DEATH SPIRAL CONVERTIBLES

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Death spiral convertibles are privately held convertible securities (preferred stock or debentures) with a conversion price that is set at a discount from the average (or sometimes the minimum) of past stock prices in a look-back period. Although, in theory, these securities have the potential to reduce agency costs of debt and problems related to adverse selection, they have been called "death spirals" because of their potential to create dilution and stock price declines. On the basis of all 487 issues announced before August 1998, we find that this bad reputation is indeed justified: an investor who buys the common stock of the issuer loses, on average, 34 % of his wealth one year after the issue date. Although our sample period coincides with one of the strongest bull markets in U.S. history, in 85 % of the cases one-year post-announcement returns are negative. The most important predictor of poor long-term performance is the discount. However, we also find that issuers also experience a significant decline in operating profitability relative to benchmark firms.

Key words : convertibles, financial innovation, anomalies, capital structure

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1. *Introduction*

In April 1997 Casmyn Corporation, a gold mining company, with assets in Zimbabwe and Zambia, issued for \$ 32 million convertible preferred securities. Unlike normal convertibles with a fixed conversion price, the Casmyn convertible had a conversion price which was set at an (over time increasing) discount from the lowest trading price in an (over time increasing) look-back period. Specifically, until three months after the issue date, the look-back period was 15 days and the discount was 8.5 %. Eighteen months after the issuance date the discount reached its maximum of 39 %, while the look-back period had been increased to 60 days. Note that the owner of the preferred is always sure that the conversion option is in the money. The security also creates the possibility of extensive equity dilution, up to the number of authorized shares.

For example, suppose that the current stock price, as well as the lowest price in the look-back period is \$12.5, and, the applicable discount is 20 %. This implies that an investor who owns a preferred stock with \$ 1000 nominal value can convert the security into 1000/(.8x12.5) = 100 shares. Hence, by converting and selling 100 shares at \$ 12.5 the investor can earn a risk-free rate of return of 25 % on his \$ 1000 investment. Note that this return is independent of the stock price: if the stock price had been \$ 1.25, the investor could have sold 1000 shares and obtained the same 25 % return on investment. As a result, a very risky mining company can issue a financial security that is risk-free, at least as long as the company honors the conversion.[2]

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[2] Sometimes companies in distress prevent conversion by refusing to file a registration statement, or in more extreme cases, file for Chapter 11. Such resistance is usually followed by contract renegotiation. For example, on January 13 1999 Base Ten Systems announced that all the remaining convertible preferred stock would be exchanged for a new convertible preferred with a fixed \$ 4 conversion price. In return, for each \$ 1 million nominal value preferred holders received 40,000 warrants with a fixed exercise price of \$ 3 per share. Moreover, the exercise price on their existing warrants was lowered from \$ 16 to \$ 4. This, however, did not solve the company's problems: in October 2000, Base Ten was trading at 50 cents per share, in spite of a previously executed 4 to 1 reverse stock split. In another case, in January 1999 Dynagen, who had issued 8 consecutive death spirals (series A to H) by that time, refused to honor conversions after a consultant concluded that the stock price decline from \$ 30 to 50 cents was caused by a" short selling scheme orchestrated by certain convertible

Ten months later, Casmyn's share price had dropped from $ 10 at the time of the issue to 25 cents and the number of shares outstanding had increased from 13 million to 40 million. This spectacular stock price decline attracted the attention of the media. Barron's[3] ran a story on the company, describing the convertibles as "death spiral convertibles", although, dependent on one's point of view, the instrument is referred to as "floorless convertibles", "floating-priced convertibles", "lesser-of convertibles", "future priced convertibles", "discounted convertibles", "toxic convertibles" or "junk equity" (Friese and Raissi (1999)). In this paper we will refer to the instrument as "floating-priced convertibles " or as "death spirals".

The name "death spiral" suggests that firms that issue floating-priced convertibles are doomed. The argument is that the issuance of the convertible creates ***selling pressure from preferred holders*** who, in order to lock in a profit, short the stock and, thereafter, cover their position with converted common stock. For example, suppose in the numerical example above the holder of the preferred sells 100 shares short to hedge his conversion. Suppose further that as a result of the shorting, the stock falls to $ 10 and that the investor has been able to sell his 100 shares at an average price of $ 11, i.e. for a total of $ 1100. The owner of a $ 1000 convertible can now convert the security into 1000/(.8x10) = 125 shares. So, after using 100 of the 125 shares to cover his short position, he can sell 25 additional shares for $ 250. This means that, through his hedging activities, the return of his investment has increased from 25 % to 35 %.

This negative price momentum may be accelerated by ***selling pressure from professional short sellers*** who seek out such companies as short selling opportunities. This type of activity has even reached the Internet, where we came across various "death spiral

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debt holders in cooperation with market makers involving pre-arranged or circular trading". However, between January 1999 and October 2000, Dynagen made five (series I through M) more floorless issues (at deep discounts) and it's stock price never recovered.

clubs" who systematically search SEC filings for death spirals and advise others to short the issuer's common stock[4]. Moreover, the issue announcement may be a ***signal*** that the firm is in serious trouble and is unable to raise conventional financing. For example, Illinois Superconductor issued a floating-priced convertible in June 1997 and saw its stock price decline from \$ 13 to \$ 1 in two months. Edward Laves, CEO, justified his financing choice by pointing out that the convertible placement was the only financial option after a failed secondary public offering[5].

Two other factors may contribute to the price decline. First shareholders who ***fear*** the negative consequences of the floating-priced convertible may decide to sell their shares to new, relatively more ignorant investors. Moreover, even if this fear is initially irrational, the resulting price decline may allow convertible holders to convert at a price below fair value, which will hurt shareholders. So, in the presence of a floating-priced convertible, temporary undervaluation of the stock will impose a real, permanent wealth loss on existing shareholders. Second, by diluting the equity, the fraction of shares outstanding held by the management becomes smaller, which in turn may increase ***agency costs of equity***. This reduction in managerial ownership is not compensated by an increase in ownership concentration: convertible investors are generally not allowed to own more than 4.99 % of the outstanding shares.

On the positive side, Brennan (1986) points out that making the conversion price dependent on the market price ***avoids the adverse selection*** problem (Myers and Majluf (1984)) when a firm issues equity or a normal convertible security with a fixed conversion price. Indeed, by making the conversion price float, companies no longer have an incentive to issue stock or convertibles when they believe their shares are overvalued. Moreover, as the

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[3] Barron's, April 7, 1998

[4] For example http://members .aol.com/SearchS3/Public/SEC search.html and http://www.siliconinvestor.com which has a stock talk board on floorless preferred preferred stock.

convertible is fully hedged against expropriation through risk-shifting and issuing securities of greater seniority, the company ***avoids agency costs normally associated with debt financing*** (Myers (1977)). Hence, a theoretical argument can be made that a floating-priced convertible is a powerful financial innovation, which will be especially useful for firms where information asymmetry and agency costs are potentially large, such as high growth, risky firms.

Investment firms involved in the deals point out another advantage: avoidance of having to issue equity-linked securities when the stock is ***undervalued***. For example, the Wall Street Journal[6] quotes Alexander Cappello, Chairman of Cappello Group, a Santa Monica, California firm specializing in floating-priced convertibles:

> *"Many managers believe their share prices to be too low to issue stock or a conventional preferred security, which locks in a value for the shares near the current market price"*

The argument is that companies, which expect good news to arrive before the preferred shareholders are allowed to convert, will find it cheaper to issue floating-priced convertibles than normal convertibles with a fixed conversion price. This will be especially the case for issues with relatively long waiting periods (also called the lock-up period) and for issues where each month only a fraction of the outstanding convertibles is allowed to convert.

So, whether floating-priced convertibles deserve to be called "death spirals" is ultimately an empirical issue. The issue is important, as floating-priced convertibles, in spite of some bad publicity, have not gone away: according to *PlacementTracker.com*[7], in 2000, approximately 180 issues for a total amount of $ 2 billion were announced, many by internet companies. Institutional investors such as the Wisconsin Investment Board, have threatened to sue any of its portfolio companies that get involved with floating-priced convertibles. Some issuers are suing their financial advisors for not warning them about the potentially disastrous

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[5] New York Times, May 17, 1998
[6] Wall Street Journal, September 28, Section C p1
[7] PlacementTracker.com is a division of DirectPlacement.com

consequences of this method of financing. For example in 2000 Log on America filed a lawsuit against Marshall Capital, a subsidiary of CSFB, arguing that the bank violated its fiduciary duties by recommending that the convertible issue was in the best interest of the company. Regulators also have not remained indifferent. The Wall Street Journal reported on September 28 1998 that David Irwin, head of listing qualifications at Nasdaq, was considering restrictions on the structure of floating-priced convertibles[8].

In the case of Casmyn, the name "death spiral" was well deserved. By the Summer of 1999 the CEO had fled to the Canary Islands and the stock was trading on the OTC bulletin board at 0.25 cents per share. As the number of outstanding shares had increased to the authorized maximum of 300 million, the company was considering a restructuring proposal that would increase the number of shares to 2.5 billion. In order to facilitate this restructuring process, Casmyn filed for chapter 11 in December 1999.

The first purpose of this paper is descriptive: to provide a overview of floating-priced convertible financing since its birth which we trace back to January 1995 with the first issue made by Celgene, a biotechnology company. Between the end of 1995 and July 1998 we found a surprisingly large number of 487 issues made by 277 firms. We also found a large variety in contract specifications. Contracts differ with regard to restrictions on conversion, magnitude of discounts, length of look-back periods, the existence of conversion floors as well as conversion ceilings, and so on. Moreover, some contract characteristics seem to have changed over time, apparently to encourage investors to hold rather than to sell and convert.

[8] Since February 1998 (which is largely after our sample period) the convertibles are subject to NASD rules 4310 and 4460 which require that each issuer shall require shareholder approval from shareholders if the potential dilution is larger than 20% of the outstanding equity. As the potential dilution depends on the market price, one could always argue that the potential dilution will be bigger than 20% (unless the contract has a floor). Hence, the NASD requires that shareholders approve the issue of the floorless convertible. Failure to obtain approval implies that the company will be delisted. For more details see http://members.aol.com/SearchS3/Public/NASD_Future_Priced.html

The second purpose of the paper is to test whether Casmyn's experience is typical: do, on average, companies that issue floating-priced convertibles experience subsequent negative abnormal returns? The answer here is an unambiguous "yes": investors who bought common stock of convertible issuers lost, on average, 34 % of their wealth in the year after the issue. In 85 % of the cases, the one-year post-announcement returns are negative. This result is even more striking considering that our sample period coincides with one of the strongest bull markets in US history.

The last part of the paper tries to explore the reasons for the price decline, or "death spiral". The first hypothesis, which one may call the "faulty contract design hypothesis" , argues that a floating-priced convertible is a poorly designed financial innovation, which invites short selling by the buyers and/or their followers. If this hypothesis is true, one would expect that the characteristics of the contract (such as the size of the discount, and various restrictions on conversions and short sales) should have a major impact on subsequent stock price performance. The implication is that shareholders should pay a lot of attention to contract design or that regulators should protect investors by outlawing certain contract features The second hypothesis, the "signaling hypothesis", argues that the convertible signals poor operating performance of the issuer. In other words, there is something wrong with the company, not with the financial instrument. In this case, floating-priced convertibles should be considered as life prolonging, rather than as a cause of death. This hypothesis predicts that measures of operating performance will tend to decline systematically after the issuance.

We find support for both hypotheses: operating performance, measured by return on assets and operating cash flow over assets, declines significantly, relative to matching non-issuing firms, during the years following the issue announcement. The likelihood of issuing a floating-priced convertible is directly proportional to the operating performance in the year before the issue, which is consistent with the view that floating-priced convertibles are "last resort" financing. At the same time, we find that, after controlling for accounting-based measures of operating performance, the design of the contract, in particular the conversion discount, remains a significant determinant of long-term share price performance. Moreover, we find that the contracts with the largest potential for dilution are issued by most poorly performing firms at the time of the issue. Although these firms don't display any significantly lower operating performance than their peer groups during the years after the issue, they under-perform their peers in the stock market. Hence, we conclude that issuers are, on average, "bad" firms who, out of despair, issue last resort financing that, on average, is bad for long-term investors, in particular for firms that are in the worst shape at the time of the issue.

The case of Casmyn is a typical example. Although the massive conversion discount (up to 39 percent) and the resulting dilution contributed to the collapse of the shares, one could also point to the spectacular decline in operating performance: two years after the issue, the price of gold had fallen by more than 50 %. In addition, several lawsuits were filed in the US, Canada and the Bahamas, accusing the CEO, Amyn Dahya, of fraudulent transfers and waste of corporate assets. For example, while this small company lost $ 52 million between 1994 and 1998, the CEO paid himself $ 4.3 million in salary and bonuses.

This paper is organized as follows. First, in section 2 we start with a theoretical discussion of the valuation of floating-priced convertibles and their optimal exercise policy. In section 3 we describe in detail the various contract characteristics and in section 4 we show that some of these characteristics have changed dramatically during the sample period. In section 5 we document the long-term post-issue poor performance of the companies in our sample. In section 6 we test whether the performance is influenced by the existence of various contract characteristics. Section 7 we examine the operating performance of the issuers during the period surrounding the issue year. Section 8 summarizes our conclusions.

2. Valuation and optimal exercise policy of floating-priced convertibles

Floating-priced convertibles are private placements, which makes it impossible to test whether these securities are "priced" correctly. However, in order to better understand the design of the instrument, we believe it is useful to elaborate on valuation and optimal conversion policies.

2.1 Optimal conversion policy and valuation: the base case

Assume a convertible with a nominal value of F, which we assume to be constant (i.e. the convertible pays no dividends payable in additional convertible securities). Investors have the right, at each time t (where t measures the number of days elapsed since the issue date t = 0), to convert the preferred at a discount d (0 < d < 1) from the reference price R_t . Assume that the stock price at which the converted shares can be sold is equal to S_t .

With these assumptions, it follows that, at each point in time, the conversion value of the convertible is equal to

$$CV_t = S_t F / (R_t (1 - d)) \qquad (1)$$

In the special case where the reference price and the selling price are the same, the conversion value is equal to F/(1 - d). This would be the case when (1) there is a one day look-back period, i.e. the reference price is equal to the closing price on the day before the investor informs the company that he wants to convert his securities, and (2) the investor sells (short), at the closing price, all the shares that he is expected to receive after conversion. Based on the values of the numerical example at the beginning of this paper, if $S_t = R_t =$ \$ 12.5 and F = \$1000, the conversion value of the convertible is equal to \$ 1250. Note that if we also assume that the convertible does not pay dividends (or interest) and there are no restrictions on conversion, the investor has an incentive to convert immediately and earn a risk free rate of return of

$$(F/(1 - d))/F - 1 = d/(1 - d) \qquad (2)$$

which is equal to 25 % in our numerical example. Issuing a convertible would essentially be equivalent to an equity issue where the shares are issued at a discount from the market price. This implies that the value of the convertible should, at any time, be equal to its conversion value or

$$V_t = F/(1 - d) \tag{3}$$

In an efficient market, the convertible should be issued at a premium above the nominal value. We are not aware, however, of a single case where the convertible is issued at a price above its nominal value. Quite the opposite: in some cases the convertible is issued at a discount from the nominal value. Note that, if the issue price is fair, there is no reason why the stock price of the issuer should decline, even if the convertible holder is able to convert stock below the market price. For example, suppose that the issuer was an all-equity financed firm with assets of $1000 and 100 shares outstanding, or $ 10 per share. Assume the company now issues a convertible with nominal value of $ 1000 and a conversion discount of 20 percent at its fair value of $ 1250. After the conversion, the company will have assets of $ 2250 shared by 225 shares or again $ 10 per share.

This numerical example can also be used to illustrate one of the problems with floating-priced convertibles. Suppose that the issue is priced correctly at $ 1250, but that the stock price after the issue announcement falls to $ 5, without any justifiable reason, possibly because of fear created by the arrival of the death spiral. Now, convertible holders can convert at $ 4 and the number of shares after conversion will increase to 350. Although the "true" value of the cash flows is unchanged at $ 2250, the true, long-term stock price is now 2250/350 = $ 6.42. In other words, in contrast to the normal situation, *irrational fear can become a self-fulfilling prophecy*. Note that in this case the convertible holders did not benefit from the dilution: it makes no difference to them whether they sell at $10 and convert at $ 8, or whether they sell at $ 5 and convert at $ 4.

2.2 Valuation and market impact

Even without a look-back option, an investor can earn a higher rate of return than d/(1 - d) if he is able to sell the converted shares at a higher price S_t than the reference price R_t. This can be achieved through short selling, provided the short sales have an impact on the market price so that $S_t > R_t$. In our numerical example at the beginning of the paper, the investor was able to short 100 shares at an average price of \$ 11 and sell an additional 25 shares at \$10, so that $S_t =$ \$ 10.8. As the investor was able to buy at a conversion price of \$ 8, this \$ 2.8 gain is equivalent to a 35 % return on investment. Note that the ability to influence prices through short sales would make the policy of converting all the preferred stock immediately (in order to maximize market impact) even more interesting. Hence, as before, the value should be equal to the conversion value, but with S_t larger than R_t

$$V_t = S_t \; F / (R_t (1 - d)) \qquad (4)$$

2.3 Valuation and dividend payments

The analysis above implies that convertible investors have an incentive to convert immediately. However, the contract above assumes that the convertible preferred does not pay a dividend. If the preferred pays a dividend in additional preferred stock (as in the case of Casmyn) at a rate of δ per day it follows that, assuming $S_t = R_t$, the value of the floorless becomes

$$V_t = F (1 + \delta)^t / (1 - d) = F_t / (1 - d) \qquad (5)$$

Early conversion is no longer optimal as long as the dividend yield is higher than the risk free rate. However, this argument assumes that convertible investors have no wealth constraints or borrowing constraints. With such constraints, tying up money in one investment may imply foregoing the next lucrative convertible issue. With wealth constraints the relevant risk free opportunity cost may well be the rate of return on the next available deal, which may be far above the typical dividend yield on preferred stock.

2.4 Valuation and the look-back option

Besides dividend payments, convertible contracts may have other features to discourage early conversion: (1) waiting periods before conversion can take place (2) restrictions on the number of securities that can be converted during a given period or (3) escalating discounts as in the case of Casmyn, where the discount increased from 8.5 % to 39 % over an 18 month period. Moreover, by allowing investors to pick the reference price as the lowest price or the average of a series of prices in a look-back period, a similar result can be obtained, at least in theory. Indeed, by increasing the look-back period, companies can encourage investors to wait for significant price increases in the firms' stock, rather than shorting and converting immediately.

For example, suppose that there is a significant probability that a company, T days from now, obtains FDA approval for a new drug. Assume that if the drug is approved, the stock will rise by ε on the day of the announcement T, so that $S_T = S_{T-1} + \varepsilon$. If the FDA denies approval, the stock will fall by ε. Moreover, assume that the investor can convert at a discount of d % of $R_T = \text{Min}(S_T, S_{T-1})$, i.e. the convertible has a two-day look-back period and the nominal value is F, a constant[9]. If the FDA approves the drug application, $R_T = S_{T-1}$ and the value of the cash flows from selling $F/(1 - d) S_{T-1}$ shares at $S_{T-1} + \varepsilon$ will be larger than the proceeds from selling and converting at time T-1. If, on the other hand, the drug is not approved, the investor can then still short the stock at $S_{T-1} - \varepsilon$ and convert at a discount from the market price for total proceeds equal to $F/(1 - d)$.

Note that it is no longer optimal to convert early, if the investor believes that the probability that some "good news" will arrive in the not-so-distant future is substantial. Indeed, if he converts immediately, he will realize $F/(1 - d)$. But if he waits until time T to

[9] F is assumed to be constant to illustrate the "pure" effect of the look-back option. If F would increase over time (because of dividends paid-in-kind) the value of the look-back option would be even stronger.

make a decision, the present value of his proceeds, in the worst case (no FDA approval) will be equal to $(F/(1 - d))(1 + r)^{-T}$. In the other case the present value of the proceeds will be equal to $(S_T F/ S_{T-1} (1 - d))(1 + r_s)^{-T}$, where r and r_s are equal to the risk-free rate and the expected rate of return on the stock.

More formally, we can state that (without market impact)

$$V_t = F_t / (1 - d) + L_t (\sigma, n, \tau) \tag{6}$$

where L_t is the value of a look-back option to choose the reference price R_t as the average of the lowest n prices in a look-back period of length τ. Note that in our example, τ =1 and n = 1.

The first part of (6) measures the value of the convertible if the reference price is equal to the current market price (i.e. no market impact and no look-back option). The second part of the value is the value of the option to choose R_t as a different (lower) price than the price at which the converted shares are sold. In the absence of short selling pressure, this difference has to be created by price jumps, which are driven by the volatility of the stock σ. It is obvious that the value of the look-back option declines as τ increases and rises as the investor has more choice, i.e. when n is small and τ is large. In the case of Casmyn, the option was highly valuable during the first three months of the contract when n = 1 and τ =15

2.5 Impact of conversion floors and caps

In some cases companies specify that the conversion price cannot be higher than a maximum price, S^h (a cap) or lower than a minimum price S^l (a floor). So, in general, we can state that the value of a death spiral convertible (ignoring market impact) is equal to

$$V_t = F_t / (1 - d) + L_t (\sigma, n, \tau) + C_t (S_t, \sigma, S^h) - P_t (S_t, \sigma, S^l) \tag{7}$$

where C is the value of a call option to buy F_t / S^h shares at a price of $S^h (1 - d)$ and P is the value of a put option to sell F_t / S^1 shares at $S^l (1 - d)$. Giving the investors a call option (or sometimes attaching warrants to the offering) is again an incentive to delay conversion and to discourage short selling. By putting a floor in the contract, the issuer may minimize the potential dilution from the convertible, but on the other hand may encourage investors to convert early. This will be particularly important if the market perceives that the security is a “death spiral”.

3. Data

Floating-priced convertibles are private placements. As such, they are not widely covered by typical data sources such as SDC or the Dow Jones Retrieval Service. However, when a company completes a private placement, it will, most of the time, file an 8-K form with the SEC. Moreover, in order to allow the convertible holders to sell the converted shares the company always has to file an S-3 registration statement. Hence, all 8-K filings and S-3 filings available on the SEC Edgar database since January 1994 until June 30, 1998 were searched for floating-priced convertible preferred issues and debentures. We started in 1994 because it corresponds to the start of the Edgar database. Note, however, that as we did not find any issues before 1995, we are confident that our sample includes all issues made before July 1998. We stop on July 1, 1998, because we want to examine the long-term performance employing the CRSP database, which ends on December 31 1999. Our “announcement” date is either the date of the 8K filing or the date of the first S-3 filing after the issue, except for a few instances where a company issued a press release immediately after closing the deal, in which case the press release date is the announcement date. Note that this is the same data collection method used by death spiral investor clubs to detect potential short selling candidates.

In total we find 487 observations made by 277 different firms. Twenty firms issued at least 4 consecutive convertible issues during the sample period (see Table 1). The fact that a company issues many convertibles may indicate that at least for these firms the issue was well received by shareholders. However, casual empiricism shows that this is not the case. By December 31, 1999, 15 of the 20 firms were delisted or went bankrupt.

Figure 1 shows that, except for January 1998, our announcement dates are not clustered in a particular month. After the initial run up, the number of convertibles seems to be relatively stable around 15 issues per month.[10] Figure 2 shows that only 144 out of the 277 firms in our sample are still listed by December 31, 1999. From the bottom of the figure, we can infer that except for 14 companies which were taken over and 2 firms that went bankrupt, all the firms disappeared because of failure to meet one or more listing requirements, such as a minimum share price, minimum equity, minimum float, etc. So, one could argue that a remarkably large number of firms (116 out of 277 or 41%) were in serious trouble by the end of 1999. Table 2 shows that 28 % of all issuers belonged to two industries: computer and data processing services and drugs. Approximately 50% of the firms are in the technology sector or the medical sector. Table 3 shows that the average size of the firms[11] in the sample is $ 72 million (median $ 43 million). More than 50 percent of our firms went public after 1992. Hence, consistent with the theoretical arguments made supra, floating-priced convertibles are issued by firms for which adverse selection problems are potentially large, i.e. small, young, risky firms.

