $F_\theta(X)$ in the same power form as Eliezer and Klafter:

$$F_\theta(X) = \beta X^{2\lambda} \quad \theta = \{\beta, \lambda\} \tag{5}$$

Minimization of the MLE is described in the Appendix.[14]

We construct separate MLE for the Poisson process regulating the negative shocks, where we use empirical pre-shock data to trigger the shocks:

$$L(\xi_0 | X) = \prod_{n=2}^{i_N} \frac{(\xi_0)^{i_n} \exp(-\xi_0)}{i_n!} \tag{6}$$

where i_n is an indicator function for the (negative) jumps.[15] The distribution of jump sizes was regulated by the beta distribution with parameters γ_1 and γ_2. I was unable to construct a stable MLE beta distribution estimator for the jump sizes. Hence, I estimated the indexes of the beta distribution from the first two empirical moments of the bootstrapped sample.

Averaged results of the estimation of the 11 resampled portfolios – each with one of the original funds thrown out – are provided in Table 2.

Inspecting Table 2, we observe that β and γ are highly statistically significant, whereas λ is not significant at all. Yet, the attempts to replace λ by zero reduce the model to a geometric diffusion with jumps. It does not experience explosive surges as we expect from the model of the system of equation (1).

Table 2: Results of the estimates of parameters of the Markov collapse-revival model of the equation 1

Parameter	*Estimate*	*Std. dev.*
β	1.000	9.745×10^{-3}
λ	1.640×10^{-4}	1.318
σ	1.249×10^{-2}	4.102×10^{-4}
ξ_0	0.1500	—
γ_1	16.22	—
γ_2	13.48	—

Expected destruction of value of the endowment on collapse extracted from the bootstrapped sample is M=54.61%. Standard deviations of the collapse process were obtained by the method of moments and are not directly comparable to the parameters of nonlinear diffusion obtained by the MLE. Nonlinearity parameter λ is not statistically significant but setting λ=0 seriously changes the dynamics.

The whole reason for the surge is that for an infinitesimal initial endowment X, the derivative of the nonlinear term is proportional to $X^{\lambda-1} = \infty$. Hence, the initial small endowment grows to the finite amount almost instantly. However, when the endowment becomes large, it starts to suffer from collapses.

As of now, I cannot reliably estimate λ, and it could be impossible in view of the very limited data sample. Yet, instead of the null hypothesis, I suggest that λ is a small but positive number. To observe the results of that, I provide a simulation of the behavior of the system of equation (1), with parameters taken from Table 2.

SIMULATION RESULTS

I show the results of the nonlinear growth without collapses, that is, with ξ_0 or M artificially set to zero, in Figure 1. As the system is stochastic, what is shown is really a single path. The growth of the initial 'small' endowment (the money invested in the hedge fund from the start) is explosive from the beginning, but then

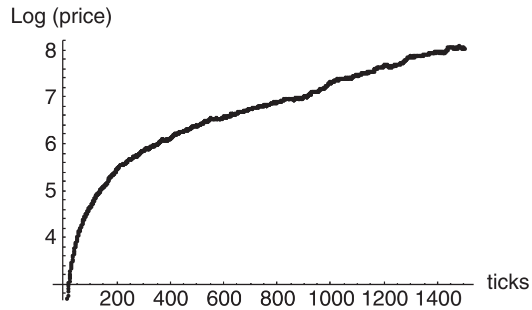

Figure 1: The growth of a small initial endowment for the model of equation (1) without collapses. The parameters are as follows: $\beta = 1.0$, $\lambda = 1.64\text{E-}4$, $\sigma = 1.29\text{E-}2$. Estimation was performed from the bootstrapped sample of the real returns of 11 hedge funds investing in the IPO. Time scale on the horizontal axis is arbitrary.

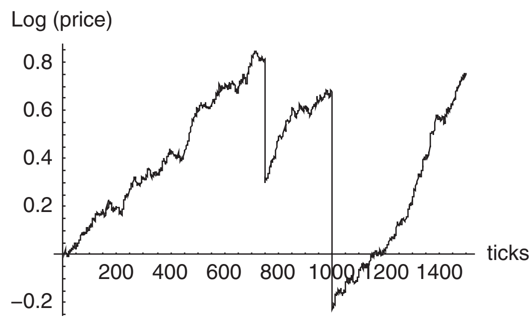

Figure 2: Simulation with the full growth-collapse model. Collapse parameters are as follows: $\xi_0 = 0.15$, $\gamma_1 = 16.22$, $\gamma_2 = 13.48$ and are also estimated from the bootstrapped sample of the same 11 funds. The expected level of destruction of value on collapse is $M = 54.61$ per cent and corresponds to the statistics of the bootstrapped sample.

reduces to a normal exponent when the first term in the right-hand-side of the first equation (1) becomes dominant over the nonlinear term.