Table 3 also shows that, on average, firms issued for $ 6.2 million convertibles, which represents about 13 % of the market value of the issuer's equity. Two outliers: Electronics Communications and Tel Com Wireless Cable TV issued a convertible that represented 218% and 208% of their market capitalization at the time of the issue. Finally, companies issue convertibles when their stock prices are relatively low: in our sample, the average stock price at the time of the issue is $ 5.125. This may suggest that many of the issuers were already in

[10] This number seems to be relatively stable over time : PlacementTracker.com informed us that from August 1 1998 until December 31 2000, 387 floating-priced convertibles were announced, or about 13 issues per month.
[11] Size is measured as the market value of equity on the day prior to the issue.

trouble at the time of the issue. Alternatively, it is consistent with the hypothesis that issuers tend to issue floating-priced convertibles, rather than common equity, because they believe their stock is significantly undervalued.

Table 4 shows the list of the 21 investors that were involved in financing 10 issues or more. Most investors are private partnerships. We were told by various sources in the industry that several of these investors are managed by the same entity. For example, the champion of death spiral convertibles is clearly Angelo Gordon who manages AG Super Fund, Raphael, Leonardo, Halifax, GAM Arbitrage and possibly Ramius. Another example is Citadel Partners who manages Olympus Securities and Nelson Partners.

4. Contract characteristics

Floating-priced convertibles are not standardized contracts. Table 5 provides a summary of some of the contract characteristics in the sample.

4.1. Lockup period

On average, the investor has to wait 86 calendar days from the closing before he is allowed to convert at the floating conversion price. At that time, normally the company will file an S-3 registration statement so that investors can sell the shares after conversion. The existence of a lockup period is consistent with the argument that issuers believe that in the near future (before conversion becomes possible) some good news is about to come out, i.e. the stock is currently undervalued. By issuing a floating-priced convertible rather than a public equity issue or a normal convertible with a fixed conversion price, the company avoids issuing undervalued securities.

4.2 Fees

The proceeds that companies receive are less than the nominal value of the convertibles. On average, the cash fees are equal to 8% of the gross amount issued. The maximum fee was 24% and the smallest fee was 0.2%. Note, these numbers exclude other non-cash compensation such as warrants and other securities.

4.3. Dividend yield (coupon rate)

The average dividend yield (coupon rate) was 6.7%. Dividends or coupons can be payable in cash (257 cases), additional convertible securities (127 cases) or common stock issued at a discount (194 cases). The fact that the number of cases exceeds the number of dividend (coupon) paying issues reflects the fact that often the company has an option to choose the payment method.

4.4. Conversion discounts

The convertible allows the investor to convert at a discount from some reference price in a look-back period. In some cases the discount accelerates, presumably in order to convince the investor to delay conversion. Table 5 shows the mean, median, standard deviation, maximum and minimum of the distribution of discount factors (i.e. the number to be multiplied with the reference price in order to obtain the conversion price). Note that in the typical issue convertible holders had the right to convert at a 20% discount. The largest discount was 48%.

4.5. Lookback period and the number of prices to calculate the reference price

A convertible allows investors to convert at a discount from the "reference price". The reference price is the average of n lowest closing prices in a period of τ days prior to conversion.[12] Table 5 shows that, on average, n is equal to 6 and τ equals 10. Note that the larger n, the more difficult it will be to manipulate the reference price. Indeed, suppose n =1. In that case, a preferred stockholder who would want to manipulate the price could concentrate his short selling efforts on one day. This would suggest that, in order to reduce

[12] Sometimes the look-back period changes as in the case of Casmyn. In this case the look-back period was defined as the average look-back period over the life of the contract.

the likelihood of manipulation, the optimal strategy for the company would be to make n sufficiently large.

Table 5 also shows some characteristics of the distribution of the look-back ratio n/τ. The median ratio is equal to the maximum of 100%, which suggests that typically investors have the right to convert at a discount from the average closing price in a 5-day look-back period. Note that, ceteris paribus, the smaller this ratio, the larger the value of the look-back option : when $n < \tau$, the reference price is lower than the average price during the previous τ days.

4.6 Conversion price floors and caps

We can distinguish four types of contracts (see figure 3). The most common contract (56% of the cases), is a convertible where the conversion price is capped, followed by contracts where the convertible has no cap or floor (30% of the cases). In 52 cases (11% of the sample) we found contracts with a cap and a floor. The least popular contracts (3% of the sample) are those without a cap, but with a floor.

It is interesting that the contracts with the largest potential gain for the preferred stockholders (a cap, no floor) are also the most popular, while the issues with the smallest potential gain (no cap, a floor) are almost non-existent. Moreover, from a theoretical point of view it is easy to see that only contracts without a floor (421 out of the 487 cases) eliminate the adverse selection problem as pointed out by Brennan (1985).

4.7 Conversion/selling limitations.

A typical contract will specify that the convertible holder is not allowed to own more than 4.99% of the equity. This means that substantial holders will have to sell the converted shares in the open market once they reach the 4.99% limit. This will effectively prevent a large convertible holder from taking control of the company, and can therefore be classified as an anti-takeover provision. However, as this restriction encourages investors to convert-and-sell it may generate a lot of selling pressure. In order to discourage this behavior, in 142 out of the 487 cases, companies put various limitations on the amount of shares that could be sold after conversion. Typically these restrictions are volume restrictions. For example, the May 1997 Casmyn contract specifies that

> *"the holders of shares obtained after conversion will be limited on resales of such shares as the greatest of (i) 10% of the average trading volume of the common stock for the five trading days preceding any such sale date (ii) 25,000 shares (iii) 10% of the trading volume for the common stock on the date of any such sale"*[13]

4.8 Restrictions on short sales

A floating-priced convertible seems to be a perfect instrument to benefit from short selling small thinly traded securities. A normal short seller has to repurchase the shares to close his position. The resulting buying pressure may substantially reduce profits from selling short shares of small, thinly traded stocks. However, a convertible holder can always repurchase at a discount from the market price. As this market price is based on a look-back period, the preferred holder/short seller is hedged against the arrival of stock price jumps triggered by the arrival of good news. Moreover, because brokers and market makers understand that the convertible holder can always come up with the shares, and buy them at a low price, the short seller in possession of a floating-priced convertible does not have to keep a 50% cash margin: the short sale is considered by many to be covered, as opposed to naked shorting.

Considering this possibility, it may seem surprising that we found only 58 cases where the offer prospectus prohibited short selling. Actually in 406 cases the prospectus explicitly mentioned that preferred owners are allowed to sell short. In 23 cases we could not find information on whether short selling was permitted or not. Information about short sale restrictions is obtained from reading the "plan of distribution" section of the S-3 filings.

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[13] Source: Casmyn May 22, 1997, S-3 Filing, page 24

Investors in floating-priced convertibles argue that they don't short to manipulate, but they short to hedge, especially in contracts with a cap on the conversion price. For example, suppose that the company issues a convertible that allows investors to convert at a 20% discount from the market price, with a conversion cap of $ 20, which is 30% above the current stock price of $ 15. If, subsequently the stock rises to $ 30 the convertible may want to hedge its profits by shorting the stock at $30. By doing this, the owner of a convertible is assured to make a minimum profit of $ 10 per share on the 50 stocks obtained by converting at $ 20. However, from then on, the convertible holder has an incentive to see the price fall below $ 25 (i.e. when the conversion price becomes smaller than $ 20). So, the ideal scenario for a convertible holder is a stock price rise above the conversion cap followed by a short sale, followed by a price decline.

Even in contracts without a conversion cap, investors in floating-priced convertibles may want to hedge because when an investor submits a conversion notice, it may take a few days before the company actually delivers the shares. Without short selling, the investor incurs the risk that the stock price declines between the time of the conversion notice and the moment when he is able to sell the converted shares. One could argue that a company should be indifferent whether the investor sells the shares before the conversion notice, or afterwards: the resulting dilution and price pressure should be the same. However, as the reference price R_t is determined *before* the conversion notice, price pressure before the conversion notice produces more dilution (and larger returns) for the investor .

4.9 Warrants

In 198 cases we found that the preferred shareholders were given warrants to buy common stock and in 12 cases warrants to buy more preferred stock. Apparently warrants on common stock are introduced to reduce the incentives to short the stock. Whether this feature is effective in reducing selling pressure, is an empirical issue, especially considering that some warrants have reset provisions : the exercise price may be reset at a lower level if the stock price falls.

4.10 Delivery options: ability to pay cash rather than issuing shares.

Some contracts provide the company with the alternative to pay the convertible holder cash rather than issuing shares, when the company's stock price is below a certain threshold. For example, the May 22 S-3 filing of Casmyn specifies that if during a consecutive 20-day period the stock price is below $ 6, the company has the option to pay a "cash conversion price" rather than issuing stock. This renders short selling risky as the convertible holder may be forced to cover his short position in the open market. On the other hand, it requires that the company is sufficiently cash rich to finance the purchase. If the firms in our sample are cash poor (as was the case for Casmyn), this provision will be a paper tiger.

4.11 The time series behavior of contract characteristics

Figures 4, 5 and 6 describe how the contract characteristics of our sample change over time. Figure 4 shows the percentage of deals in the sample at time t (measured on the horizontal axis), that had conversion restrictions, restrictions on short sales, warrants, and escalating discounts.

Although we observe a significant decrease in conversion restrictions since the middle of 1996, the most striking feature of figure 4 is the very significant increase in the use of warrants. Apparently more and more companies want to give convertible investors an incentive to see stock prices rise: while by May 1996 15 % of the deals had warrants attached, this number increased almost three-fold by the end of the sample period. We also see some mild increase in restrictions on short sales as well as in the use of escalating discounts. So, there seems to be a trend to encourage investors to hold on for the long run through carrots (the warrants and the escalating discount) as well as sticks (short selling restrictions). The fact that conversion restrictions are relaxed does not, at first, seem to fit this trend. However, if companies want to encourage investors to hold out for potential price jumps (or escalating discounts), they should also give them the freedom to fully benefit from these jumps (or discounts) when they occur.

Figure 5 tries to detect some trends in three other, quantifiable, characteristics of the contracts. The figure shows the average value of the characteristic, based on contracts that were in the sample in month t (measured on the horizontal axis). Here the most significant change is the decline in the look-back ratio (n/τ) after June 1997. Recall that the smaller this ratio, the larger the value of the look-back option. Again, this finding is consistent with the hypothesis that issuers have been increasingly encouraging preferred holders to hold out for "the long run". The initial discount has slightly declined over time. Note that the temporary jump in lock-up period in late 1995 is not significant because by the end of 1995 there are only 15 observations in the sample, which makes the average highly dependent on outliers.

Finally figure 6 shows to what extent contracts specified a cap and/or a floor on the conversion price. Although contracts with no cap and a floor (the least interesting for convertible investors) did not exist prior to January 1996, the distribution of contract types has generally remained rather stable over time. The most popular contracts are the ones that are most interesting for the convertible holders: with a cap but without a floor.

In short, the most significant evolution in contract design seems to be the attachment of warrants to the convertibles, together with measures to give more opportunities to investors to benefit from the exercise of the look-back option (relaxation of conversion restrictions, reduction in the look-back ratio). These findings are consistent with the hypothesis that issuers made attempts to change the contracts in order to encourage investors to hold out, rather than to simply short and convert.

In order to better assess the statistical significance of the apparent changes in contract design, we regress each characteristic on time. A time dummy, the explanatory variable, is created by initializing a variable to 1 in January 1995 and incrementing the variable by 1 for each of the 48 months in the sample. We look for a time trend in 8 characteristics, 5 dummy variables and three continuous variables. The dummy variables are set equal to 1 when i) warrants, ii) a conversion cap, iii) a conversion floor, iv) a short sale constraint and v) a lockup period are found in the contracts and zero otherwise. The 3 continuous variables are the discount, the look-back ratio and the relative size of the issue. For the dummy variables, the dependent variable of the regression is the frequency of observing a contract with characteristic i with i=1,...,5, in month j with j =1,...,48. For the continuous variables, the dependent variable is the cross-sectional mean of the variable in month j with j=1,...,48. For each of the 8 regressions, we use OLS, WLS and SUR to estimate the intercept and slope coefficients using the number of issues in month j relative to the total number of issues as weight.

The results are presented in Table 6. We find evidence of a statistically significant time trend in three characteristics, namely the use of warrants, the look-back ratio and the discount. The slope coefficient is positive for the first characteristic and negative for the last two. The results indicate that the decrease in the discount over time is compensated by a decrease in the look-back ratio, i.e., a more valuable look-back option, and an increase in the use of warrants. This suggests that the design of the contract has evolved over time and that issuers are searching for an optimal contract, optimizing over the discount, the look-back ratio and the warrants.

4.12 Correlation between contract features

A more direct way to estimate the structure of the contracts is to measure the correlation between the contract features. For five contract characteristics, we defined a dummy variable. This variable was set equal to 1 if the deal had warrants, a conversion cap, a conversion floor, a short sale constraint or a lock-up period, and zero otherwise. The

Spearman correlation coefficients between all these dummy variables and two continuous variables (the discount and the look-back ratio) are shown in Table 7.

The most significant findings are that (1) contracts with warrants attached tend to have smaller initial discounts and smaller look-back ratios (2) deals with smaller initial discounts have smaller look-back ratios and are more likely to have a conversion cap. Apparently companies trade off contract characteristics: when the discount is relatively small, the preferred holders are compensated with extra warrants, caps on the conversion price and more valuable look-back options. Note that these findings fit nicely with the previously reported changes in contract design over time: companies seem to move to deals with smaller discounts, smaller look-back ratios and more warrants, presumably to discourage early conversion.

5. The long-term stock market performance of floating-priced convertible issuers

Because the results of long-term event studies are often dependent on the methodology chosen, we estimate four different measures of long-term "abnormal" returns: 1) cumulative market adjusted returns 2) buy-and-hold market adjusted returns 3) abnormal returns based on the Fama-French (1993) three-factor model in calendar time and (4) abnormal returns based on the Fama-French three factor model, but now in event-time, using Ibbotsons (1975) RATS procedure.

5.1 Cumulative raw returns and cumulative market adjusted abnormal returns

As a first step, starting 12 months before the announcement date and ending 12 months after the announcement date, we calculate cumulative average "raw" returns (CRR) and cumulative average "abnormal" returns relative to the equally weighted market index (CAREW) and the value weighted market index (CARVW). We stop after 12 months because as we move along we tend to lose many observations, mainly because of the high delisting frequency of the stocks in our sample.

The results are shown in figure 7 and Table 8A. In the period prior to the issue date (month –12 through –1) the raw returns were positive in 10 of the 12 months. This changes significantly afterwards: in 11 of the 12 months after the event month, mean returns were negative. In particular, the cumulative average *raw* return (CRR) during this 12 month-period is – 30.1 %. (t = -3.51). This significant decline becomes even more apparent if we adjust for general market movements. The cumulative average abnormal return is equal to – 40.3 % (t = - 4.71) relative to the equally weighted market index (CAREW) and – 54 % (t = -6.38) relative to the value weighted market index (CARVW). Table 8A shows that during the 12 months prior to the issue, firms underperformed the equally weighted market index by 5.1 % (t=-1.12) and the value weighted index by 10.78 % (t=-2.44).

Note that each of the 467 events for which we could find announcement returns on the CRSP tape was included in the sample, which means that many firms had multiple event dates. This corresponds to a portfolio investment strategy where the weight of a given firm becomes more important as the firm issues more death spirals. While this procedure maximizes the number of observations and hence the power of our test, it will also create more cross-sectional dependence of the observations in our sample. We repeated the analysis, but now excluding subsequent issues by the same firm. This reduced our sample from 467 to 261. The results, shown in panel 8B, are very similar, although less negative. For example, for the 12 month post-announcement period, we find CRR = -14.7 % (t = -1.31) CAREW = -26 %(t= -2.38) and CARVW = - 39 % (t = - 3.55). The fact that these numbers are significantly smaller than the numbers reported in table 8A suggests that follow-up issues lead to much more drastic price declines than the first issue. Indeed, panel 8C shows after the second and subsequent issue, companies perform significantly worse than after the first issue. In the 12-month post-announcement period, CRR = -51.39% (t = -5.20) CAREW = -60% (t = -6.04) and CARVW = -74.5% (t = -7.57). One explanation could be that as more investors learn about the negative consequences of the first death spiral, they start massively bailing out if the firm continuous with this type of financing. Alternatively, the fact that a company repeatedly issues floating-priced convertibles is a signal that operating performance is seriously declining.

5.2 Buy-and-hold returns

In addition to CAR's, we estimate buy-and-hold returns (BHR) for two reasons 1) CAR's are biased predictors of BHR's and 2) CAR's do not fulfill one of the objectives of long-run event studies, i.e., to find the value of investing in the average sample firm relative to an appropriate benchmark. The results are reported in Table 9A that gives the buy-and-hold raw return (BHRR) and the buy-and-hold returns relative to the EW index (BHAEW) and to the VW index (BHAVW) for the same sub-periods and samples as those investigated in Table 8.

The different BHR's are similar in magnitude to the CAR's and similar inferences can be drawn from both CAR's and BHR's. The abnormal buy-and-hold returns are found to be negative before and after the issue. For example, the CRR is equal to –30 % in the 12-month period after the issue date and the BHRR is found to be equal to –34 % in the same sub-period for the sample that contains all the issues. While BHR's tend to be higher in absolute value than CAR's on average, counterexamples can be found. In the post-event period, the CARVW is equal to -75% and the BHAVW -73% for the sample that excludes the first issue.

The big difference between the CAR's and the BHR's is not their magnitude but their statistical significance. The t-statistics obtained for the BHR's are much higher than their CARs' counterparts. This is due to the positive skewness of the BHR's. Though not reported in the table, skewness coefficients as high as 4.0 are not uncommon for the BHR's. CAR's in comparison are less skewed due to the fact that monthly returns are summed rather than compounded. Barber and Lyon (1997) argue that conditional on observing a negative sample mean, positive skewness imparts a negative bias in the cross-sectional standard deviation and a positive bias in the test statistic. To correct for skewness, we calculate the statistic:

$$\sqrt{n}\left(\hat{S}+\frac{1}{3}\hat{\gamma}\hat{S}^2+\frac{1}{6n}\hat{\gamma}+\frac{1}{27}\hat{\gamma}^2\hat{S}^3\right)$$

suggested by Hall (1992) where $\hat{\gamma}$ is an estimate of the coefficient of skewness and $\hat{S}$ is the ratio of the sample mean by the cross-sectional sample standard deviation of return for the sample of n events.[14]

The skewness-adjusted t-statistics are indeed much lower than their standard t-statistics[15] Despite this, the null hypothesis of no abnormal performance is rejected in the post-issue period regardless of the sample and the benchmark. There is less evidence of a statistically significant negative abnormal performance in the pre-issue period. Similar conclusions were reached with the CAR's.

Finally, we report in Table 10 the percentage of positive buy-and-hold returns and abnormal returns in both sub-periods. The numbers are much lower than those one would expect by chance. 85 % of all one-year post-announcement returns are negative. Relative to the value-weighted index, the percentage of positive abnormal returns is equal to 20% before the issue and drops below 10% after the issue, using the sample that contains all the events. When the first issues are excluded, the percentages are 20% and 4%, respectively.

5.3 Fama-French factors : the calendar-time portfolio approach

An alternative approach to measure long-term stock price performance is to assess the performance of an event portfolio in calendar-time relative to either an asset pricing model or

[14] The skewness-adjusted t-statistic differs from the one used by Barber and Lyon (1999) equation (5). Barber and Lyon skewness-adjusted t statistic was originally developed by Johnson (1978). Hall (1992) argues that Johnson statistic fails to correct properly for skewness. The difference between the two statistics is the term $\frac{1}{27}\gamma^2\hat{s}^3$. In our case, inconsistent results were obtained with Johnson's skewness-adjusted t-statistic, such as a negative conventional t-statistic but a positive skewness-adjusted t-statistic.

another benchmark. For each calendar month in the event period of interest, an EW and/or VW portfolio is formed that includes all the sample firms that participated in the event within the prior n periods. Portfolios are rebalanced monthly to drop all the firms that reach the end of the period and add all firms that have just participated in the event. We use the calendar-time portfolio method based on the three-factor model developed by Fama and French (1993). In the Fama-French (1993) three-factor model, the first factor is the excess return on the value weighted market portfolio. The second factor, SMB, is the return on a zero investment portfolio formed by subtracting the return on a large firm portfolio from the return on a small firm portfolio. The third factor, HML, is the return of another mimicking portfolio of high book-to-market stocks less the return on a portfolio of low book-to-market stocks,

$$R_{p,t} - R_{f,t} = a_p + b_p\,(R_{m,t} - R_{f,t}) + s_p\,SMB_t + h_p\,HML_t + e_{pt} \qquad (8)$$

The intercept of the Fama-French (1993) time-series regression equation is a measure of the average abnormal performance analogous to Jensen's alpha within the CAPM framework. It measures the average monthly abnormal return on the portfolio of event firms, equal to zero under the null hypothesis of no abnormal performance.

The calendar-time portfolio approach offers some advantages over tests that employ either cumulative or buy-and-hold abnormal returns. Fama (1998) argues that factor-based approaches to performance evaluation are useful in capturing systematic patterns in average returns. Consequently, they are less likely to yield spurious rejections of market efficiency. Further, the time portfolio approach solves the dependence problem and works well when returns are overlapping. The cross-sectional correlations of individual event firm returns are automatically accounted for in the portfolio variance at each point in calendar time. Finally,

[15] Skewness-adjusted t-statistics are not biased free. It is well known that standard error estimates and t-statistics on non-random samples cannot easily be corrected. See Mitchell and Stafford (2000).

unlike other methods, the Fama-French (1993) approach does not require data on size or book-to-market for sample firms.

The Fama-French regression is run on two different time periods. The first starts 12 months before the event until the event (but excluding the event month). The second covers a 13-month time period that starts in the event month. The time-series sample size is twice as high for the first than for the second time period given the clustering of the issues in the 1995-1998 time period. The regression parameters are estimated using GMM.

Table 11 shows the results of the Fama-French regressions for the two subperiods and for three samples: the sample that contains all 467 events, the sub-sample of 261 observations that excludes follow-up events by the same firm, and, the sample of 206 follow-up issues. The positive regression coefficients on the SMB variable and negative coefficients on the HML variable shows that the companies in our sample are typically small growth stocks.

The most important conclusion from Table 11A is that it confirms the results of tables 8 and 9: after the issue, companies experience economically significant excess returns of –1.8 % per month (or about -22 % after 1 year) for the total sample, and –0.7 % per month (or approximately –8.5 % per year) for the sub-sample that excludes multiple issues by the same firm. However, due to the small power of our Fama-French regressions an abnormal return of – 22 % per year is not statistically significant (t= -1.41). Interestingly, Table 11A shows that excess returns in the year prior to the issue are basically identical to excess returns after the issue. This is consistent with the hypothesis that death spirals are issued by companies that are already experiencing serious financial difficulties, and for which a floating-priced convertible may be a “last resort” financing instrument.

As pointed out by Loughran and Ritter (1999) the power of the time-series regression approach could be low due to the fact that the regression gives the same weight to each month, i.e., fails to take into account the number of observations in each month. If there is a differential abnormal performance in periods of high activity versus periods of low activity, the regression approach will average these and may be less likely to uncover abnormal performance. Figure 1 shows that the number of issues is varying over time with a low of 2 issues in January 1995 and a high of 35 issues in December 1997. To address Loughran and Ritter's concern, we use WLS to estimate the regression parameters, using as weights the number of securities in the portfolio in each month.

The results are reported in panel B of Table 11. We do find evidence that weighting the months equally reduces the power of the test of no abnormal performance. The intercept of the regression and its t-statistics decreases from -.0199 and -1.41 with OLS to -.023 and -1.95 with WLS, respectively for the sample that includes all the events. Unlike OLS, the null hypothesis of no abnormal performance is rejected with WLS.

5.4 Fama-French factors : the event-time approach

The calendar time approach weights each month equally in the analysis, although the number of companies in the portfolio is not the same. Alternatively, table 12 shows the results employing Ibbotson’s Returns Across Time and Securities (RATS) procedure (1975) and, as before, measuring abnormal performance using the three-factor model. In this procedure, monthly returns for all firms in the sample are aligned in event time, where month 0 represents the announcement month. Each month t relative to the event we run the following cross-sectional regression :

$$R_{i,t} - R_{f,t} = a_t + b_t(R_{m,t} - R_{f,t}) + s_t\, SMB_t + h_t\, HML_t + e_{i,t} \qquad (9)$$

In contrast to the calendar-time approach where each month receives an equal weight in the analysis, the RATS procedure gives each announcement the same weight. Moreover, factor sensitivities of the sample firms are allowed to change in event-time.

The results in table 12 are broadly consistent with the results reported with the three other methodologies: companies that issue floorless convertibles experience significant negative excess returns of –29 % (t=-3.33) in the year following the issue. As before, the results are most significant for the follow-up issues where post announcement excess returns are – 50 % (t=-4.43). Companies that issue floorless convertibles are also poor performers before the issue with a 12 month pre-announcement abnormal return of –14 % (t =- 2.26). The robustness of our results makes us confident that we have identified a new anomaly here: the market does not fully incorporate the negative consequences of floating-priced convertibles.

6 Measuring the impact of contract characteristics

6.1 Performance and contract design

Our findings raise the fundamental question whether the poor performance of the issuers is a direct consequence of a poorly designed contract, or is it simply reflecting poor operating performance. This issue is important as regulators are currently considering restrictions on the structure of the convertibles (see footnote 8). If the stock market decline simply reflects poor operating performance, an argument could be made that, without the floorless convertible, these companies would have collapsed as well, and possibly even sooner.

In order to test whether contract design matters, we test whether the following 7 characteristics have an impact on long-term performance: (1) the attachment of warrants (2) the existence of a conversion cap (3) the existence of a conversion floor (4) the existence of short sale constraints (5) the existence of a lock-up period (6) the size of the initial discount and (7) the value of the look-back ratio. For each contract characteristic, we form two groups. For example, to examine the impact of warrants we form a group of all 198 issues with attached warrants and a group of 292 issues without warrants. In order to examine how the relative performance of both groups changes in event time, we employ Ibbotson's Returns Across Time and Securities (RATS) procedure (1975) and, as before, measure abnormal performance using the three-factor model. The results in table 13, section A (and also figure

8A) show the cumulative abnormal return over two subperiods: 12 months before the announcement date, CAR(-1, -12), and 12 months after (and including) the event date CAR(0,+12). One striking finding from Table 13: for all 14 subsamples, the CAR(0,+12) is negative and ranges from – 11% to –58%.

After 12 months the CAR for the sample with warrants is an insignificant –15.98% (t = -0.44), while the corresponding statistic for the sample without warrants is –36.7% and highly significant (t = -3.22). The difference between the two CARs is 20.60% which is statistically significant at the 10% level (t = -1.65). However, from figure 8A that, only after 8 months, the cum-warrant sample seems to start doing better than the other sample. Table 13 B and 13 C (and figure 8B and 8C) show the impact of including a cap and a floor, respectively, on long-term performance. Interestingly, issues with a cap perform 21.41% (t = 1.69) better after one year than issues without a cap. Adding a floor, however, does not seem to help, quite the opposite: the CAR (0,+12) is –58.4% (t = -4.94) vs. –24.1% (t = -2.63) for the truly floorless sample, a significant difference of 34.4% (t = 2.4). The finding that a floor leads to a more severe price decline is consistent with the hypothesis that the existence of a floor creates a situation where convertible holders “stampede for the exit” by selling and converting as quickly as possible, in order to avoid holding the bag when the conversion floor is reached. We can conclude that, from the point of view of shareholders, floors are “bad” and caps are “good”. Interestingly, this may explain why contracts without a cap and with a floor are almost non-existent, while contracts with a cap and without a floor are the most popular.

Surprisingly, panel 13D and figure 8D, show that imposing short-selling constraints does not improve post-issue performance. Actually, companies that impose short-sale constraints earn excess returns of –51.3% (t = -2.84), which is 25.8% less than the sample without short-selling constraints. However, this difference is not statistically significant (t = -1.11) and mainly caused by a 16% difference on the announcement month (see figure 8D).

One explanation is that companies that put in short selling constraints are fundamentally in deep trouble and the decline is related to the issuance of the convertible. This story is consistent with their poor 12-month pre-issue period when these companies experience negative excess returns of –55.14% (t = -2.71). Alternatively, the results are consistent with the hypothesis that short selling constraints are impossible to monitor, and therefore ineffective. One investment banker told us that, while SEC rules do not permit shortselling against privately owned securities, SEC regulations are difficult to enforce if the securities are sold to off-shore investors (through, so-called, regulation S offerings). This may explain why we found only 58 deals where the offer prospectus limits shortselling.

Figures 8E and 8F show that, in the long run, (1) companies that have a lockup period tend, at least in the long run, to do better than companies without a lock-up period and (2) deals with a discount above the median perform worse than deals with a discount below the median. However, although in both cases the return difference is larger than 15% over the 12-month post-announcement period, the results are not statistically significant (see Table 13). Finally, the look-back ratio has also no meaningful impact on long-term performance.

In summary, only warrants and caps seem to improve one-year post-announcement performance in a statistically and economically significant way. Negative covenants, such as floors and short sale restrictions are ineffective and even counterproductive. This may explain why such negative covenants are rare.

6.2 Delisting and contract design

One of the major problems in examining the relation between long-term returns and contract characteristics, is the sharp decrease in the sample size over time, due to delisting. Note that the CRSP tape does not report prices, once the stock starts trading on the OTC. Biased estimates would result from an estimation done on a sample that includes only listed stocks. An alternative solution is to introduce a dummy variable that takes a value of 0 if the stock is delisted as of December 1999 and 1 otherwise. To the extent that the delisting dummy is a good proxy for performance, the impact of contract characteristics on performance can be investigated by regressing the delisting dummy on the characteristics. Unlike returns, the delisting code is available for every single observation in the sample. The regression can be run on the entire cross-section generating estimates free of a survivorship bias. Further, given the availability of the delisting code at any point in time, the impact of contract characteristics on performance can be studied both in the short run and the long run. This is done by estimating the parameters of a Logit model, a popular alternative to discriminant analysis for classifying individuals, into one population or another, with the delisting dummy as the contract characteristics as explanatory variables.

More specifically, let N be the cross-sectional sample size, i.e., the number of issues, and Y a vector of size N with Y_i, with $i = 1 \ldots N$, a dummy variable that takes a value of 0 if the firm is delisted as of December 31, 1999 and 1 otherwise. A stock is classified as delisted for CRSP delisting codes above or equal to 400. Let X be a (N*K) matrix of explanatory variables that capture the most important characteristics of the contracts. The Logit model is estimated using a set of 7 dummy variables. These are set equal to 1 if an issue has warrants, a conversion cap, a conversion floor, short-sale constraints, a lock-up period, a relative issue size above the cross-sectional median, a lookback ratio above the cross-sectional median and zero otherwise, respectively.

With the Logit model the probability P of delisting conditional on the set of explanatory variables is given by:

$$P(Y=0) = F(X' B) \tag{10}$$

with:

$$F(X' B)= 1/[1+\exp(-X' B)] \tag{11}$$

where X'B denotes the transpose of X and B, the vector of regression parameters, which is estimated using maximum likelihood. The maximum likelihood estimates of the regression parameters are computed using an iteratively reweighed least-squares algorithm. The null hypothesis that the explanatory variables have no impact on the probability of delisting is tested using a likelihood ratio test, which has a chi-square distribution under the null.[16]

Five Logit models are estimated. The first three models are regressions performed on a sample that i) includes all the events, ii) excludes the follow-up issues and iii) excludes the first issues. The next model is conditional on the dummy that captures the relative size of the issue. Finally, in light of the change in the design of the contracts over time, we define a time dummy that takes a value of 1 when the issue date takes place after December 31, 1996 and 0 otherwise. Though arbitrary, the choice of this date gives two sub-periods of equal length.

The results are presented in table 14. Robust conclusions emerge from the analysis. First, regardless of the sample used to run the regression and regardless of whether the regression is unconditional or conditional, the null hypothesis that the explanatory variables have no effect on the probability of delisting is always rejected at a very high level of statistical significance. This suggests that contract characteristics have an impact on the probability of delisting. One exception is for the issues that took place before December 31, 1996 for which the null is marginally rejected. This could be due to the relative small sample size and power considerations. Second, the most discriminating variable is the discount. The parameter estimate is negative, i.e., the higher the discount the higher the probability of

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[16] As is well known when evaluating Logit models, the estimated regression parameters do not indicate the increase in the probability of the event occurring given a one unit increase in the corresponding explanatory variable. Rather, the coefficients capture the effect of a change in one explanatory variable upon $\ln[P/(1-P)]$ where P is the probability. While the sign of the coefficient indicates the direction of the change, the magnitude depends on $f(X' B)$, the derivative of the Cumulative Distribution Function (CDF) with respect to a change in the explanatory variable, which captures the steepness of the CDF at X' B. Obviously, the steeper the CDF, the greater the impact of a change in the value of an explanatory variable will be.

delisting, and is highly statistically significant in every single model. The discount dominates every other variable. The other relevant variables are the conversion cap and the lookback ratio. While their importance and statistical significance is model specific, systematic patterns emerge. The sign of the parameter obtained for the cap is positive suggesting that the presence of a cap decreases the probability of delisting. Also, as expected, the higher the lookback ratio the higher the probability of delisting.

The difference between the three Logit models performed on the samples that i) includes all the issues, ii) excludes the follow-up issues iii) excludes the first issues suggests that the existence of a conversion floor matters more for the first issue than for the subsequent issues while the opposite is true for the conversion cap. When conditioning on the relative issue size, the discount emerges as the only discriminating variable for small issues. For large issues, the discount matters relatively less than for small issues but other contract characteristics such as the lookback ratio, the cap and the short-sale constraints matter more. When conditioning on time, it appears that contract design is much more relevant in the second than in the first subperiod. In fact, in the first subperiod, no characteristic except the discount and the existence of a floor had a significant impact on the delisting probability.

A surprising result is the fact that the existence of warrants has no impact on the probability of delisting. This result could stem from the reset provisions and/or its correlation with the discount and the lookback ratio. Another puzzling result is the sign of the short-sales dummy. Even though the regression parameter estimate is never statistically significant, except once, the sign is positive suggesting that the probability of delisting is higher in the presence of short-sales constraints. This result is consistent with the post-issue abnormal stock return behavior in figure 8D. Short sale constraints are ineffective and possibly interpreted as a negative signal by market participants.

The results reported in table 14 allow us to understand why the discount has decreased over time (see table 6). A higher discount being associated with a higher probability of delisting, issuers have lowered the discount over time to minimize that risk. To compensate for the decrease in the attractiveness of the issue due to a lower discount, issuers have increased the value of the contract in two ways by 1) increasing the value of the lookback option i.e., by lowering the lookback ratio and 2) attaching warrants. This has not been fully successful as far as reducing the delisting probability. If a decrease in the lookback ratio decreases the probability of delisting, the use of warrants does not seem to have any impact on delisting. Nevertheless, the combined results of table 6 and table 14 provide evidence of learning. Agents use a trial and error process to correct the initial flaws of financial contracts (especially, high discounts) and, hopefully, to improve their design.

Additional insights about the relevance of the contract characteristics can be gained by looking at the delisting time, as defined by the number of months between the delisting date and the issue date. The justification for including warrants, a cap, a floor, short-sales constraints and a lookback option, is to give less incentives to market participants to sell short the stock. Given that short selling may drive the stock price down and possibly below the level necessary to maintain a listing, any characteristic that reduces the incentives to sell short should, if effective, lengthen the survival time. Conversely, the absence of such a characteristic, if effective, should shorten the survival time.

To test the null hypothesis that the contract characteristics have no impact on the time to delisting, we create three additional dummy variables. The first dummy takes a value of 0 if the stock is delisted in the first 12 months after the issue and 1 otherwise. The second dummy takes a value of 0 if the stock is delisted in the first 24 months after the issue and 1 otherwise, conditional on the stock not being delisted in the first 12 months. The last dummy takes a value of 0 if the stock is delisted 24 months after the issue date and 1 otherwise, conditional on the stock not being delisted in the first 24 months. We estimate three Logit models, regressing each dummy variable on the contract characteristics. The regressions are run on a sample that i) includes all the issues, ii) excludes the follow-ups and 3) excludes the first issues. Both for single and multiple issues, we calculate the delisting time as the number of months between the issue date and the delisting date. The null hypothesis that the contract characteristics have no impact on the delisting time is probably best tested using the sample that excludes the follow-up issues. Also, the relatively small sample size prevents us from running separate regressions for small and large issues. To control for the relative size of the issue, we add size as an explanatory variable.[17]

The results are presented in table 15 and 16. Table 15 gives the cross-sectional mean of three continuous variables (the discount, the size of the issue and the lookback ratio) for listed and delisted stocks as a function of the delisting time. The table shows that delisted stocks have on average a higher discount, a larger issue size and a higher lookback ratio than listed stocks. Further, the difference in the mean increases with the delisting time both for the discount and the lookback ratio. This suggests that the ability of these two variables to predict delisting is higher in the long run than in the short run.

Turning to the regressions in table 16 and looking at the chi-square statistics that test the null hypothesis that the contract characteristics are irrelevant, we find that the probability of rejecting the null tends to increase with the delisting time. For example, when we focus on the subsample that excludes follow-up issues, the contract characteristics have no explanatory power at predicting delisting in the 12-month period following the issue date. Not a single

[17] The regression parameter estimates obtained with the last two dummies could be biased due to the fact that for all the issues that took place in 1998, say in July of 1998, we have at most 18 months of data. The bias arises for the stocks that were not delisted by December 31, 1999. For example, a stock delisted during the year 2000 will be incorrectly classified as listed with the second dummy. A similar problem arises with the third dummy for all the stocks that will be delisted in 2001. To assess the impact of this bias, the regressions are run with and without these observations. Similar results are obtained with both samples. The chi-square statistics that test the goodness-of-fit of the model are obtained after removing these observations.

variable is statistically significant. These results are not due to the lack of power as the chi-square statistic increases with the delisting time. The null hypothesis is marginally rejected with the second dummy and is rejected with the third dummy, suggesting that the contract characteristics have some explanatory power at predicting delisting in the long run.

It is quite informative to look at the set of variables that have predictive power and at the pattern in their point estimates. Once more, the discount emerges as the variable with the most consistent predictive power: in 6 out of the 9 estimations the regression coefficient is negative and statistically significant. However, the discount is irrelevant for predicting delisting in the short run but becomes relevant in the long run. The only other variable that matters for long-term survival is the warrant. The presence of warrants in the contract decreases the probability of delisting but only in the long run. There is also some evidence that a the floor reduces the probability of delisting in the short run.

To summarize, we find that the contract characteristics have an impact on the probability of delisting. The best predictor of delisting is the discount, at least for delisting after 12 months. Regardless of the conditioning variable such as the ranking, the relative size, the time of the issue and the time to delisting, the discount is a statistically significant variable. While this finding is consistent with the contract design hypothesis, it could also be explained by the signaling hypothesis, if high discount issuers systematically experience worse post-issue operating performance than low-discount issuers.

7. The operating performance of floating-priced convertible issuers

One of the goals of the paper is to test whether the convertible is responsible for the stock price decline, the “contract design hypothesis”, or whether it signals that the operating performance of issuers will decline “abnormally” in the future, the "signaling hypothesis”. A necessary, although not sufficient, condition for the signaling hypothesis is that convertible issuers should experience worse post-issue operating performance than “comparable” control firms. Hence, we need to measure operating performance and choose control firms.

7.1 Measuring operating performance and selecting comparable firms

To measure operating performance, we use a methodology similar to the one employed by Loughran and Ritter (1997), who examine the operating performance of firms conducting seasoned equity offerings. For the sample of issuing firms, operating performance is measured by the median 1) operating income to assets ratio, 2) profit margin, 3) return on assets, 4) operating income relative to sales, 5) capital expenditures plus research and development relative to assets and 6) market value of equity relative to book value of equity[18]. Control firms are selected in two ways: first, with the Loughran-Ritter matching algorithm and then with the propensity score matching algorithm.

7.1.1 The Loughran Ritter matching algorithm

The matching algorithm suggested by Loughran and Ritter (1997) is used to select control firms. In the fiscal year prior to the issue, defined as year –1, each issuing firm is matched with a Compustat listed non-issuing firm chosen on the basis of 1) industry, 2) asset size and 3) operating income. Barber and Lyon (1996) suggest matching on prior performance to account for the mean-reversion in accounting ratios. Candidate matching firms are those listed on the NYSE, AMEX or NASDAQ that have not issued floorless convertibles during the five years prior to the offering. From this universe, firms in the same industry, as defined by the two-digit SIC code, with asset size at the end of year –1 between 25% and 200% of the issuer are ranked by their year –1 operating income (OIBD) relative to total assets. The firm with the closest OIBD/assets ratio is picked up as the matching firm. If there are no issuers in

[18] As in Loughran and Ritter (1997), operating income (OIBD) is defined as operating income before depreciation, amortization and tax but after adding back interest income. The argument for adding back interest income is the same as in Lougran and Ritter (1997). Companies that raise funds may “park” the proceeds into interest generating securities which are included in total assets.

the appropriate industry meeting the asset size requirement, the constraint on assets is tightened and the industry requirement is dropped. All the non-issuers with asset size within 90% to 110% of the issuers are ranked according to the OIBD/assets ratio and the firm with the closest ratio is chosen as the matching firm.

The matching algorithm is applied to all the issuers with a non-missing OIBD/assets ratio in the fiscal year before the issue announcement i.e., year -1. The sample size drops to 415 observations as many of the firms are not available on Compustat in that year. Panel A of Table 17 displays the median operating performance of issuers and non-issuers in year –1.

The results suggest that issuers are poor performers. All the median values of operating performance are highly negative. In contrast, median ratios obtained for non-issuers are much less negative. The comparison of the two groups suggests that issuing firms are relatively big spenders as measured by the capital expenditures and R&D ratio. Finally, as is reflected in the significantly higher market to book ratio, the market perceives issuers as relatively high growth firms in their industry. Hoping that investments will payoff in the future, the market seems to tolerate the issuers' poor accounting operating performance.

Panel A also reports Z-statistics for the Wilcoxon matched-pairs signed rank tests of the hypothesis that the distributions of the issuer and non-issuer ratios are identical[19]. The Z-statistics obtained for the six accounting ratios suggest that the algorithm fails to match issuers and non-issuers. The null hypothesis is rejected at a high level of statistical significance. Although the procedure aims at matching on the basis of performance as measured by the OIBD/assets ratio, the performance of issuing firms is so bad that the median OIBD/assets

[19] The Z-statistics are estimated as follows. In any given year relative to the issue year, and for any of the 6 accounting ratios defined above, the difference in the performance between issuers and non-issuers is calculated for all the pairs of issuing and non-issuing firms. The absolute values of the differences are ranked and the rank of the positive estimates are summed. Let D denote the sum. The Z-statistic is calculated as: $Z=D-E(D)/S$, where the mean $E(D)$ and the variance V are equal to $n(n+1)/4$ and $n(n+1)(2n+1)/24$, respectively and where S denotes the standard deviation. Under the null hypothesis that the issuer and the non-issuer accounting measures are drawn from the same distribution, Z follows a unit normal distribution.

ratio for the comparable firms, -10.6%, is 19.6% above the ratio obtained for issuing firms, -29.0%, with a statistically significant difference. In addition, the algorithm fails to match issuers and non-issuers along the five remaining measures of operating performance.

Two arguments may be advanced to explain the failure of the algorithm to match issuers and non-issuers. The first pertains to the operating characteristics of issuing firms. It could be that they are the worst performers in their respective industry and asset class, explaining why they cannot be matched to any other firm. The second pertains to the algorithm. The Loughran and Ritter (1997) procedure could fail for two reasons. First, partial matches based on only three characteristics, industry, asset size and profitability as measured by the OIBD/assets ratio may not yield the best relevant group for comparison. A match performed on additional variables may be necessary. Second, the requirements imposed on asset size may not be judicious. The problem is that little guidance exists to choose the "optimal" constraints to be imposed on the matching variables.

The inability of the algorithm to match issuers and non-issuers is worrisome. It is well-known that the estimate of a causal effect (issuing a floating-priced convertible) obtained by comparing a treatment group (issuers) with a non-experimental comparison group (non-issuers) may be biased because of problems such as self-selection or a systematic judgement made by the researcher[20]. The extent of the potential sample selection bias depends on the overlap between the distribution of the characteristics, i.e., the accounting ratios, of the treatment and control groups. The smaller the overlap in all the characteristics, as seems to be the case here, the less comparable the groups and the larger the bias. This calls for the use of a different matching algorithm to test the robustness of the results reported in Panel A.

7.1.2 A propensity score matching algorithm

[20] The average difference in outcomes between treatment (issuers) and control (non-issuers) groups is an unbiased estimate of the treatment effect only when units are randomly assigned to the treatment, as is the case in

Propensity score matching algorithms are becoming increasingly popular to construct suitable control groups in non-experimental studies. They are quite successful at generating accurate estimates of the treatment effect in non-experimental settings when the treated group differs substantially from the pool of potential controls[21]. They offer three major benefits. First, no constraints need to be imposed on the matching variables. Second, they accommodate a high number of matching variables. This property is quite desirable when the dimensionality of the observable characteristics is high. The task of constructing a matched sample becomes impossible when there are several characteristics in which the treatment and control groups differ, a problem referred to as the "curse of dimensionality". Third, they produce accurate estimates of the treatment impact even when there exists very few units that are comparable to the treatment units. This alleviates the bias due to systematic differences between the treated and comparison units[22].

Different versions of the propensity score matching algorithm have been suggested in the literature. The most simple version, referred to as the "nearest-match" method, works as follows. Given a set of observable characteristics, i.e., the accounting ratios, the conditional probability of receiving treatment, i.e., issuing a floating-priced convertible, is estimated with a parsimonious logistic function using a sample that contains the treated and control units. The treated units are ranked according to the estimated conditional probability, referred to as the propensity score. Each treated unit is then matched to the single control unit with the closest propensity score. The role of the score is to reduce the dimensionality of the matching

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experimental studies. See Lalonde (1986). The problem is that firms do not issue floating-priced convertibles at random.

[21] See Dehejia and Wahba (1998).

[22] For an interesting and pioneering application of the propensity score algorithm in finance, see Villalonga (2001). The paper re-examines whether the discount of diversified firms can be attributed to diversification. Two important results emerge. First, estimates of the effect of diversification on firm value obtained from single equation models suffer from a sample selection bias. Second, the diversification discount disappears when a comparable benchmark based on the propensity score is used.

problem. Matching on the propensity score allows one to maximize the comparability between the treated and control groups.