The simulation of the full model with the parameters taken from Table 2 shows that the periods of explosive growth are punctuated by collapses when the finite portion – slightly more than half – of the whole portfolio value is destroyed (Figure 2). This is what I believe happens in practice. After a relatively short period of expansion through a relatively few 'hot' investments, the hedge fund becomes too large to be able to invest its money wisely.

CONCLUSION

Although the math of the collapse-revival model may seem obscure, the economic interpretation is pretty transparent. The 'good' IPO deals are few and far between. When the hedge funds remain relatively small, their managers can pick a few exceptionally good deals and grow explosively. However, their own growth results in emerging competition with the other funds for the same limited number of deals and their performance falters. If the funds stay in the game long enough, they can again find a few good deals and renew their fortunes but more frequently, their management simply folds the fund down.

Owing to nonlinearity of the system, a biological analogy seems especially apt. A relatively few predators living in a pond with prey can quickly grow in size and numbers. Yet, when their size and numbers increase, they begin to compete with each other for ever more scarce prey until their numbers collapse to below a 'sustainable' level after which the whole game restarts.

This heuristic outlook is supported by the empirical analysis of Boyson *et al.*[16] They observe a significant degree of contagion between the hedge fund returns, which they define following Bekaert *et al*[17] as 'correlation over and above what one would expect from economic fundamentals'.

One of the consequences of the rate of growth of the portfolio proportional to the rate in power less than one ($2\lambda = 3.28 \times 10^{-4}$ see equations 1 and 5 and Table 1) is that *the whole notion of return on investment may be misleading* for the hedge funds, as well for as any other holdings with limited liquidity and infrequent valuation. Observed assets of the hedge funds can change in a discontinuous fashion preventing the application of the familiar concept of return on investment. One probably has to deal with the notions such as cumulative price growth (or decay) of an initial endowment.

Unsolved problems are many. In particular, systems with nonlinear growth are not time-scale invariant, and hence their simulation strongly depends on the sample size. Correctly simulated processes must include scaling factors so that the parameters of significance do not depend very much on the longevity of observation or the frequency of sampling. This problem is currently under investigation.

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14 Factor 2 in Equation (5) is a mnemonic of the fact that we square the returns first, and only then raise them to the power λ, to avoid complex numbers.

15 By the properties of the Poisson distribution, ξ_0 is, essentially the proportion of negative jumps in the entire time series.

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APPENDIX

The logarithm of the MLE of equation (4) is given by the function:

$$l(\beta,\lambda,\sigma) = -\frac{N-1}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{n=2}^{N}\left(\frac{X_n}{\frac{X_{n-1}}{X_n} - 1 - \beta X_n^{2\lambda-1}}\right)^2 \tag{A1}$$

First-order conditions for the maximum of the MLE are the following:

$$\begin{aligned}
\hat{\sigma}^2 &= \frac{1}{(N-1)}\sum_{n=2}^{N}\left(\frac{X_n}{\frac{X_{n-1}}{X_n} - 1 - \beta X_n^{2\lambda-1}}\right)^2 \\
\hat{\beta} &= \sum_{n=2}^{N}\left(X_n X_{n-1}^{2\lambda-2} - X_{n-1}^{2\lambda-1} - \beta X_{n-1}^{4\lambda-2}\right) = 0 \\
&\sum_{n=2}^{N}\left(X_n X_{n-1}^{2\lambda-3} - X_{n-1}^{2\lambda-2} - \beta X_{n-1}^{4\lambda-3}\right) = 0
\end{aligned} \tag{A2}$$

The system (A2) is a nonlinear system of equations for the parameters $\{\beta, \lambda, \sigma\}$. First, one solves the third and second equation recursively as a system. Then one estimates σ^2 using β and λ as inputs. Rather lengthy formulas for the partial second derivatives of the MLE provide the variance of the estimates.