The nearest-match version of the propensity score algorithm is used to generate the sample of matching firms. This is done as follows. Let:

- j: be the fiscal year prior to the issue announcement date defined as year –1. Given that the first (last) issue took place in 1995 (1998), j takes the four values, 1994, 1995, 1996 and 1997.
- i be an issuing or non-issuing firm, with $i=1,\ldots N_j$, where N_j is the cross-sectional sample size in year j, with $N_j=I_j+NI_j$ where I_j and NI_j is the number of issuers and non-issuers in year j, respectively. Summing over the j's, the total number of issuers and non-issuers is equal to I and NI, respectively[23].
- $X_{i,j,l}$ be the characteristic l observed for firm i in year j, with $l=1,\ldots 7$. The characteristics are 1) assets, 2) OIBD/assets, 3) profit margin, 4) ROA, 5) OIBD/sales, 6) CE+RD/sales, 7) market/book ratio.
- $Y_{i,j,k}$ be an industry dummy taking a value of 1 if firm i in year j belongs to industry k, as defined by the two-digit sic code, and 0 otherwise.
- $D_{i,j}$ be a dummy variable equal to 1 for issuers and 0 for non-issuers.

The following steps are followed to generate the sample of matching firms in the fiscal year j, say 1994, before the announcement:

- **Step 1**: Estimate the propensity to issue, Pi,j, using the logit function,

$$P_{i,j}=Pr(D_{i,j}=1 \mid X_{i,j,l}, Y_{i,j,k}), \text{ for } i=1,\ldots Nj.$$

- **Step 2**: Rank the Ij estimated propensity scores obtained for the issuers in ascending order.

[23] None of the accounting variables must be missing on Compustat in year j for an issuer to be included in the analysis. In contrast, only those issuers with a non-missing OIBD/asset ratio are included in the previous analysis. The Loughran and Ritter (1997) algorithm imposes fewer data requirements than the propensity score algorithm. This explains the slightly higher sample size in the former than in the latter case, 415 versus 402 observations, respectively.

- **Step 3**: Match each issuing firm to the single non-issuing firm with the closest propensity score and obtain a sample of NI_j nearest-match control firms[24]. Note that by construction the sample size NI_j is equal to I_j.

Given that the issue announcement dates occur in four different years, the logit function must be re-estimated in each fiscal year *j*, 1994, 1995, 1996, 1997.

- **Step 4**: Repeat steps 1 through 3 for each fiscal year *j*.
- **Step 5**: Pool the estimated propensity scores across the fiscal years *j* and obtain a total sample of *I* issuing firms and *NI* non-issuing firms with *I* equal to *NI* by construction.
- **Step 6**: Rank the *I* estimated propensity scores obtained for issuers in ascending orders and create propensity score sorted groups.

The last step is useful to perform both unconditional and conditional tests. The former tests are performed on the whole cross-section of issuers. The latter are performed on propensity score sorted groups. Ten or two groups are formed depending on the desired level of cross-sectional dispersion [25].

The matching procedure suggested above has a possible limitation. Even though industry effects are controlled for by including industry dummies in the logit regression, issuers and non-issuers are unlikely to be matched by industry. Barber and Lyon (1996) consider several variations of performance-matched methods. They focus on two alternatives. The first looks for the matching firm with the closest performance in the same two-digit SIC code. They find that tests statistics based on this alternative are mis-specified. The second alternative considers all matching firms regardless of their two-digit SIC code. Unlike the previous case, the test statistics are well specified. Although the second alternative dominates the first from a statistical point of view, Barber and Lyon (1996) chose the

[24] To be able to maintain the equality between the number of issuers and non-issuers in every single year after year *j*, the second, third,…, nearest match is also saved to substitute for a (first) nearest-match non-issuing firm

industry-based performance matching method arguing that “there are good reasons why performance might vary by industry.”

The propensity score algorithm can be adjusted in a very simple way to match firms on industry. This is achieved by constraining the algorithm in step 3 of the matching procedure to select the nearest-match within the subset of non-issuers that are in the same two-digit SIC code as issuers. Following Barber and Lyon (1996), we generate two samples of matching firms by running the algorithm with and without this industry constraint. The two sets of results are compared below.

7.1.3 Matching issuers and non-issuers with the propensity score algorithm: empirical evidence

7.1.3.1 Unconditional tests

The results obtained with the propensity score algorithm with and without the industry constraint are presented in Panels B and C of Table 17, respectively. Two conclusions emerge. First, compared to the Loughran and Ritter (1997) algorithm and regardless of whether the industry constraint is imposed or not, the procedure is significantly more successful at matching issuers and non-issuers. Second, the performance of the matching procedure is enhanced when the industry constraint is not imposed. This result is expected as the algorithm selects a matching non-issuing firm from a larger pool of controls. The propensity scores can be used as a goodness-of-fit measure. The median propensity scores are equal to .29 for issuers and to .26 for non-issuers in Panel B. Although the difference seems small, the null hypothesis of the equality of the distributions is rejected. They are equal to .29 for issuers and non-issuers in Panel C and the null hypothesis is not rejected[26].

that drops out from Compustat or is delisted after time –1.

[25] Issuers whose scores are below (above) the cross-sectional median are assigned to the first (second) group.

[26] Similar conclusions hold with the mean propensity scores.

Panel B shows that the median accounting ratios of issuers are still lower than those obtained for non-issuers. This confirms the results obtained with the Loughran and Ritter algorithm that issuers are the worst performers in their respective industry. For example, the median OIBD/assets ratio is equal to –24.94% and –20.41% for issuers and non-issuers, respectively[27]. The Z-statistics are lower than those obtained with the Loughran and Ritter (1997) algorithm but the null hypothesis that the distributions of the issuer and non-issuer ratios are identical is still rejected.

The evidence reported in Panel C shows that the matching procedure works much better when the industry constraint is not imposed. The median accounting ratios obtained for issuers and non-issuers are quite close. More importantly, the null hypothesis that the distributions of issuer and non-issuer ratios are identical is not rejected. This holds true for every single accounting ratio. These results show that it is possible to find non-issuing firms that are as bad as issuing firms in other industries.

We face the same dilemma as Barber and Lyon (1996) about the choice of the matching sample. From a statistical point of view, a better match is obtained when the industry constraint is not imposed. From an economic point of view, matching by industry seems intuitively preferable. We follow Barber and Lyon (1996) and report only the results obtained with the "industry-matched" sample[28].

7.1.3.2 Conditional tests

The conditional tests are performed on the propensity score based deciles obtained from the "industry-matched" sample. The results are reported in Panels A and B of Table 18 for issuers and non-issuers, respectively. A significant cross-sectional dispersion in the

[27] The difference in the matching performance of the Loughran and Ritter algorithm and the propensity score algorithm stems from the facts that the latter 1) matches issuers and non-issuers on a higher number of characteristics and 2) does not impose a requirement on asset size. An analysis of the control sample generated by the propensity score algorithm shows that only 54.73% of the non-issuers have assets between 25% and 200% of the issuers' assets. The 25%-200% range imposed by Loughran and Ritter (1997) is too tight.

median operating income is observed across groups. Not all the issuers are bad firms. For example, issuers in the first decile display a small but positive operating performance, as measured by the median OIBD/assets or OIBD/sales ratios. An interesting pattern emerges. The lower the operating performance, the higher the propensity score, i.e., the higher the probability that firms will issue a floating-priced convertible. The propensity scores decrease monotonically with measures of operating performance. For example, the two extreme deciles, 1 and 10, have propensity scores equal to .03 and .95, and median OIBD/assets ratios equal to +1.86% and –121.45%, respectively. The same results are obtained for other ratios, such as the ROA ratio (see figure 9). Finally, the Z-statistics reported in Panel C of Table 18 suggest that the matching algorithm works better conditionally than unconditionally. The null hypothesis testing the equality of the distributions of issuer and non-issuer ratios is rejected only in a few cases, mostly for the groups in the lowest and the highest deciles.

The conditional tests are also performed on two groups formed according to whether propensity scores are below or above their cross-sectional median. The results are reported in Panels D and E of Table 18 for the issuers and the non-issuers, respectively. The previous findings are confirmed and issuers can be split into "good" firms (low scores) and "bad" firms (high scores)[29]. The Z-statistics are presented in Panel F. The null hypothesis of the equality of the distributions of issuer and non-issuer ratios is rejected only for the "bad" issuers. Regardless of the number of groups based on propensity scores, 2 or 10, the matching algorithm works well conditionally.

From an economic point of view, the results suggest that the propensity score, or its rank, is a good proxy for operating performance in the year prior to the issue. The monotonic relationship between the rank of the propensity scores and the operating performance suggests

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[28] All the tests are performed on both samples. Results are available on request.
[29] Unconditionally and relative to the population of firms, all the issuers are bad firms. It is only conditionally that issuers can be split into "good" and "bad" issuers.

that the likelihood of issuing a floating-priced convertible is strongly negatively correlated with operating performance. This is consistent with the hypothesis that these convertibles are last-resort financing instruments.

7.2 The operating performance in the pre- and post-announcement period

The median of the accounting ratios is estimated from four years before until two years after the announcement. The results obtained for issuers and non-issuers are reported in Panels A and B of Table 19, respectively and in figure 10.

The results in Panel A confirm the previous findings obtained in the fiscal year -1 that convertible issuers are poor performers. All the median values of the performance measures are highly negative. Moreover, they tend to get worse as the issuance year gets closer. The worst measures of performance are obtained in the fiscal years -1 or 0 depending on the performance measure. For example, the ROA and OIBD/assets ratios reach their lowest values, -48.52% and -28.30% in the fiscal year 0, respectively. While the median profit margin and sales margin recover after two years, the two performance measures that should be highly correlated with stock returns, i.e., the OIBD/assets and the ROA ratios do not recover significantly. Also, a significant decrease in capital expenditures and market to book ratio is observed. As discussed above, in the pre-issue period, the market hopes that investments will payoff. The optimism vanishes in the two years following the issue. These results should be interpreted with caution as companies that go bankrupt are removed from the Compustat database. This implies that the results obtained for the 235 surviving companies in the fiscal year +2 are biased upward and the recovery overstated.

Panel B shows the results for the matching non-issuing firms. Non-issuers experience a negative median operating performance in the fiscal years before the issue. Non-issuers do better than issuers but the change in the performance is negative and higher for the former than for the latter. Stated differently, the operating performance of issuers is bad in the years preceding the issue. In contrast to this relative steady state, the performance of non-issuers keeps deteriorating over the same time period. In fiscal year -1, when the matching is done, issuers and non-issuers display a similar level of operating performance. In the two years after the issue, non-issuers recover much faster than issuers: both the ROA and the OIBD/assets ratios display a much stronger mean-reverting pattern (see figure 10).

Panel C of Table 19 reports the Z-statistics obtained for the Wilcoxon matched-pairs signed rank tests of the hypothesis that the distributions of issuer and non-issuer ratios are identical. The Z-statistics suggest that the post-operating performance of issuers and non-issuers differ mostly with respect to the measures of profitability. The operating performance of issuers and non-issuers mean revert but the speed of reversion is faster for the latter than the former, explaining the relative difference and its statistical significance.

Panel D of Table 19 reports the Wilcoxon matched-pairs signed rank tests of the equality of distributions between the change in issuers and non-issuers ratios. The changes are calculated for three sub-periods. They are measured over the fiscal years -1 to 0, -1 to +1 and -1 to +2, respectively. For example, the Z-statistic obtained for the change in the ROA of issuers relative to non-issuers is equal to -4.35 between the fiscal years -1 and +2. Panel D shows that regardless of the sub-period and relative to non-issuers, the OIBD/assets and ROA ratios of issuers decline significantly. The changes are not statistically significant for the other accounting ratios, such as the market-to-book ratio. These results are important as the comparison of the surviving issuers to the surviving non-issuers generates tests that are free of survivorship bias.

There is also evidence that the decline is not equal across issuers. This can be observed by splitting the sample into "good" and "bad" issuers. As discussed in the previous section, issuers with a low propensity score display a higher operating performance relative to those issuers with a high propensity score. The results reported in Panel E show that the "good" issuers in the fiscal year –1 are the ones that subsequently under-perform most. Specifically, regardless of the length of the measurement period, and regardless of whether we use OIBD/Assets or ROA as a performance measure, good issuers always significantly under-perform their control group. In contrast, as Panel F indicates, the evidence that "bad" issuers exhibit under-performance is less significant. For example, based on the OIBD/Assets ratio, bad issuers only experience significant negative abnormal performance from year –1 until year +1, but not during the other two measurement periods (-1 to 0 and –1 to +2). Stated differently, bad issuers remain bad and good issuers become bad.

These results of table 19 are consistent with the signaling hypothesis. Floating-priced convertibles signal that the performance gap between issuers and their peers will widen in the future. This signal is most pronounced for the relatively "good" firms.

7.3 The abnormal stock price performance revisited

The control sample can be employed to re-examine the abnormal stock price performance of issuers. Let *i* be an issuing firm and *l* the nearest-match non-issuing firm. Let $R_{i,t}$ and $R_{l,t}$ be their respective returns in month *t*. A new measure of abnormal return, $AR_{i,t}$, can be estimated as the difference of the surviving issuers and surviving non-issuers stock returns,

$AR_{i,t}=R_{i,t}-R_{l,t}$, for all *i* and *t*.

This new measure is attractive for two reasons. First, abnormal returns are estimated as the difference of the surviving issuers and surviving non-issuers. They should be free of the survivorship bias that plagues other estimates, such as those based on the EW or VW indices. Second, research done on long-term event studies suggests that controlling for a small number of characteristics, such as size and book-to-market, is not sufficient to yield well specified test statistics especially in non-random samples[30] Additional variables should be considered when

[30] See Brav (2000); Brav, Greczy and Gompers (2000) ; Kothari and Warner (1997)

matching sample firms to control firms[31]. This is difficult to implement because of the "curse of dimensionality" referred to in the section 7.1.2. A major benefit of the propensity score algorithm is its ability to accommodate a high number of matching variables. The bias in the test statistics should be lower as abnormal returns are controlled for (asset) size, book-to-market, industry and operating profitability. The major attractiveness of this new measure of abnormal return is the lower bias both in the point estimates and the test statistics.

The control sample cumulative abnormal returns (CARC) are estimated unconditionally and conditionally by summing the abnormal returns $AR_{i,t}$ over distinct sub-periods. First, as in section 5, they are summed from month -12 to -1 before the announcement and from month 0 to +12 after the announcement. For comparison purposes, the cumulative raw returns (CRR), as well as the cumulative abnormal returns relative to the equally-weighted (CAREW) and value-weighted (CARVW) indices are re-calculated to take into account the new and lower sample size. The unconditional results are reported in Panel A of Table 20.

In the 12-month pre-announcement period, the CARC estimate, equal to –2.05%, is very close to zero (t = -.25). It is much lower in magnitude than the CRR, CAREW and CARVW estimates, equal to 9.76%, -10.09% and -15.73%, respectively. As discussed in the previous section, the propensity score algorithm is successful at matching issuers and non-issuers on operating performance in the fiscal year –1. As is apparent here, it works quite well at matching firms with respect to the abnormal stock price performance in the twelve-month period before the issue. Both sets of results are consistent.

In contrast, in the 12-month post-announcement period, issuers under-perform their peers after controlling for (asset) size, market-to-book, industry and profitability. The CARC estimate is negative unconditionally and highly statistically significant. Its value, equal to -

[31] See Lyon, Barber and Tsai (1999).

33.60%, is less negative than the CAREW and CARVW estimates equal to -37.32% and -50.86%, respectively.

The conditional results are presented in Panels B-D of Table 20. Issuers are first split into "good" and "bad" firms depending on whether the propensity score is below or above its cross-sectional median in the fiscal year –1. The results are reported in Panels B and C, respectively. Student t-statistics testing the null hypothesis of the equality of the CAR estimates across groups appear in Panel D. As measured by the CARC, "good" and "bad" issuers display the same level of abnormal performance in the 12-month period before and after the announcement. Consistently with the unconditional results, the estimate is statistically significantly different from zero only in the latter period. These findings, combined with the evidence of section 7.2 are consistent with the "faulty contract hypothesis": although after the issue "good" firms experience worse (relative to their peers) operating performance than "bad" firms, their post-issue stock price performance is virtually identical. So, the 12-month post-announcement abnormal return cannot be uniquely explained on the basis of bad operating performance.

One could argue that examining returns over a 12-month post-issue period is too short. Following the approach of section 6 we estimate the "very" long-term performance by measuring the delisting status of "good" and "bad" firms at various points in time. As is explained in section 6.2, the delisting frequency is proxied by a dummy variable that takes a value of 0 if the stock is delisted as of December 1999 and 1 otherwise. Conditional on delisting, it is also estimated by three dummies that capture the conditional delisting frequency over three different time horizons: short-term (less than 12 months), medium-term (between 12 and 24 months), and long-term (24 months and above), respectively. The results are shown in table 21.

The table provides evidence in support of a statistical relationship between operating performance in the fiscal year -1 and delisting in the first 12 months after the issue announcement date. The conditional delisting frequency is equal to 13.04% for the "good" issuers and 20.00% for the "bad" issuers and the difference is statistically significant. As the number of months after the issue announcement date increases, the differential in the conditional delisting frequency of the bad and the good issuers decreases and becomes statistically insignificant. After 24 months, the conditional delisting frequency is equal to 17.48% and 17.21% for the good and the bad issuers, respectively. Bad firms seem to be delisted more quickly and more frequently than good firms, so there is no evidence that good firms have a worse post-issue stock-market experience than bad firms. So, one explanation (consistent with the faulty contract hypothesis) for the joint result that, compared to good firms, bad firms experience (i) better post-issue operating performance and (ii) equal or worse long-term stock market performance is that bad firms have to issue floating-priced convertibles with contract features that are much worse for long-term investors.

7.4 Contract design and propensity scores

If, compared to good firms, bad firms have to issue convertibles that have the potential to be more dilutive and harmful to long-term stockholders, we should observe a significant relation between contract design and our measure of firm quality, i.e. the propensity scores. The contract characteristics are summarized by the 5 dummy variables defined in section 4.11 and by the 3 continuous variables that capture the discount, the look-back ratio and the relative issue size.

The relationship between the contract characteristics and the operating performance is examined in Table 22. Panel A reports the average contract characteristics for the propensity score based deciles. An interesting pattern emerges. The higher the propensity score, i.e., the lower the operating performance in year -1, the higher the discount, look-back ratio and the relative issue size. The average discount is equal to 11% for the first decile and is more than 50% higher in the last decile. Panel B presents the results obtained by splitting the issuers into “good” and “bad” firms. Confirming the evidence obtained with the deciles, a statistically significant difference is found for the discount, the look-back ratio and the issue size. The bad issuers make the biggest issues and offer the highest look-back ratio and the highest discount. So, together with the results of section 7.2 and 7.3, the evidence in Table 22 is consistent with the faulty contract design hypothesis: companies in trouble at the time of the issue are forced to accept convertible deals that don’t encourage investors to delay conversion (i.e. deals with large discounts, high look-back ratios and issues that represent a significant part of the capital structure). Although these bad firms don’t experience significantly worse operating performance than their peers (other bad firms) during the two years after the issue, the existence of the floating-priced convertible produces significant under-performance in the stock market.

7.5 Signaling or faulty contract design: a final test

Section 6 concludes that the contract characteristics have an impact on the probability of delisting and that the best predictor of delisting in the long-run is the discount. Specifically, high-discount issuers are more likely to be delisted after 1 year. While this results is consistent with the faulty contract design hypothesis, it could also be explained by the signaling hypothesis if discounts and the issuer’s post-issue operating performance are negatively correlated.

Table 23 and 24 measure the median operating performance of respectively high conversion discount and low conversion discount issues, 4 years before the issue, until 2 years after. The outline of the tables is similar to the outline of Table 19 (panels A to D). Focusing on the results for OIBTD/Assets and ROA (the two measures one would expect to be closely related to stock returns), there is no evidence that the operating performance of high discount issuers is significantly worse than the operating performance of low discount issuers. First, regardless of the discount, issuers significantly underperform their benchmark firms in year 0, year +1 and +2. Second, when focusing on the results of panel D, low conversion discount issuers and high conversion discount issuers underperform significantly in 5 of the 6 tests. Table 25 reports the z-statistics of a test of the equality of distributions of the *abnormal* performance (relative to their non-issuer benchmarks) of high discount and low discount issuers for three sub-periods : year -1 to +0, year –1 to + 1 and year –1 to +2. Again, we cannot reject the hypothesis that the distributions are equal, at least when we use ROA and OIBD/assets as performance measures.

So, we conclude that the findings of section 6, i.e. the fact that high discount issuers are more likely to be delisted than low discount issuers, cannot be explained by differential operating performance. Hence, the results of section 6, together with the results in Table 23, 24 and 25, are consistent with the hypothesis that at least one feature of the contract design, i.e. the discount, has a significant impact on long-term stock price performance.

8. Conclusion

A floating-priced convertible is a potentially useful financial innovation that, in theory, should be an ideal financing instrument for small risky firms, where agency costs of debt and asymmetric information are large. However, the empirical evidence in this paper shows that, on average, investors who buy common stock of the issuer lose 34 % of their wealth during the year following the issue. This is not due to outliers: 85 % of the issuing firm experience negative returns in the year after the issue. More than 40 % of the issuers are delisted from the exchange two years after the issue announcement, mainly because of failure to meet one or more listing requirements such as a minimum share price. The price decline is most severe for companies that repeat the experience: after follow-up issues, stock prices decline by 50 %

during the year following the announcement. This result is remarkable, considering that our sample period coincides with one of the strongest bull markets in U.S. history.

The basic economic question is whether this price decline is a result of the floating-priced convertible contract (the faulty design hypothesis) or whether it simply reflects the fact that issuers tend to be "bad" firms that would have collapsed anyway (the signaling hypothesis). There are a number of ex ante reasons that make the faulty contract hypothesis very plausible: First, the design of the contract encourages convertible investors to increase their returns by shorting and converting; second, professional short-sellers (possibly aided by investor panic) can bring down the value of the company by increasing the dilution that results from conversion at low stock prices. Note that, because of the dilution created by conversion at prices below "fair" value, investor panic and short-selling activities are having a permanent negative effect on the underlying value per share of the company.

Several findings are consistent with the "bad signal" hypothesis: (1) issue announcements are preceded by negative abnormal stock returns and poor accounting-based measures of operating performance (2) the likelihood of issuing a floating-priced convertible (as measured by propensity scores) is negatively related to various measures of operating performance in the year prior to the issue (3) shareholders approve the issuance of death spirals, in spite of their tarnished reputation (4) on average, accounting-based measures of operating performance tend to decline during the years after the issue, relative to comparable firms. This may explain why floating-priced convertibles (unlike harmful mutations in nature) have not become extinct. According to *PlacementTracker.com*[32], between August 1998 (the end of our sample period) and January 2001, 387 floating-priced convertibles were announced. Hundred and eighty-one were announced in 2000, many by Internet stocks.

[32] PlacementTracker.com is a subsidiary of DirectPlacement.com

Among the issuers, some relatively well-known names such as Etoys, Log On America and Shop at Home, companies which by the end of 2000 had lost more than 90 percent of their market value since the date of issuance.

However, other results in the paper suggest that "signaling" is not the full story. First when we split up the sample in "bad" and "good" firms (based on their operating performance in the year before the issue) we find that (1) relative to their peer group, bad firms perform better than good firms, when performance is measured by accounting-based measures of operating performance but (2) bad firms and good firms perform equally bad in the stock market after the issue. At the same time the contract design of floating-priced convertibles issued by bad firms has the potential to create much larger dilution: contracts have larger discounts and represent a more important part of the firm's capital structure. All of these observations are consistent with the predictions of the faulty contract design hypothesis. A second finding consistent with this hypothesis is that the discount is the best predictor of the long-term performance of the issuer. In particular, the probability of being delisted after the issue increases significantly when the issue has a high discount. This result holds, in spite of the fact that the post-issue operating performance of high discount and low discount issuers is similar.

We found that issuers and investment bankers have tried to respond by changing the design of the contract by eliminating some of the worst features. Specifically, we observe a decline in the discount and an increase in the look-back ratio and the use of warrants over time. Some of these changes have worked: reducing the discount improves significantly the long-term survival of the issuers. Hence our findings suggest that investors should worry about contract design in particular, the size of the discount. On the other hand, restrictive measures such as floors on the conversion price or short-sale restrictions are not really improving long-term performance, quite the contrary, which may explain why such contract restrictions are relatively rare.

This paper is another event study that reports anomalous abnormal returns after the public announcement of corporate news. Although one could argue that these results can always be explained by inappropriate measurement of risk (see e.g. Fama (1998)), the challenge for efficient market theorists here is more difficult. We cannot imagine any model of market equilibrium that predicts that small, risky firms should expect rates of return of –34 % per year in a bull market. Note that our long-run returns are measured in a sample period that starts in January 1995 and ends in December 1999. During that period the S&P 500 increased by 250 %. On the other hand, the abnormal returns cannot be explained by the "window of opportunity" hypothesis proposed by Ritter (1991), Loughran and Ritter (1995) and Ikenberry, Lakonishok and Vermaelen (1995) to explain the long-term abnormal returns observed after, respectively, IPO's, seasoned equity offerings and share buybacks. According to this hypothesis companies issue equity to take advantage of an overvalued stock price, and repurchase stock to take advantage of an undervalued stock price. Floating-priced convertibles do not seem to be driven by opportunism, but rather by despair, or possibly ignorance.

Some further research is needed to address some of the more puzzling findings of this paper. For example, some companies (the death spiral champions) issue many consecutive floating-priced convertibles. As many of these firms are small, managers own a significant stake in the equity. Why do managers deliberately wipe out the value of their own equity stake? For example, from 1996 Dynagen issued 13 consecutive death spirals, and lowered its share price from $ 30 to 25 cents in the process. One explanation could be that the convertible allows managers to buy time, keep control (and consume private benefits from control) and avoid bankruptcy. In the case of Dynagen, we have an additional explanation. Because executives have the power to reissue stock options at a lower exercise price, managers in some ways also have a reset provision. In effect, in February 2000, the two executive officers of Dynagen granted themselves 8.5 million stock options at an exercise price of 25 cents. Further research on corporate governance in death spiral issuers is warranted to test whether this type of behavior is typical.

Table 1

Death Spiral Champions

Companies that issued more than 3 floating-priced convertibles in the sample period, followed by their status code on December 31 1999.

Company Name	Number of issues	Listing Status
SWISSRAY INTERNATIONAL	12	552
CYCOMM INTERNATIONAL	8	582
CSL LIGHTING MANUFACTURING	7	582
DYNAGEN	7	552
SYQUEST TECHNOLOGY	7	585
AMERICAN RESOURCES OF DELAWARE	6	552
EA INDUSTRIES	6	561
VIRAGEN	6	552
CEL SCI	5	Listed
FREDERICK BREWING	5	552
GLOBAL INTELLICOM	5	561
SGI INTERNATIONAL	5	560
AMERICAN INTERNATIONAL PETROLEUM	4	Listed
APPAREL TECHNOLOGIES	4	584
INFINITE MACHINES	4	Listed
INNOPET BRANDS	4	582
MEDIX RESOURCES	4	584
NETWORK IMAGING	4	Listed
UNIVIEW TECHNOLOGIES	4	Listed
USCI	4	561

Delisting codes and motivations:

552	Price fell below acceptable levels
560	Insufficient capital
561	Insufficient float
582	Failure to meet equity requirements
584	Delisted by current exchange - does not meet exchange's financial guidelines for continued listing
585	Protection of public interest

Table 2
Industry Distribution

Industry classification of issuers, based on 4 digit SIC codes.
Only industries with more than 2 companies are shown.

Industry	Number of issuers	Percent of all issuers
Computer and data processing	41	15.1
Drugs	36	13.3
Computer and office equipment	16	5.9
Communication Equipment	14	5.2
Electronic Components	12	4.4
Medical Instruments and supplies	11	4.1
Pharmaceutical preparations	5	1.8
Telephone communication	5	1.8
Cable and TV services	4	1.5
Eating and drinking places	4	1.5
Commercial Physical research	3	1.1
Communications services	3	1.1
Crude Petroleum and Natural Gas	3	1.1
Health and allied services	3	1.1
Miscellaneous electrical equipment	3	1.1
Non-store retailers	3	1.1
Professional and commercial equipment	3	1.1
Research and testing services	3	1.1
Total	172	59%

Table 3
Size Distribution of the Issuers

Distribution of market values of the issuer at the time of the issue (in millions of dollars) and the relative importance of the convertible.

	Market Cap.	Issue size /Market cap
Mean	67.5	13.1%
Median	39.2	9.3%
Maximum	739.2	217.9%
Minimum	1.0	0.4%
Standard deviation	82.2	17.5%

Table 4
Death Spiral Investors

Name of the investor and number of issues in which the investor participated during the sample period. Only investors who participated in more than 10 issues are included.

Name	Number of issues
AG Super Fund L.P.	40
Raphael L.P.	38
Leonardo L.P.	33
Halifax Fund L.P.	21
GAM Arbitrage Investments	30
Olympus Securities Ltd.	28
Nelson Partners	28
Ramius Fund Ltd.	26
Capital Ventures Int'l	24
Sovereign Partners L.P.	22
RGC International Investors LDC	21
Heracles Fund L.P.	14
Themis Partners L.P.	13
Dominion Capital Fund Ltd	13
CC Investments LDC	13
Wharton Capital Partners Ltd	12
JNC Opportunity Fund	12
Southbrook International Investors Ltd	12
KA Investments LDC	12
Lakeshore International Ltd	11

Table 5

Summary Statistics of Convertible Contracts

Characteristic	Mean	Median	Standard Deviation	Maximum	Minimum
Lockup period (days)	86	78	85	730	0
Fees (% of gross amount issued)	8	7.4	4.1	24.2	0.2
Dividend Yield (%)	6.7	6	2	15	1
Conversion discounts factors (%)					
Initial	84.5	83	10.2	105	50
Final	79.1	80	8.1	96	52
Look-back period (days)	10	5	10	60	1
N° of look-back prices	6	5	5	40	1
Look-back ratio	82%	100%	35%	100%	3.3%

Table 6

Regression of Contract Characteristics on a Time Trend

ESTIMATOR	**OLS**			**WLS**			**SUR**		
STATISTIC	INTERCEPT (t-stat)	SLOPE (t-stat)	R^2	INTERCEPT (t-stat)	SLOPE (t-stat)	R^2	INTERCEPT (t-stat)	SLOPE (t-stat)	R^2
WARRANT	.081 (1.32)	.011 (4.55)	.325	0.53 (.84)	.015 (6.24)	.481	.019 (.42)	.016 (7.94)	.614
CAP	.589 (7.97)	.003 (1.09)	.005	.689 (9.40)	-.0008 (-.291)	-.023	.621 (8.32)	.0011 (.35)	-.023
FLOOR	.133 (1.88)	.002 (.62)	-.0153	.145 (2.94)	-.0004 (-.22)	-.024	.164 (2.74)	-.0004 (-.18)	-.025
SHORT-SALE	.151 (3.72)	-.002 (-1.24	.013	.124 (2.73)	-.0002 (-.134)	-.025	.144 (3.43)	-.0004 (-.84)	-.008
LOCK-UP	.246 (3.03)	.007 (2.05)	.073	.321 (3.98)	.002 (.61)	-.016	.299 (3.92)	.0030 (.93)	-.004
DISCOUNT	.199 (8.80)	-.0014 (-1.47)	.0285	.210 (11.99)	-.0022 (-3.33)	.202	.208 (9.67)	-.0020 (-2.21)	.091
LOOKBACK	1.15 (28.78)	-.013 (-7.94)	.614	1.23 (25.43)	-.016 (-8.82)	.663	1.15 (28.78)	-.013 (-7.94)	.614
SIZE	.138 (7.59)	-.0003 (-.43)	-.021	.132 (5.50)	-.00002 (-.022)	-.0256	.139 (7.49)	-.00041 (-.53)	-.019

Regression of contract characteristics on a time trend. The time trend is a variable initialized to 1 in January 1995 and incremented by 1 for each of the 48 months in the sample. For the 5 dummy variables (warrant, cap, floor, short-sale, lock-up), the dependent variable is the frequency of observing a contract with characteristic i, with i = 1, …, 5 in month j with j = 1, … 48. For the continuous variables (discount, lookback and size), the dependent variable is the cross-sectional mean of the variable i, with i = 1, …, 3, in month j with j = 1, …, 48. The three estimators are OLS, WLS, using as weight the number of issues in month j relative to the total number of issues and SUR (seemingly unrelated regression).

Table 7
Unconditional Correlation Matrix Between the Various Contract Characteristics

Warrant, cap, floor, short sale and lock-up are dummy variables that take a value of 1 when the contract includes the characteristic and zero otherwise. Discount and look-back are continuous variables.
(p values appear in parentheses)

	Warrant	Cap	Floor	Short-sale	Lock-up	Discount	Look-back
Warrant	1						
Cap	0.12 (0.01)	1					
Floor	-0.07 (0.15)	0.1 (0.03)	1				
Short sale	0.04 (0.39)	-0.09 (0.04)	0.08 (0.09)	1			
Lock-up	0.013 (0.77)	0.02 (0.062)	-0.02 (0.73)	-.10 (0.04)			
Discount	-.26 (0.001)	-0.15 (0.001)	0.03 (0.47)	0.01 (0.92)	0.08 (0.09)	1	
Look-back	-0.31 (0.001)	-0.08 (0.10)	0.02 (0.62)	0.02 (0.64)	-0.06 (0.17)	0.48 (0.001)	1

Table 8

Cumulative average raw returns (CRR) and cumulative average abnormal returns relative to the equally weighted market index (CAREW) and the value weighted market index (CARVW), for selected sub-periods (months relative to the issuance date). T –statistics are in parentheses.

PANEL 8A : All events included (467 observations on event date 0)

Subperiod	CRR	CAREW	CARVW
[-12 to -1]	14.7 % (3.22)	-5.1% (-1.12)	-10.75% (-2.44)
[0 to +12]	-30.1% (-3.51)	-40.4% (-4.71)	-54% (-6.38)

PANEL 8B : Follow-up issues excluded (261 observations on event day 0)

Subperiod	CRR	CAREW	CARVW
[-12 to -1]	12.44% (1.63)	-7.7 % (-0.99)	-13.10 (-1.73)
[0 to +12]	-14.7% (-1.31)	-26% (-2.37)	-39% (-3.56)

PANEL 8C : First issues excluded (206 observations on event day 0)

Subperiod	CRR	CAREW	CARVW
[-12 to -1]	17.58% (2.37)	-1.74 % (-.25)	-7.83% (-1.15)
[0 to +12]	-51.39% (-5.20)	-60.01% (-6.04)	-74.49% (-7.57)

Table 9

Buy and hold returns RAW returns (BHRR), abnormal returns relative to the equally-weighted index (BHAEW) and abnormal returns relative to the value-weighted index (BHAVW) for selected sub-periods.
T-statistics appear in parentheses. The first is the conventional t-statistic.
The second is the skewness-adjusted t-statistic suggested by Hall (1992).

PANEL 9A : All events included

Subperiod	BHRR	BHAEW	BHAVW	Sample size
[-12 to -1]	10.23 %	-10.15%	-16.90%	482
	(1.36)	(-1.36)	(-2.26)	
	(1.63)	(-1.11)	(-1.68)	
[0 to + 12]	-34.17%	-43.78%	-58.07%	488
	(-9.30)	(-12.13)	(-16.00)	
	(-4.60)	(-4.95)	(-4.96)	

PANEL 9B : Follow-up issues excluded

Subperiod	BHRR	BHAEW	BHAVW	Sample size
[-12 to -1]	-.16 %	-20.35%	-26.75%	271
	(-.02)	(-2.95)	(-3.86)	
	(-.07)	(-1.52)	(-1.65)	
[0 to +12]	22.05%	-32.78%	-46.72%	276
	(-3.78)	(-5.68)	(-8.05)	
	(-2.71)	(-3.50)	(-4.01)	

PANEL 9C : First issues excluded

Subperiod	BHRR	BHAEW	BHAVW	Sample size
[-12 to -1]	23.57 %	2.95%	-4.25%	211
	(1.61)	(.20)	(-.29)	
	(2.05)	(.28)	(-.21)	
[0 to + 12]	-49.95%	-58.10%	-72.84%	212
	(-14.52)	(-17.50)	(-22.00)	
	(-3.63)	(-4.38)	(-6.56)	

Table 10

Buy and hold percentage positive RAW returns (BHRR), abnormal returns relative to the equally-weighted index (BHAEW) and abnormal returns relative to the value-weighted index (BHAVW) for selected sub-period.

PANEL 10A : All events included

Subperiod	BHRR	BHAEW	BHAVW	Sample size
[-12 to -1]	34.03%	21.78%	20.12%	482
[0 to +12]	15.37%	12.71%	9.36%	488

PANEL 10B : Follow-up issues excluded

Subperiod	BHRR	BHAEW	BHAVW	Sample size
[-12 to -1]	36.16%	21.77%	19.33%	271
[0 to +12]	21.38%	18.12%	13.77%	276

PANEL 10C : First issues excluded

Subperiod	BHRR	BHAEW	BHAVW	Sample size
[-12 to -1]	31.28%	21.80%	20.38%	211
[0 to +12]	7.55%	5.66%	4.24%	212

Table 11
Long-Term Performance Before and After Convertible Issue Announcements: Fama-French Calendar-Time Portfolios

Firms are sorted in three samples: the first sample (All issues included) contains all 488 announcements in our sample period. The second sample (Follow-up issues excluded) of 276 observations ignores all follow-up issues of convertibles by the same firm the third sample on 212 observations (First issues excluded) excludes all the first issues. For each sample, we form portfolios in calendar time. The pre-announcement portfolio contains all stocks that within the next 12 months will announce a convertible issue; the post-announcement portfolio contains all stocks that have announced a convertible issue during the previous 12 months. Excess performance is measured using the three-factor model :

$$R_{p,t} – R_{f,t} = a_p + b_p (R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + e_{pt}.$$

Where $R_{p,t} – R_{f,t}$ is the excess portfolio return in calendar month t, a_p measures the average monthly abnormal return, $R_{m,t} – R_{f,t}$ is the monthly excess return on the equally weighted market index, and SMB_t and HML_t are the size and book-to-market factors, respectively. The regression parameters are estimated with OLS and WLS. Heteroskedastic consistent T-statistics are shown in parentheses.

Panel 11A: OLS ESTIMATOR

	All issues included		Follow-up issues excluded		First issues excluded	
	Pre-announcement [-12, -1]	Post-announcement [0, 12]	Pre-announcement [-12, -1]	Post-announcement [0, 12]	Pre-announcement [-12, -1]	Post-announcement [0, 12]
a_p	-0.018 (-1.53)	-0.019 (-1.41)	-0.007 (-0.71)	-.007 (-0.46)	-.006 (-.34)	-.043 (-2.90)
b_p	1.69 (5.22)	0.80 (2.76)	1.23 (4.20)	0.81 (2.83)	1.42 (2.77)	0.70 (2.05)
s_p	1.76 (5.32)	1.11 (3.61)	1.61(5.29)	1.24 (3.80)	2.02 (4.12)	1.04 (3.09)
h_p	0.15 (0.27)	-1.28 (-2.32)	-0.42 (-0.90)	-1.57 (-2.85)	-.014 (-.02)	-1.07 (-1.66)
R^2	0.46	0.47	0.62	0.51	0.32	0.41

Panel 11B: WLS ESTIMATOR

	All issues included		Follow-up issues excluded		First issues excluded	
	Pre-announcement [-12, -1]	Post-announcement [0, 12]	Pre-announcement [-12, -1]	Post-announcement [0, 12]	Pre-announcement [-12, -1]	Post-announcement [0, 12]
a_p	-.011 (-.94)	-.023 (-1.95)	-.009 (-0.80)	-.012 (-.93)	-.011 (-.68)	-.039 (-2.39)
b_p	1.47 (5.08)	.67 (2.20)	1.21 (4.32)	.72 (2.88)	1.67 (3.25)	0.63 (1.46)
s_p	1.75 (4.89)	1.20 (4.37)	1.61(4.91)	1.44 (4.91)	1.90 (4.08)	1.28 (2.91)
h_p	0.29 (0.52)	-1.51 (-2.48)	-.60 (-1.17)	-1.68 (-3.20)	-.09 (-.11)	-1.28 (-1.45)
R^2	0.58	0.57	0.63	0.60	0.47	0.41

Table 12
Long-term Performance Before and After Convertible Issue Announcements: Fama-French Event-Time Portfolios

Firms are sorted in three samples: the first sample (All issues included) contains all 488 announcements in our sample period. The second sample (Follow-up issues excluded) of 276 observations ignores all follow-up issues of convertibles by the same firm the third sample on 212 observations (First issues excluded) excludes all the first issues. For each sample, all firms are aligned in event time, where month 0 represents the announcement month. The abnormal performance is measured using monthly data and using Ibbotson's (1975) Returns Across Time and Securities (RATS) methodology and applying the Fama-French (1993) three-factor model :

$$R_{i,t} – R_{f,t} = a_t + b_t (R_{m,t} - R_{f,t}) + s_t SMB_t + h_t HML_t + e_{pt}.$$

Where $R_{p,t} – R_{f,t}$ is the excess portfolio return in event month t, a_t measures the average monthly abnormal return, $R_{m,t} – R_{f,t}$ is the monthly excess return on the equally weighted market index and SMB_t and HML_t are the size and book-to-market factors, respectively. The t-statistics are calculated using the time-series standard deviation of the average monthly abnormal returns.

Panel 12A : Cumulative abnormal returns T-statistics appear in parenthesis

	Pre-announcement Period CAR (-12, -1)	Post-announcement Period CAR (0, +12)
All issues included	-13.91 (-2.26)	-29.03 (- 3.33)
Follow-up issues excluded	-12.55 (-1.65)	-15.63 (-1.41)
First issues excluded	-14.93 (1.61)	-50.52 (-4.43)

Panel 12B : Cumulative abnormal returns Pre-announcement period

Event	All issues included CAR (-12,1-)	Follow-up issues excluded CAR (-12, -1)	First issues excluded CAR (-12, -1)
-12	-0.75	-0.51	-1.20
-11	-2.25	-1.29	-3.80
-10	-4.74	-2.85	-7.64
-9	-5.64	-5.80	-5.90
-8	-8.49	-9.70	-7.45
-7	-13.60	-12.37	-14.73
-6	-12.53	-11.66	-12.70
-5	-12.85	-10.31	-15.00
-4	-14.04	-14.25	-12.87
-3	-13.87	-13.43	-13.67
-2	-12.47	-10.45	-14.57
-1	-13.91	-12.55	-14.93

Panel 12C : Cumulative abnormal returns Post Announcement period

Event	All issues included CAR (0,12)	Follow-up issues excluded CAR (0, 12)	First issues excluded CAR(0,12)
0	0.61	-1.71	3.29
1	-5.12	-4.21	-6.67
2	-9.91	-8.62	-11.57
3	-13.81	-12.90	-14.94
4	-18.72	-17.45	-20.45
5	-17.62	-14.32	-23.28
6	-21.39	-18.80	-26.28
7	-21.22	-15.75	-31.02
8	-22.13	-17.31	-31.18
9	-23.03	-16.32	-34.26
10	-27.56	-19.46	-40.45
11	-28.85	-19.01	-44.34
12	-29.03	-15.63	-50.52

Table 13
Abnormal Performance and Contract Design

For each contract characteristic, the sample is divided in two groups. Monthly returns for all firms in each sample are aligned in event-time, where month 0 represents the announcement month. Abnormal performance is measured using monthly data and using Ibbotson's (1975) Returns Across Time and Securities, or RATS, methodology and applying Fama-French (1993) three factor model :

$$R_{i,t} - R_{f,t} = a_t + b_t(R_{m,t} - R_{f,t}) + s_t SMB_t + h_t HML_t + e_{i,t}$$

Where $R_{i,t} - R_{f,t}$ is the excess return of security i in event-month t. For that same month, a_t measures the average monthly abnormal return, $R_{m,t} - R_{f,t}$ is the monthly excess return on the equally weighted market index, and SMB_t and HML_t are the size and book-to-market factors, respectively. T-statistics are shown in parentheses. Using this approach, a_t is our estimate of the average abnormal return which is estimated each event-month and cumulated over time (CAR) in two subperiods, relative to the event date: (-12,-1) and (0,+12) . * indicates significantly different from zero at the 10 % level; ** significantly different from zero at the 5 % level.

Contract characteristic	CAR(-12,-1)	CAR(0,+12)
A. Warrants		
Warrants attached	-28.2 (-2.65)	- 16 (-1.53)
No warrants attached	-3.8 (-0.44)	-36.7 (-3.22)
Difference	-25.2 (-1.78)*	20.7 (1.65)*
B. Conversion Cap		
Conversion cap	-9 (-0.88)	-22.1 (-2.68)
No conversion cap	-21.6 (-2.12)	-43.5 (-2.14)
Difference	12.5 (1.33)	21.4 (1.69)*
C. Conversion Floor		
With conversion floor	14.3 (0.67)	-58.4 (-4.94)
No conversion floor	-17.5 (-2.11)	-24.1 (-2.63)
Difference	31.8 (1.35)	-34.4 (-2.4)**
D. Short sales constraints		
Short sales allowed	-9.8 (-1.45)	-25.6 (-2.45)
Short sales not allowed	-55.1 (-2.71)	-51.3 (-2.84)
Difference	45.4 (-2.05)**	25.7 (-1.11)
E. Lock up period		
Deals with lock-up period	-14.7 (-1.92)	-16.8 (-1.11)
Deals without lock-up period	-14.1 (-1.95)	-32.8 (-2.66)
Difference	-0.7 (-0.07)	16 (0.74)
F. Initial Discount		
Initial discount below median	-16.5 (-2.13	-11.8 (0.63)
Initial discount above median	-11.7 (-1.25)	-36 (- 5.79)
Difference	-4.8 (-0.41)	24.2 (1.30
G. Lookback ratio		
Lookback ratio below median	-12.9 (-1.00)	-11.3 (-0.59)
Lookback ratio above median	-15.9 (-2.64)	-23.7 (-1.93)
Difference	3.0 (0.29)	12.4 (0.56)

Table 14

Logit Model of Delisting Status on Contract Characteristics

SAMPLE / CONTRAST CHARACTERISTIC	UNCONDITIONAL			CONDITIONAL			
				RELATIVE ISSUE SIZE		ISSUE DATE	
	ALL EVENTS INCLUDED	FOLLOW-UP EXCLUDED	FIRST ISSUES EXCLUDED	BELOW MEDIAN	ABOVE MEDIAN	BEFORE DEC 31, 1996	BEFORE DEC 31, 1996
SAMPLE SIZE							
DELISTED	231	113	118	107	122	77	161
LISTED	238	152	86	126	110	78	161
INTERCEPT	.53	.66	.45	.47	.53	.71	.34
(p-value)	(<.01)	(.01)	(.14)	(.84)	(.07)	(.012)	(.11)
WARRANT	-.026	.12	.19	.04	-.02	-.23	.12
(p-value)	(.84)	(.49)	(.37)	(.84)	(.92)	(.35)	(.44)
CAP	.24	.15	.27	.23	.39	-.27	.39
(p-value)	(0.06)	(.42)	(.19)	(.22)	(.04)	(.26)	(.013)
FLOOR	.22	.46	-.10	.30	.11	.59	.15
(p-value)	(.21)	(.06)	(.72)	(.23)	(.68)	(.06)	(.49)
SHORT-SALE	-.22	-.36	-.10	.22	-.52	-.33	-.17
(p-value)	(.24)	(.12)	(.75)	(.48)	(.04)	(.35)	(.44)
LOCK-UP	-.14	-.15	-.11	-.11	-.21	-.1	-.21
(p-value)	(0.28)	(0.37)	(0.58)	(0.58)	(0.25)	(0.64)	(0.17)
DISCOUNT	-.69	-.57	-.86	-.93	-.50	-.79	-.68
(p-value)	(<.01)	(<.01)	(<.01)	(<.01)	(<0.01)	(<.01)	(<.01)
LOOKBACK	-.34	-.40	-.27	-.07	-.60	-	-.38
(p-value)	(.05)	(.08)	(.33)	(.77)	(.015)		(.05)
χ^2	59.99	31.24	30.26	39.40	33.47	15.25	55.30
(p-value)	(<.01)	(<.01)	(<.01)	<0.01)	<.01)	(.01)	(<.01)

The regression gives the probability of being listed given a set of 7 explanatory variables. The dependent variable is a dummy variable that takes a value of 0 if the firm is delisted before Dec 31, 1999 (CRSP delisting code higher than or equal to 400) and 1 otherwise. The explanatory variables are composed of 5 dummy variables and 2 continuous variables. The dummies are set equal to 1 if the issue has i) warrants, ii) a conversion cap, iii) a conversion floor, iv) a short-sale constraint, v) a lock-up period and zero otherwise. The continuous variables are the discount and the look-back ratio. Unconditional regressions are performed on two samples. The first includes all the events , the second excludes all the follow-up issues and the third only considers the follow-up issues. Conditional regressions are performed on the sample that includes all the events. The maximum likelihood estimates of the regression parameters are computed using an iteratively reweighed least-squares algorithm. For each parameter, a Wald chi-squared statistic is computed as the square of the parameter estimate divided by its standard error estimate. The p-value of the Wald chi-square statistic appears below the parameter estimate. The null hypothesis that none of the explanatory variables has any effect on the probability of listing is tested using a likelihood ratio test that has a chi-square under the null. The p-value appears in parenthesis.

Tahle 15

Time to delisting and contract characteristics

SAMPLE	ALL ISSUES				FOLLOW-UP EXCLUDED				FIRST ISSUES EXCLUDED			
VARIABLE	SAMPLE SIZE	DISCOUNT %	SIZE %	LOOKBACK %	SAMPLE SIZE	DISCOUNT %	SIZE %	LOOKBACK %	SAMPLE %	DISOUNT %	SIZE %	LOOKBACK %
DELISTED IN YEAR 1	84	17.41	16.78	84.48	37	16.60	16.44	86.54	49	18.05	17.04	83.52
LISTED IN YEAR 1	392	14.95	12.07	82.47	291	12.63	12.63	80.79	161	15.24	11.23	84.93
DELISTED IN YEAR 2	95	17.44	13.91	90.23	47	18.21	13.14	88.11	48	16.68	14.66	92.26
LISTED IN YEAR 2	297	14.15	11.49	79.91	184	19.86	12.51	78.92	113	14.62	9.75	81.61
DELISTED AFTER YEAR 2	56	20.29	12.49	100.0	30	19.28	13.46	100.0	26	21.46	8.92	100.0
LISTED AFTER YEAR 2	241	12.72	11.26	75.96	154	12.80	11.94	75.19	87	12.58	9.99	77.33
DELISTED UNCONDITIONAL	235	18.11	14.64	90.82	115	17.97	14.85	90.16	121	18.24	14.44	90.09
LISTED UNCONDITIONAL	241	12.72	11.26	75.97	157	12.81	11.94	75.19	87	12.58	9.99	77.33

This table shows the cross-sectional mean of three continuous contract characteristics (the conversion discount, the relative size of the convertible and the look-back ratio) as a function of the time to delisting. The statistics are calculated for the whole sample, the sample that excludes follow-up issues and the sample that only includes follow-up issues.

Table 16

Logit Model of Delisting Time on Contract Characteristics

SAMPLE	ALL EVENTS			FOLLOW UP EXCLUDED			FIRST ISSUE EXCLUDED		
TIME TO DELISTING	**≤ 1 YEAR**	**> 1 ≤ 2 YEARS**	**>2 YEARS**	**≤ 1 YEAR**	**>1 ≤ 2 YEARS**	**> 2YEARS**	**≤ 1 YEAR**	**> 1 ≤ 2 YEARS**	**> 2 YEARS**
SAMPLE SIZE									
DELISTED	83	92	55	37	45	30	46	47	25
LISTED	375	283	238	224	179	154	151	104	84
INTERCEPT	.86	1.40	1.30	1.20	1.26	1.13	.44	1.68	1.98
(p-value)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(.21)	(<.01)	(<.01)
WARRANT	.004	-.17	.50	-.07	.02	.51	.18	-.33	.85
(p-value)	(.98)	(1.16)	(.01)	(.74)	(.92)	(.05)	(.47)	(.19)	(.04)
CAP	.30	.017	.11	.19	-.016	.22	.30	.044	-.33
(p-value)	(.04)	(.91)	(.58)	(.38)	(.94)	(.40)	(.17)	(.86)	(.37)
FLOOR	.62	.024	.12	.36	.29	.51	1.05	-.23	-.56
(p-value)	(.02)	(.90)	(.64)	(.27)	(.33)	(.17)	(.03)	(.45)	(.22)
SHORT-SALE	.18	-.04	-.43	-.15	-.023	-.41	.88	-.13	-1.06
(p-value)	(.43)	(.86)	(.11)	(.28)	(.94)	(.21)	(.10)	(.73)	(.08)
LOCK-UP	-.11	-.24	.04	-.008	-.27	.014	-.20	-.14	.19
(p-value)	(.45)	(.12)	(.84)	(.97)	(.19)	(.96)	(.35)	(.55)	(.60)
DISCOUNT	-.27	-.55	-1.03	-.04	-.65	-.75	-.41	-.56	-1.93
(p-value)	(.11)	(<.01)	(<.01)	(.85)	(<.01)	(.01)	(.13)	(.04)	(<.01)
LOOKBACK	.08	-.26	NA	-.16	-.0006	NA	.41	-.46	NA
(p-value)	(.64)	(.25)		(.56)	(.98)		(.21)	(.23)	
SIZE	-.06	-.56	-.70	-.72	-.12	-.83	-.91	-2.37	.05
(p-value)	(.03)	(.23)	(.19)	(.18)	(.84)	(.13)	(.16)	(.02)	(.98)
χ^2	21.79	21.61	48.23	4.83	12.68	21.59	23.14	16.81	38.30
(p-value)	(<.01)	(.04)	(<.01)	(.77)	(.12)	(<.01)	(<.01)	(.03)	(<.01)

The regression gives the probability of being listed given a set of 7 explanatory variables. The dependent variable is a dummy variable that takes a value of 0 if the firm is delisted before Dec 31, 1999 (CRSP delisting code higher than or equal to 400) and 1 otherwise. The explanatory variables are composed of 5 dummy variables and 2 continuous variables. The dummies are set equal to 1 if the issue has i) warrants, ii) a conversion cap, iii) a conversion floor, iv) a short-sale constraint, v) a lock-up period and zero otherwise. The continuous variables are the discount and the look-back ratio. Unconditional regressions are performed on two samples. The first includes all the events, the second excludes all the follow-up issues and the third excludes the first issues. Conditional regressions are performed on the sample that includes all the events. The maximum likelihood estimates of the regression parameters are computed using an iteratively reweighed least-squares algorithm. For each parameter, a Wald chi-squared statistic is computed as the square of the parameter estimate divided by its standard error estimate. The p-value of the Wald chi-square statistic appears below the parameter estimate. The null hypothesis that none of the explanatory variables has any effect on the probability of listing is tested using a likelihood ratio test that has a chi-square under the null. The p-value appears in parenthesis.

Table 17

Operating Performance Measures and Market-to-Book Ratios for the Issuers and Matching Nonissuers in the Fiscal Year –1.

Each of the three panels reports median ratios for the issuing firms, all of which are present on COMPUSTAT in the year before the issue. Matching non-issuer firms are chosen by three different matching algorithms. In panel A matching non-issuing firms are chosen according to Loughran-Ritter (1987) matching algorithm. In panel B matching non-issuer firms are chosen by the propensity score and industry matched algorithm. In panel C matching non-issuer firms are chosen by the (unconstrained) propensity score algorithm. The COMPUSTAT data items to calculate the ratios are operating income before depreciation/assets (OIBD + interest income (items 13 + 62)/assets (item 6)), profit margin (net income including extraordinary items (item 172)/sales (item 12)), return on assets (net income (item 172)/assets (item 6)), OIBD/sales (OIBD + interest income (items 13 + 62)/sales (item 12)), CE + RD/assets (capital expenditures (item 128) + research and development expense (item 46)/assets (item 6)), market value/book value (shares (item 54) times price (item 199)/book value of equity (item 60)).

Ratio / t-statistic	OIBD/Assets	Profit Margin	ROA	OIBD/Sales	CE + RD/Asets	Market/Book	Propensity Score	Number of Firms
Panel A : The Loughran and Ritter (1997) Matched Sample								
Issuer median	-29.0%	-84.0%	-47.1%	-50.4%	19.1%	4.47	N.A	415
Non-issuer median	-10.6%	-12.7%	-18.2%	-7.1%	11.9%	2.07	N.A.	415
z-statistic	-12.66	-9.47	-11.15	-9.32	5.91	3.93	N.A	415
Panel B : The Propensity Score and Industry Matched Sample								
Issuer median	-24.94%	-77.02%	-44.61%	-48.0%	17.42%	4.50	.29	402
Non-issuer median	-20.41%	-49.43%	-37.83%	-28.86%	18.62%	2.84	.26	402
z-statistic	-5.62	-2.75	-4.30	-3.25	2.57	2.82	7.84	402
Panel C : The Propensity Score Matched Sample								
Issuer median	-24.94%	-77.02%	-44.61%	-48.0%	17.42%	4.50	.29	402
Non-issuer median	-30.75%	-85.96%	-48.69%	-53.0%	19.43%	3.21	.29	402
z-statistic	1.07	.42	1.55	.34	.25	1.22	1.29	402

Table 18

Operating Performance Measures and Market-To-Book Ratios for the Issuers and Matching Non-Issuers in the Fiscal Year –1 : results conditional on propensity scores

Panel A and Panel B report median ratios for the issuing firms and the non-issuing matching firms, respectively. Matching firms are chosen by the propensity score and industry matched algorithm. Results are shown for 10 deciles based on propensity scores. Panel C shows, for each decile, the Z-statistic that test for significant differences in the median ratios of issuers and matching non-issuers. Panel D and E show the median ratios of the issuing firms and the non-issuing firms, respectively. Both issuers and non-issuers are split up in two groups: the "below median" group contains all firms with propensity scores below the median and the "above median" group contains all firms with propensity scores above the median. Panel F tests whether there is a significant difference in median ratios of issuers and matching non-issuers. The COMPUSTAT data items to calculate the ratios are defined as in table 17.

Ratio / Decile	OIBD/Assets	Profit Margin	ROA	OIBD/Sales	CE + RD/Assets	Market/Book	Propensity Score	Number of Firms
Panel A : Conditional Cross-Sectional Median of Issuers (Deciles)								
1	1.9%	-3.0%	-3.4%	1.4%	13.8%	3.49	.03	39
2	-3.6%	-15.4%	-12.1%	-2.7%	19.4%	4.34	.08	42
3	-15.7%	-21.8%	-13.5%	-27.2%	14.2%	6.40	.12	39
4	-21.1%	-104.8%	-39.5%	-59.0%	15.3%	4.31	.18	41
5	-20.1%	-61.4%	-44.0%	-41.8%	12.3%	3.65	.26	41
6	-20.9%	-84.5%	-49.8%	-37.9%	10.7%	4.93	.31	39
7	-32.6%	-97.5%	-52.8%	-62.6%	20.5%	4.47	.40	39
8	-41.1%	-148.2%	-63.2%	-101.6%	16.1%	4.29	.51	43
9	-78.7%	-284.0%	-134.4%	-207.4%	36.2%	6.39	.72	39
10	-121.4%	-263.9%	-148.0%	-262.0%	33.9%	4.49	.95	40
Panel B : Conditional Cross-Sectional Median of Non-Issuers (Deciles)								
1	7.6%	.9%	1.3%	6.0%	14.0%	2.32	.03	39
2	2.9%	-12.8%	-8.1%	1.4%	16.6%	2.74	.08	42
3	-11.5%	-18.9%	-21.3%	-10.1%	25.6%	3.25	.11	39
4	-26.1%	-39.0%	-33.5%	-27.8%	19.2%	2.84	.17	41
5	-19.6%	-51.8%	-36.4%	-20.4%	18.2%	1.83	.25	41
6	-14.9%	-49.4%	-45.8%	-29.4%	18.6%	3.59	.31	39
7	-34.5%	-80.0%	-64.4%	-64.2%	15.7%	2.19	.36	39
8	-37.1%	-111.0%	-67.1%	-21.7%	11.4%	6.42	.49	43
9	-66.4%	-243.0%	-113.3%	-49.0%	22.9%	2.72	.57	39
10	-83.2%	-148.5%	-102.1%	-121.0%	25.0%	1.88	.69	40
Panel C : Conditional Z-statistics (Deciles)								
1	-2.64	-1.67	-2.90	-1.38	.54	.96	-.14	39
2	-1.74	-.62	-1.12	.57	.89	2.03	-1.23	42
3	-.73	-1.38	-.21	-1.49	-.13	1.77	3.66	39
4	.76	-1.12	-.85	-.98	-.07	1.54	-.41	41
5	-.64	-.52	-1.57	-.15	-.80	1.42	1.90	41
6	-.75	-.22	-.80	-.63	-.59	1.23	.75	39
7	.17	-.77	.01	-1.14	-.42	1.95	4.30	39
8	-3.84	-1.39	-.71	-2.63	1.19	-1.46	2.27	43
9	-2.93	-1.98	-1.98	-.98	3.22	1.24	4.38	39
10	-3.60	-3.33	-3.33	-.16	2.04	.20	5.30	40

Table 18 continued

Group \ Ratio	OIBD/Assets	Profit Margin	ROA	OIBD/Sales	CE + RD/Assets	Market/Book	Propensity Score	Number of Firms
Panel D : Conditional Cross-Sectional Median of Issuers. Conditioning variable: propensity score below or above median								
Below median	-14.0%	-26.1%	-21.7%	-17.9%	14.8%	4.20	.12	202
Above median	-46.9%	-134.6%	-65.3%	-97.6%	20.9%	4.66	.51	200
Panel E : Conditional Cross-Sectional Median of Non-Issuers. Conditioning variable: propensity score below or above median								
Below median	-9.0%	-19.5%	-21.3%	-10.2%	18.2%	2.78	.11	202
Above median	-37.0%	-111.0%	-67.8%	-48.9%	19.3%	3.59	.41	200
Panel F : Conditional Z-statistics testing the equality of distributions between the issuers and matching non-issuers. Conditioning variable: propensity score below or above median								
Below median	1.13	1.63	1.59	.93	-.01	-4.43	-.40	202
Above median	2.89	1.90	1.84	2.51	-2.27	-1.84	-4.55	200

Table 19

Operating Performance and Market-to-Book Ratios for the Issuers and Matching Nonissuers Before and After the Issue Date.

Panel A and Panel B report median ratios for the issuing firms and the non-issuing matching firms, respectively, from 4 years before the issue year until 2 years afterwards. The COMPUSTAT data items to calculate the ratios are defined as in table 17. Panel C tests whether in a given year relative to the issue year, the median ratio is significantly different for issuers and non-issuers. Panel D tests whether in a specific period relative to the issue year, the median ratios are significantly different for issuers and non-issuers. Panels E and F are similar to panel C, but now the tests are for two sub-samples: the issuers with propensity scores below the median (panel E) and issuers with propensity scores above the median (panel F).

Ratio / Year relative to offering	OIBD/Assets	Profit Margin	ROA	OIBD/Sales	CE + RD/Assets	Market/Book	Number of Firms
Panel A : Issuer Unconditional Median							
-4	-16.3%	-43.7%	-26.7%	-23.1%	14.9%	3.37	284
-3	-22.3%	-48.8%	-30.6%	-31.3%	13.7%	3.03	338
-2	-22.9%	-56.4%	-34.2%	-30.2%	14.2%	3.83	385
-1	-24.9%	-77.0%	-44.6%	-48.0%	17.4%	4.50	402
0	-28.3%	-71.8%	-48.5%	-45.6%	18.2%	3.00	373
1	-22.4%	-55.9%	-38.5%	-35.4%	15.9%	2.57	327
2	-23.8%	-49.0%	-44.7%	-26.2%	14.3%	1.84	235
Panel B : Non-Issuer Unconditional Median							
-4	-9.5%	-18.4%	-14.3%	-7.2%	12.0%	3.31	284
-3	-9.1%	-19.3%	-16.2%	-5.9%	12.8%	2.12	338
-2	-13.1%	-29.7%	-23.3%	-13.8%	13.9%	2.51	385
-1	-20.4%	-49.4%	-37.8%	-28.9%	18.6%	2.84	402
0	-13.1%	-32.3%	-24.4%	-19.9%	17.4%	2.62	373
1	-12.6%	-27.2%	-18.6%	-19.9%	19.7%	2.38	327
2	-8.1%	-30.6%	-18.7%	-8.9%	14.7%	2.09	235
Panel C : Unconditional Z-statistics testing the yearly equality of distributions between the issuers and matching non-issuers using the Wilcoxon matched-pairs signed-ranks test							
-4	-3.78	-3.52	-2.49	-3.69	.87	1.05	284
-3	-7.23	-3.39	-5.90	-4.45	2.69	2.39	338
-2	-6.13	-3.06	-6.12	-3.60	-3.12	3.81	385
-1	-5.62	-2.75	-4.30	-3.25	2.57	2.72	402
0	-4.97	-4.23	-7.04	-2.26	1.71	-.86	373
1	-4.49	-4.04	-6.88	-3.49	-.38	-.41	327
2	-4.07	-3.15	-5.91	-1.63	.25	-1.02	235
Panel D : Unconditional Z-statistics testing the equality of distributions between the change in the ratios in periods from year-1 to various years after the issue							
Year –1 to 0	-3.33	-3.02	-4.82	-.86	-.22	-1.90	373
Year –1 to+1	-3.21	-2.19	-5.05	-1.86	-.88	-.52	327
Year –1 to +2	-2.12	-1.74	-4.35	-.26	-1.44	-1.50	235
Panel E : Conditional Z-statistics testing the equality of distributions between the change in the ratios in periods from year –1 to various years after the issue. Conditioning variable : propensity score below median							
Year –1 to 0	-3.76	-3.78	-6.07	-1.32	1.13	-4.28	198
Year –1 to +1	-1.96	-1.06	-3.47	-.77	-.81	-.36	175
Year –1 to +2	-2.34	-1.53	-3.98	-.49	.18	-1.03	117
Panel F : Conditional Z-statistics testing the equality of distributions between the change of the ratios in periods from year –1 to various years after the issue. Conditioning variable : propensity score above median							
Year –1 to 0	-.93	-.72	-1.16	.23	-1.21	1.04	175
Year –1 to +1	-2.63	-2.08	-3.67	-1.82	-.36	-.33	152
Year –1 to +2	-.63	-1.02	-2.32	.01	-2.29	-.86	118

Table 20

Cumulative Average Raw Returns (CRR) and Cumulative Average Abnormal Returns Relative to the Equally-Weighted Market Index (CAREW), the Value-Weighted Market Index (CARVW) and the Propensity Score and Industry Matched Control Firms (CARC).

Panel A results are based on the total sample; panel B is based on the sample with relatively low propensity scores and panel C is based on the sample with relatively high propensity scores. The t-statistics in parentheses tests whether cumulative average (abnormal) returns are significantly different from zero. The t-statistics of panel D tests whether the corresponding cumulative average (abnormal) returns in panel B and C are significantly different from each other.

Period	CRR	CAREW	CARVW	CARC	Sample Size
Panel A : Unconditional cumulative abnormal returns					
[-12 to –1] [0 to +12]	9.76% (1.86) -26.80% (-2.76)	-10.09% (-1.85) -37.32% (-3.86)	-15.73% (-2.96) -50.86% (-5.35)	-2.05% (-.25) -33.60% (-2.82)	402 402
Panel B : Conditional cumulative abnormal returns. Conditioning variable : propensity score below median					
[-12 to –1] [0 to +12]	10.21% (1.62) -29.40% (-3.18)	-10.32% (-1.64) -39.34% (-4.64)	-15.47% (-2.74) -52.77% (-6.25)	-12.93% (-1.73) -31.81% (-2.12)	202 202
Panel C : Conditional cumulative abnormal returns. Conditioning variable : propensity score above median					
[-12 to –1] [0 to +12]	9.33% (1.22) -23.68% (-1.64)	-9.79% (-1.22) -34.83% (-2.37)	-15.96% (-2.00) -48.49% (-3.39)	9.81% (.78) -34.63% (-2.18)	200 200
Panel D : t-statistics testing the equality of the conditional cumulative abnormal returns					
[-12 to –1] [0 to +12]	(.10) (-.41)	(-.06) (-.33)	(.06) (-.32)	(.14) (.14)	

Table 21

Delisting Status of Low and High Propensity Score Issuers

The table shows, for two sub-samples constructed on the basis of propensity scores, the delisting status at various points in time relative to the issue month. "Delisting frequency" measures the fraction of issuing firms delisted by December 31 1999. Other delisting frequencies measure the fraction of issuing firms delisted after various periods relative to the issue month.

	Issuers					Non-issuers
Propensity score	Number of months to delisting	Delisting frequency	Delisting within 12 months frequency	Delisting after 12 months but before 24 months frequency	Delisting after 24 months	Delisting frequency
Below median	19.53	43.00%	13.04%	20.56%	17.48%	19.21%
Above Median	17.80	49.50%	20.00%	23.75%	17.21%	37.81%
t-statistics	-1.84	-1.58	-2.45	-.95	.08	-5.42

Table 22

Contract Characteristics and Propensity Scores

This table tests whether there is a relation between contract characteristics and propensity scores. Panel A splits up the sample in 10 deciles based on propensity scores and calculates the median characteristic for each sub-sample. Panel B splits up the sample in two sub-samples based on propensity scores. The contract characteristics are measured by 5 dummy variables and 3 continuous variables. The dummies are set equal to 1 if the issue has I) warrants, ii) a conversion cap, iii) a conversion floor, iv) a short-sale constraint, v) a lock-up period and zero otherwise. The continuous variables are the discount, the lock-up period and the relative issue size.

Propensity Score Decile	Warrant	CAP	Floor	Short-Sale	Lock-up	Discount	Look-Back	Issue Size
Panel A : Propensity Score Based Deciles								
1	.37	.79	.16	.29	.24	.11	.70	.09
2	.33	.76	.17	.05	.36	.15	.82	.12
3	.32	.38	.12	.00	.15	.15	.84	.11
4	.58	.70	.14	.16	.37	.13	.76	.09
5	.46	.66	.10	.05	.44	.15	.80	.14
6	.44	.68	.12	.15	.41	.15	.74	.12
7	.44	.56	.09	.12	.47	.17	.86	.16
8	.50	.76	.11	.08	.39	.15	.73	.14
9	.34	.84	.16	.11	.32	.17	.88	.18
10	.58	.70	.05	.14	.42	.17	1.00	.13
Unconditionial l	.44	.69	.12	.11	.36	.15	.82	.13
Panel B : Propensity Scores Above or Below Median								
Below median	.42	.67	.14	.11	.32	.14	.79	.11
Above median	.47	.71	.10	.12	.40	.16	.85	.14
t-statistic	1.26	1.34	-1.57	.28	2.3	3.38	2.92	1.99

Table 23

Median Operating Performance Measures and Market-to-Book Ratios for the Issuers and Matching Non-issuers: High Conversion Discount Issuers

Panel A and Panel B report median ratios for the issuing firms and the non-issuing matching firms, respectively, from 4 years before the issue year until 2 years afterwards. The COMPUSTAT data items to calculate the ratios are defined as in table 17. Panel C tests whether in a given year relative to the issue year, the median ratio is significantly different for issuers and non-issuers. Panel D tests whether in a specific period relative to the issue year, the median ratios are significantly different for issuers and non-issuers.

Year Relative to offering \ Ratio	OIBD/ Assets	Profit Margin	ROA	OIBD/ Sales	CE + RD/Assets	Market Book	Number of Firms
Panel A: Issuer Unconditional Medians							
-4	-14.6%	-26.5%	-24.3%	-17.2%	9.8%	4.68	133
-3	-20.8%	-37.4%	-30.6%	-24.9%	9.7%	2.89	160
-2	-21.4%	-56.4%	-34.6%	-27.1%	11.3%	3.31	186
-1	-23.0%	-73.7%	-46.5%	-28.8%	14.2%	4.56	19
0	-24.9%	-84.2%	-49.6%	-46.4%	16.0%	2.96	181
1	-22.0%	-71.8%	-42.6%	-33.6%	11.7%	1.2	160
2	-24.8%	-54.8%	-46.5%	-26.2%	10.6%	.88	121
Panel B: Non-Issuer Unconditional Medians							
-4	-8.7%	-16.5%	-9.6%	-3.6%	11.9%	3.14	133
-3	-3.9%	-16.6%	-16.1%	-4.5%	11.5%	2.11	160
-2	-12.6%	-26.3%	-19.4%	-12.1%	12.4%	2.29	186
-1	-20.4%	-44.2%	-44.2%	-21.7%	18.2%	2.79	197
0	-13.6%	-32.3%	-24.4%	-23.9%	15.9%	2.48	181
1	-10.2%	-24.8%	-16.7%	-19.8%	17.7%	2.21	160
2	.10%	-18.8%	-8.1%	.07%	12.8%	2.01	121
Panel C: Unconditional Z Statistics testing the yearly equality of distributions between the issuers and matching non-issuers using the Wilcoxon matched-pairs signed-ranks test							
-4	-4.02	-3.76	-2.99	-3.87	-.50	.87	133
-3	-5.47	-2.79	-4.05	-3.91	.51	1.30	160
-2	-5.42	-2.43	-5.17	-2.93	1.38	3.21	186
-1	-3.82	-1.32	-3.00	-1.69	.07	2.25	197
0	-3.44	-3.07	-5.08	-1.12	.39	.34	181
1	-3.84	-3.51	-5.29	-2.77	-1.07	-2.32	160
2	-3.60	-3.15	-5.26	-1.26	-.70	-2.11	111
Panel D: Unconditional Z-statistics testing the equality of distributions between the change in performance ratios from year –1 to various years after the issue.							
Year –1 to 0	-1.78	-2.69	-2.89	-.72	.51	-.45	181
Year –1 to +1	-2.50	-2.12	-3.27	-1.70	-.32	-2.29	160
Year –1 to +2	-1.99	-1.09	-3.60	.29	-.92	-2.42	121

Table 24

Median Operating Performance Measures and Market-to-Book Ratios for the Issuers and Matching Non-issuers: Low Conversion Discount Issuers

Panel A and Panel B report median ratios for the issuing firms and the non-issuing matching firms, respectively, from 4 years before the issue year until 2 years afterwards. The COMPUSTAT data items to calculate the ratios are defined as in table 17. Panel C tests whether in a given year relative to the issue year, the median ratio is significantly different for issuers and non-issuers. Panel D tests whether in a specific period relative to the issue year, the median ratios are significantly different for issuers and non-issuers.

Ratio / Year Relative to offering	OIBD/ Assets	Profit Margin	ROA	OIBD/ Sales	CE + RD/Assets	Market Book	Number of Firms
Panel A: Issuer Unconditional Medians							
-4	-18.5%	-45.9%	-26.6%	-25.2%	18.8%	3.10	147
-3	-22.4%	-52.0%	-28.9%	-35.4%	18.3%	3.77	179
-2	-24.2%	-50.6%	-34.2%	-35.4%	19.6%	4.17	193
-1	-27.1%	-84.5%	-41.6%	-51.6%	23.8%	4.50	198
0	-28.1%	-56.3%	-46.1%	-40.7%	21.3%	3.05	186
1	-21.8%	-41.9%	-37.3%	-33.4%	20.2%	3.82	163
2	-21.6%	-43.7%	-42.2%	-26.2%	18.3%	2.81	111
Panel B: Non-Issuer Unconditional Medians							
-4	-8.6%	-17.9%	-16.7%	-7.9%	12.0%	3.42	147
-3	-10.6%	-29.2%	-16.7%	-9.7%	12.8%	2.20	174
-2	-14.9%	-31.8%	-25.8%	-16.3%	14.8%	2.80	193
-1	-20.4%	-54.3%	-35.9%	-29.3%	19.0%	3.11	198
0	-12.6%	-32.4%	-24.2%	-14.5%	19.9%	3.03	186
1	-13.0%	-32.7%	-19.3%	-17.5%	21.8%	2.38	163
2	-20.3%	-52.7%	-26.8%	-25.7%	14.9%	2.20	111
Panel C: Unconditional Z-statistics testing the yearly equality of distributions between the issuers and the matching non-issuers using the Wilcoxon matched-pairs signed-ranks test							
-4	-1.40	- .93	- .63	-1.03	1.73	.42	147
-3	-4.83	-2.04	-4.27	-2.47	3.12	2.15	174
-2	-3.36	-1.87	-3.35	-2.24	2.99	1.94	193
-1	-3.83	-2.28	-2.54	-2.78	3.49	1.60	198
0	-3.23	-2.47	-4.46	-1.70	1.63	-1.43	186
1	-2.40	-1.88	-3.62	-1.86	.44	1.55	163
2	-2.15	-1.16	-2.80	-.82	1.24	.88	111
Panel D: Unconditional Z-statistics testing the equality of distributions between the change in the performance ratios from year –1 to various years after the issue.							
Year –1 to 0	-2.58	-1.45	-3.68	-.36	-1	-2.17	186
Year –1 to +1	-2.00	-.82	-3.78	-.72	-1.12	1.40	163
Year –1 to 2	-1.06	-1.35	-2.42	-.71	-1.58	.75	111

Table 25

Comparison of Abnormal Performance of High Discount and Low Discount Issuers

This table shows z-statistics that test whether, from year –1 to various years afterwards, the abnormal performance of high discount issuers is different from the abnormal performance of low discount issuers. Various performance measures are calculated employing COMPUSTAT data: operating income before depreciation/assets (OIBD + interest income (items 13 + 62)/assets (item 6)), profit margin (net income including extraordinary items (item 172)/sales (item 12)), return on assets (net income (item 172)/assets (item 6)), OIBD/sales (OIBD + interest income (items 13 + 62)/sales (item 12)), CE + RD/assets (capital expenditures (item 128) + research and development expense (item 46)/assets (item 6)), market value/book value (shares (item 54) times price (item 199)/book value of equity (item 60)). "Normal" performance is measured by the performance of the benchmark firms.

Period	OIBD/Assets	Profit Margin	ROA	OIBD/Sales	CE + RD/Assets	Market/Book	Number of Firms
(-1, 0)	0.91	-2.07	-0.50	-0.26	1.47	1.02	181
(-1,1)	-0.76	-1.45	0.13	-0.79	0.30	-2.96	160
(-1,2)	-1.22	-0.45	-1.23	0.32	0.95	-2.82	121

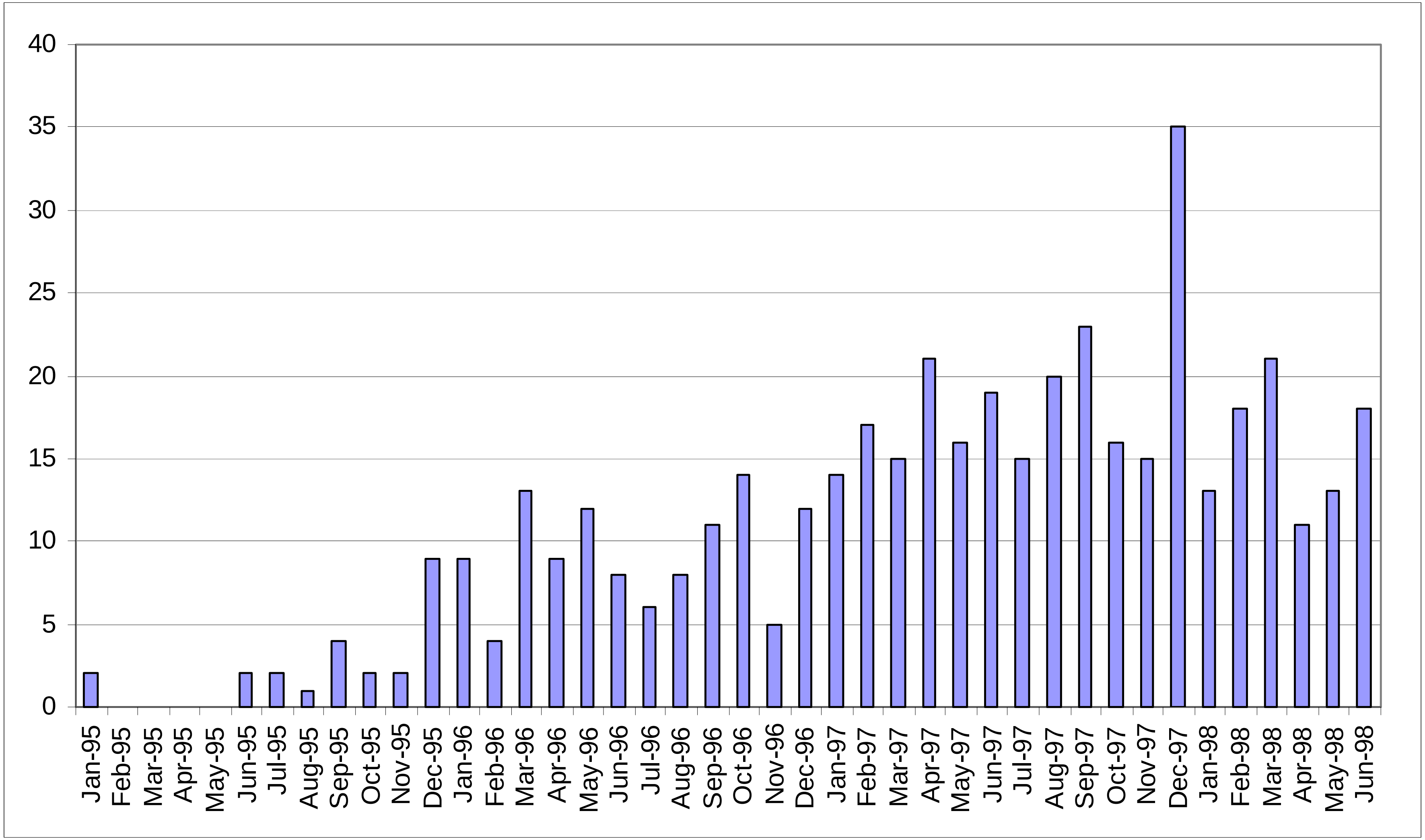

Figure 1 - **Distribution of announcement dates**.

The figure shows the number of floating-priced convertibles announced in a particular calendar month. The sample is based on 467 issues.

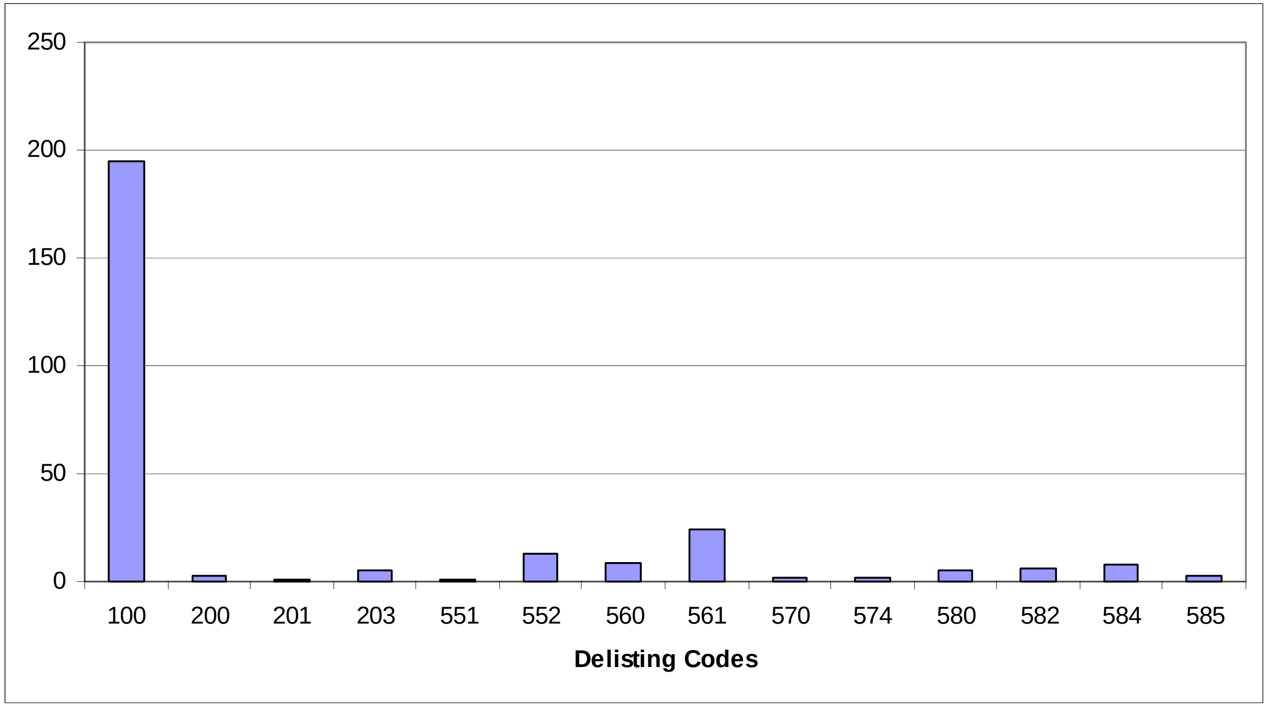

Figure 2 - **Delisting status of the 277 companies in the sample on December 31 1999**

Category	Code	Description
	100	Issue still trading NYSE/AMEX or NASDAQ
	200	Issue acquired in merger
	201	Merged into or in order to form an issue trading on NYSE
	203	Merged into or in order to form an issue trading on NASDAQ
	231	Replaces codes 201, 202 and 203
	233	When merged, shareholders primarily receive common stock. Merged stock is not maintained on the CRSP file
	551	Delisted by current exchange - insufficient number of shareholders
	552	Delisted by current exchange - price fell below acceptable level
	560	Delisted by current exchange - insufficient capital, surplus, and/or equity
	561	Delisted by current exchange - insufficient (or non-compliance with rules of) float or assets
	570	Delisted by current exchange - company request (no reason given)
	574	Delisted by current exchange - company request, bankruptcy, declared insolvent
	580	Delisted by current exchange - delinquent in filing, non-payment of fees
	582	Delisted by current exchange - failure to meet exception or equity requirements
	584	Delisted by current exchange - does not meet exchange's financial guidelines for continued listing.
	585	Delisted by current exchange - protection of investors and the public interest

* These codes are intended to alert the user to delisting events undergoing further research. The individual digits in these codes do *not* necessarily conform to CRSP's standard delisting coding system.

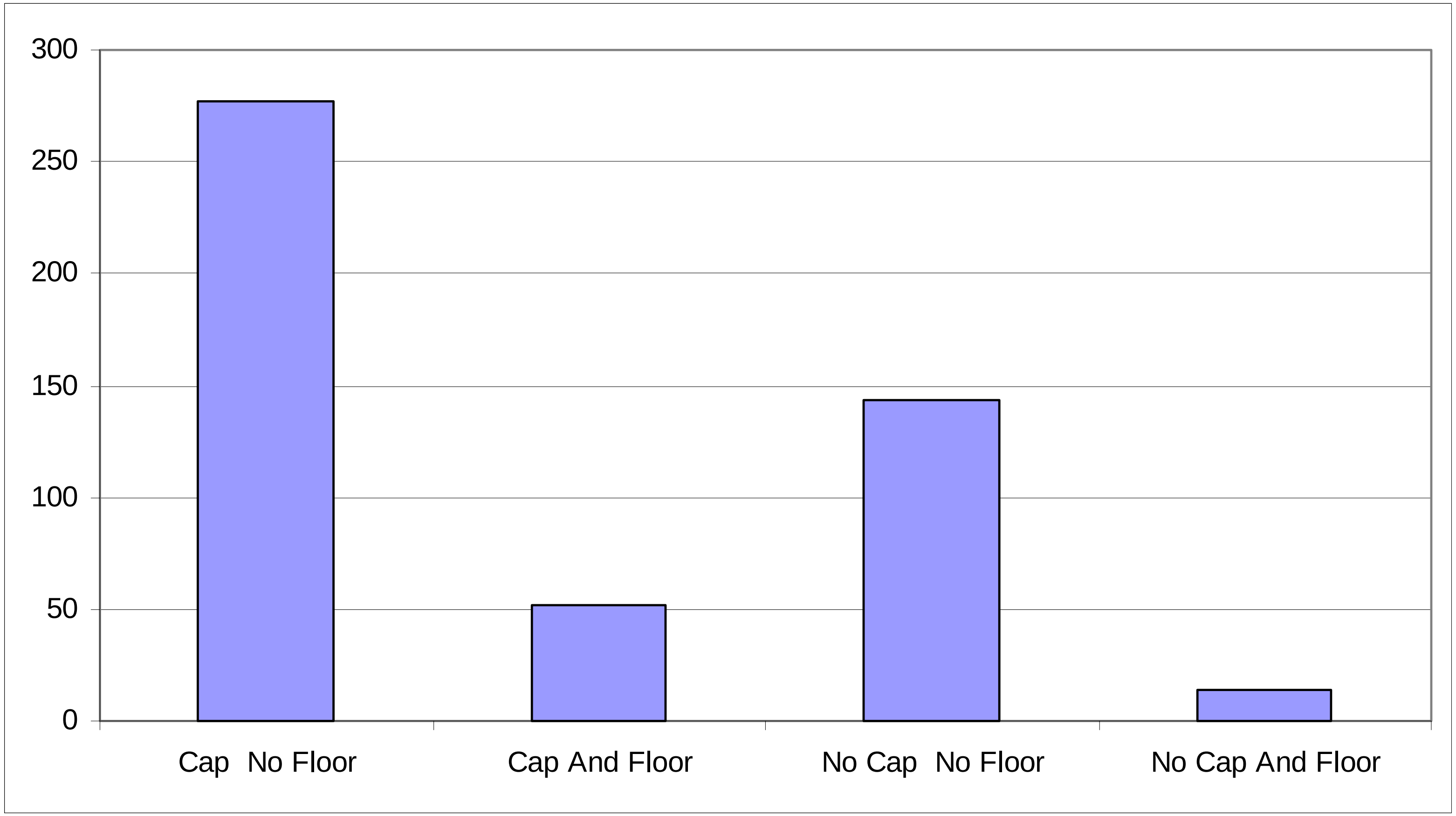

Figure 3 - **Frequency of the four types of convertible contracts** :

Contracts with a floor and a cap on the conversion price; contracts without a floor and a cap;
contracts with a cap but without a floor and contracts with a floor, but no cap. There are 487 contracts in the sample.

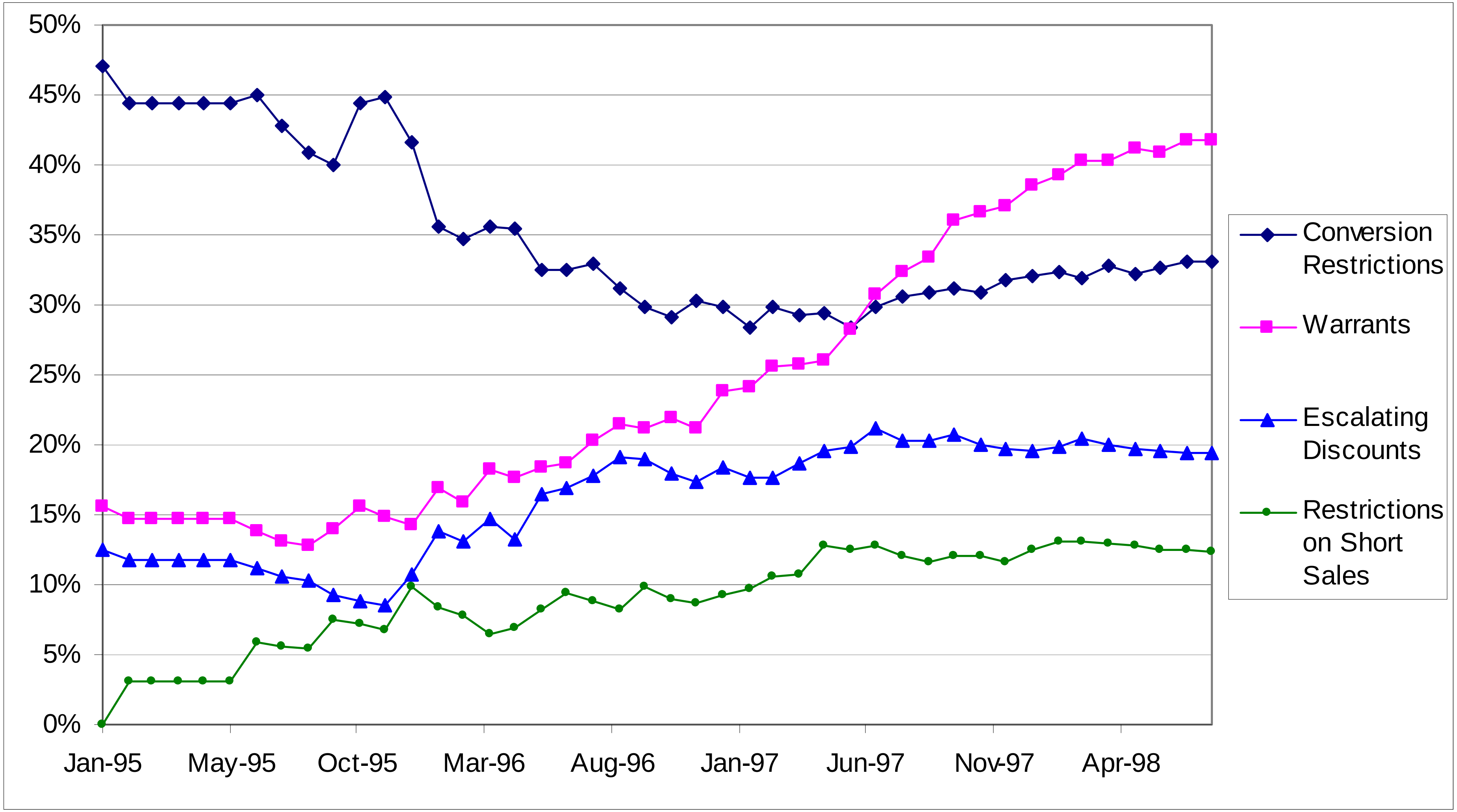

Figure 4. Convertible Structure Evolution

The figure shows, each month, starting January 1995, the cumulative percentage of the contracts that have a specific contract feature. Four contract characteristics are considered: (1) restrictions on conversion (2) whether there are warrants attached to the contract (3) whether the discount increases over time (escalating discounts) (4) whether convertible investors are allowed to sell short or not.

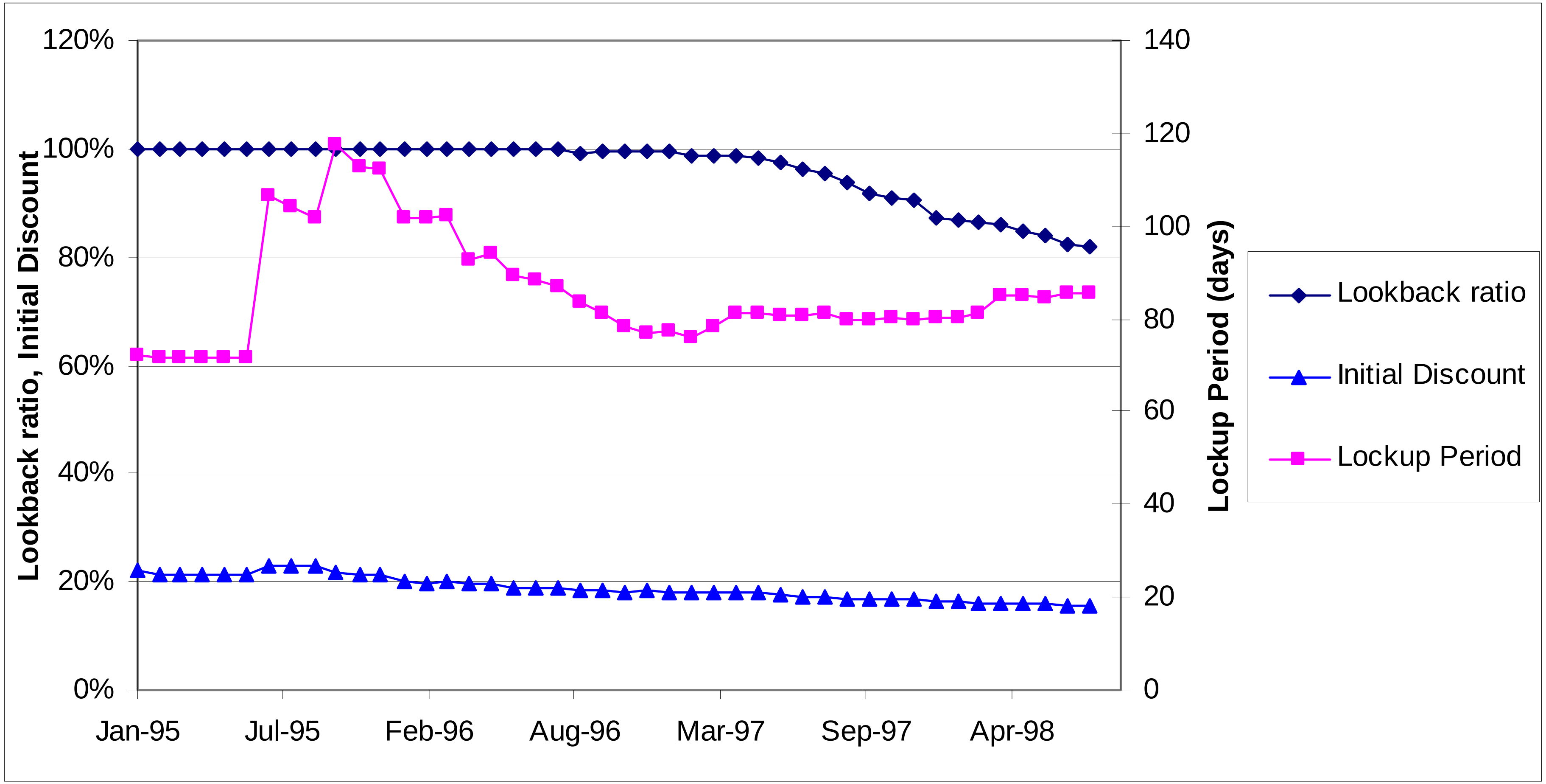

Figure 5**. Convertible Structure Evolution: quantifiable variables**

This figure shows each month, starting January 1995, the average of three contract characteristics, for all the contracts announced before or during that month. Averages for three contract characteristics are shown : (1) the look-back ratio (2) the size of the initial discount and (3) the length of the lock-up period(in days)

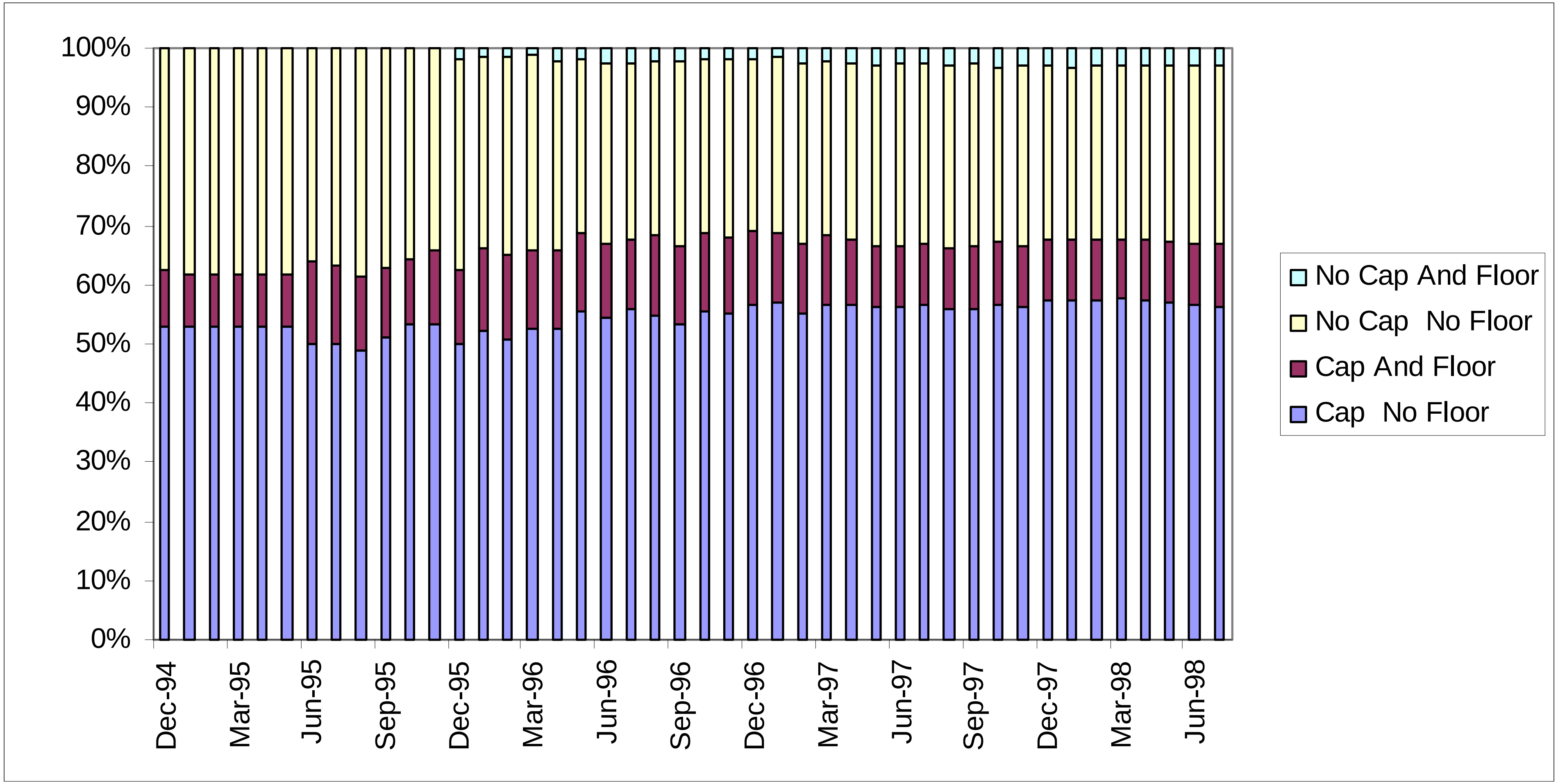

Figure 6. Convertible Structure Evolution: caps and floors.

This figure shows, each month, starting January 1995, the cumulative percentage of the contracts that have either (1) a conversion cap and a conversion floor (2) a conversion cap, but no conversion floor (3) a conversion floor, but no conversion cap and (4) neither a conversion cap, nor a floor.

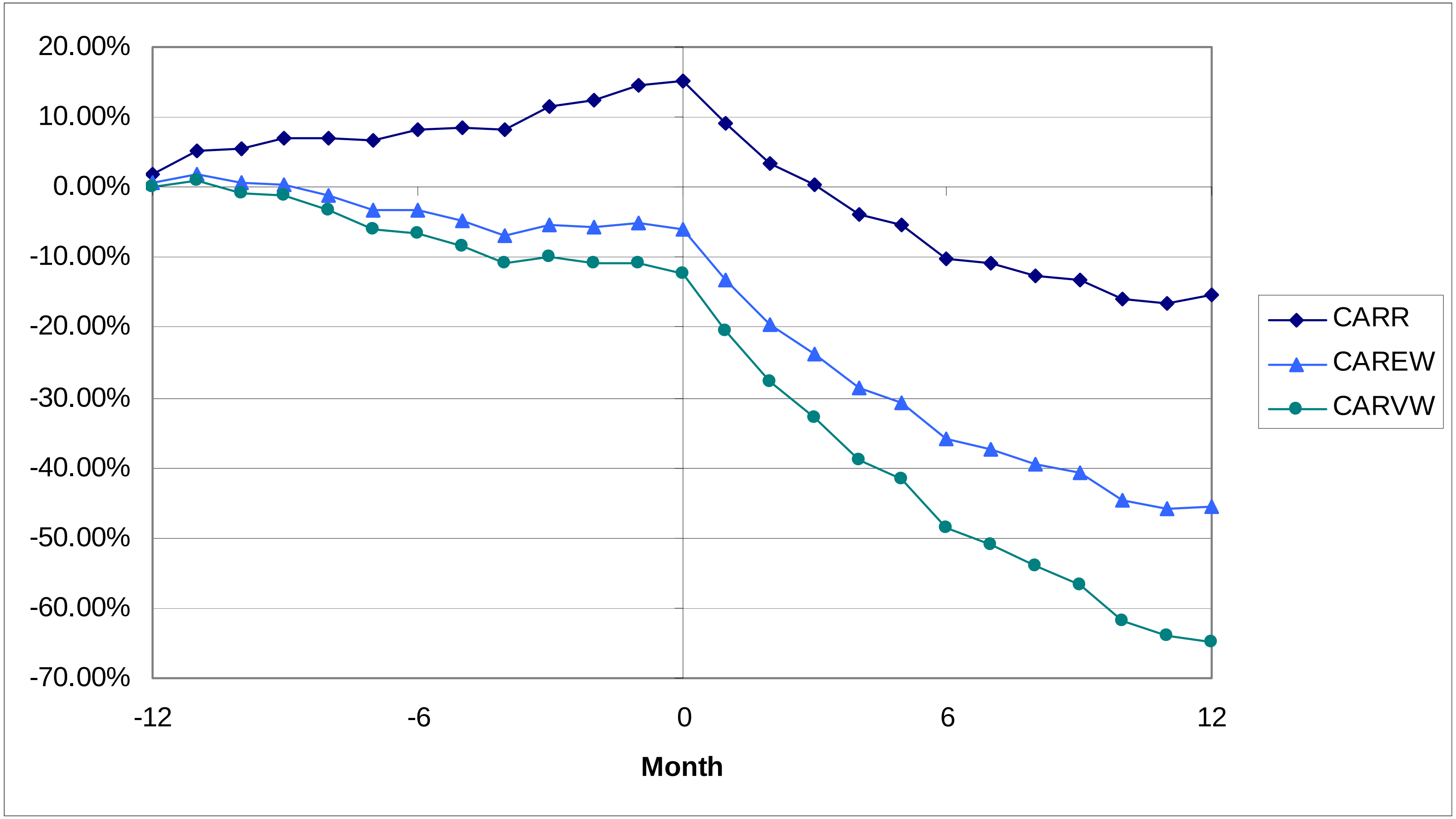

Figure 7. Price behavior around death spiral announcements.

This figure shows the cumulative average raw return (CRR), the cumulative average abnormal return relative to the equally weighted index (CAREW) and the cumulative average abnormal return relative to the value-weighted index (CARVW), 12 months before the announcement until 12 months after the announcement of all 467 floorless convertibles announced prior to August 1998.

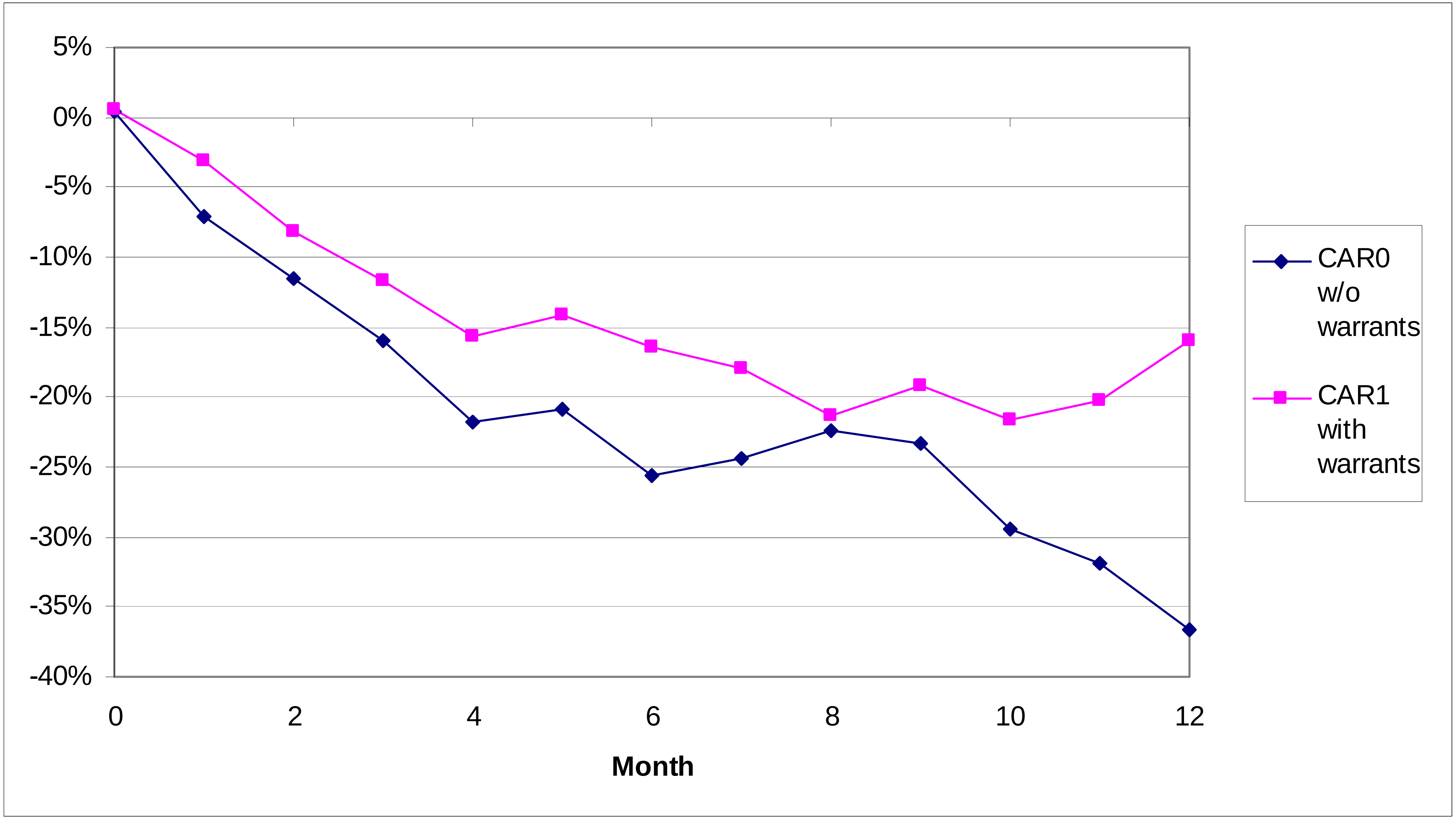

Figure 8A. Long-run Performance of Convertible Preferred Issuers; Conditioning Variable: Warrants

Cumulative average monthly returns (in %) from the announcement month until 12 months after.
We employ the RATS approach and use the Fama-French Three-factor Model.

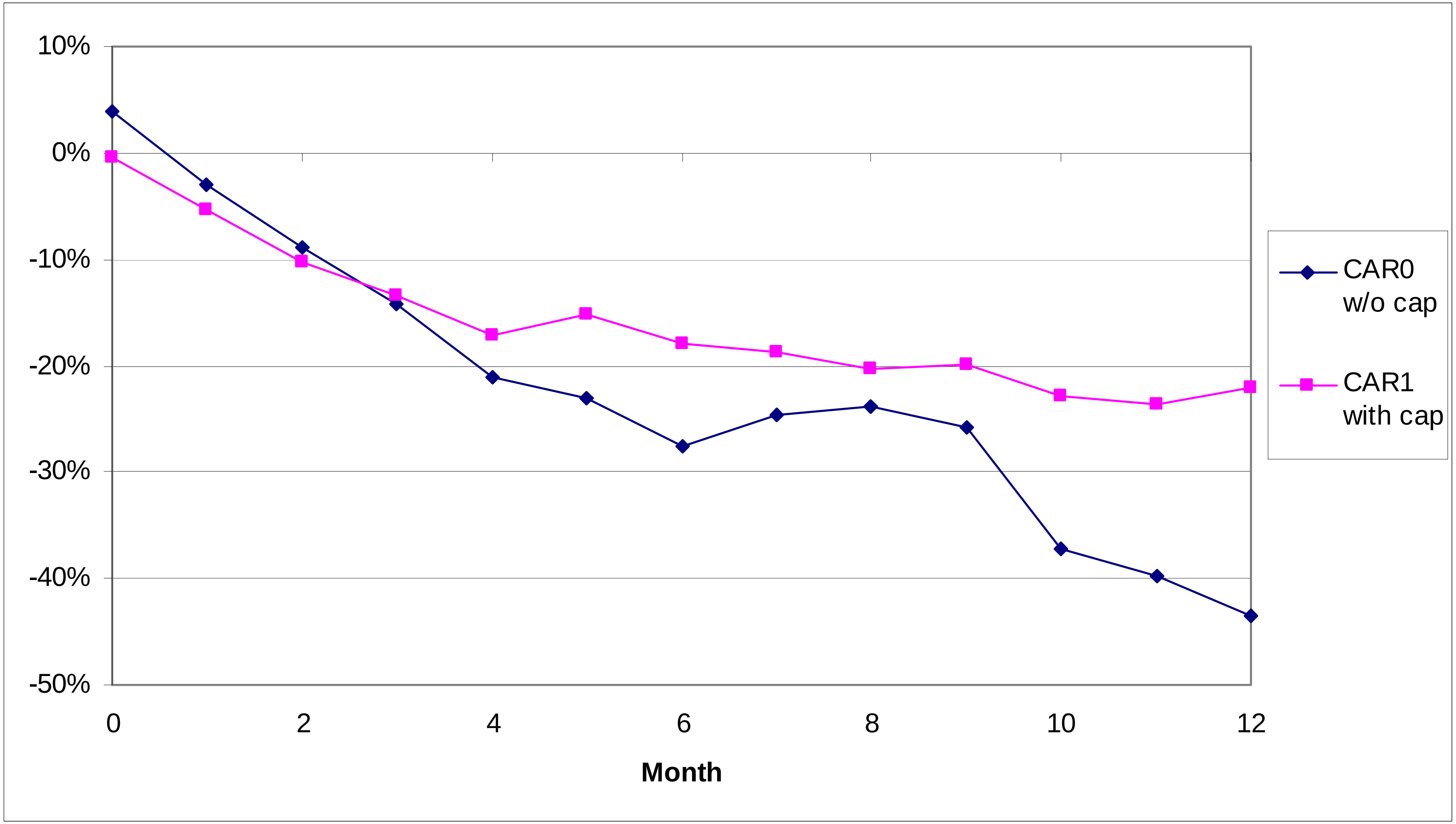

Figure 8B. Long-run Performance of Convertible Preferred Issuers; Conditioning Variable: Conversion Cap

Cumulative Average Abnormal returns (in %) from the announcement month until 12 months afterwards.
We employ the RATS procedure and use the Fama-French three factor model.

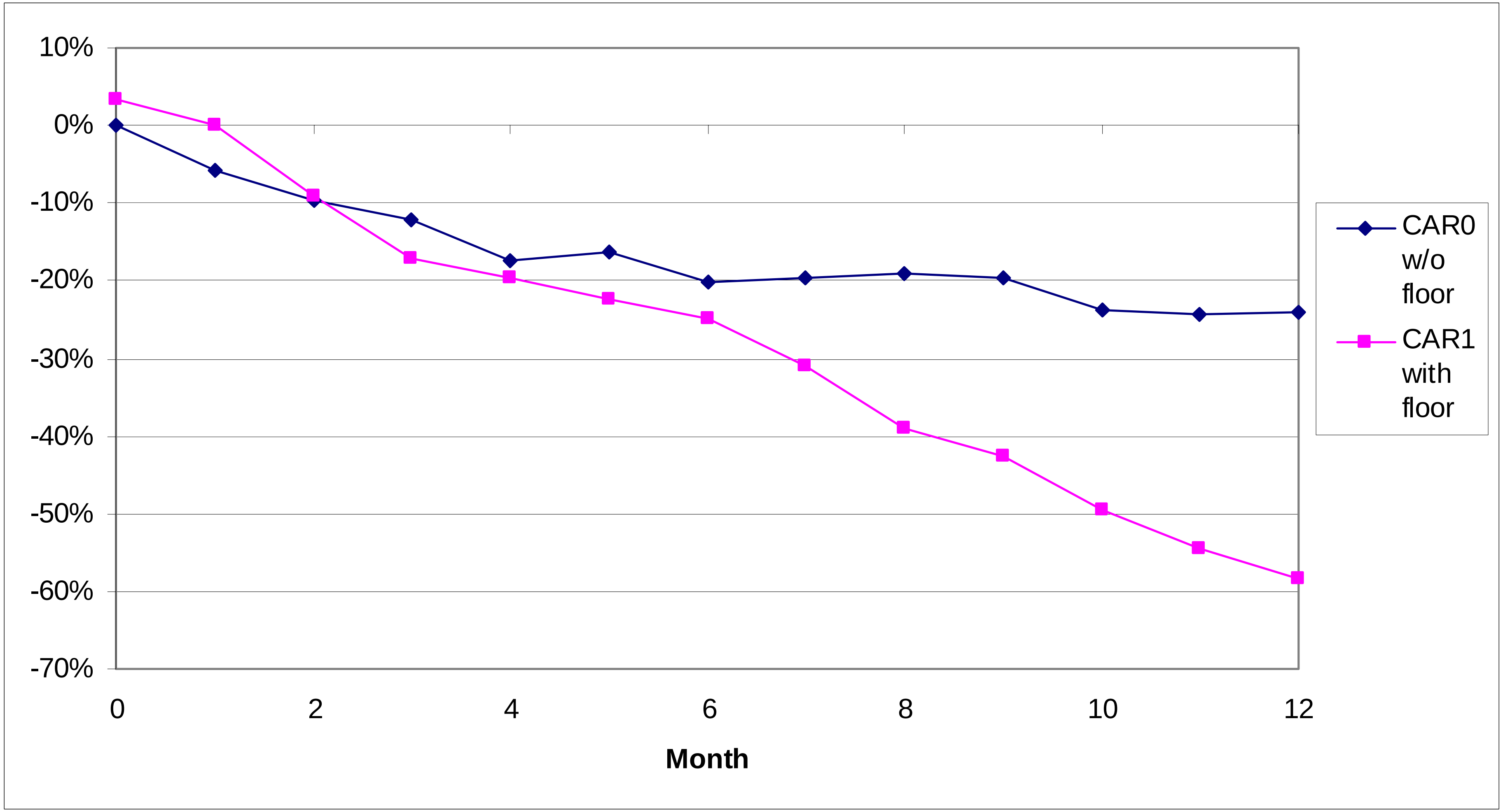

Figure 8C. Long-run Performance of Convertible Preferred Issuers; Conditioning Variable: Conversion Floor

Cumulative average monthly returns (in %) from the announcement month until 12 months after. We employ the RATS Approach and use the Fama-French Three-factor Model.

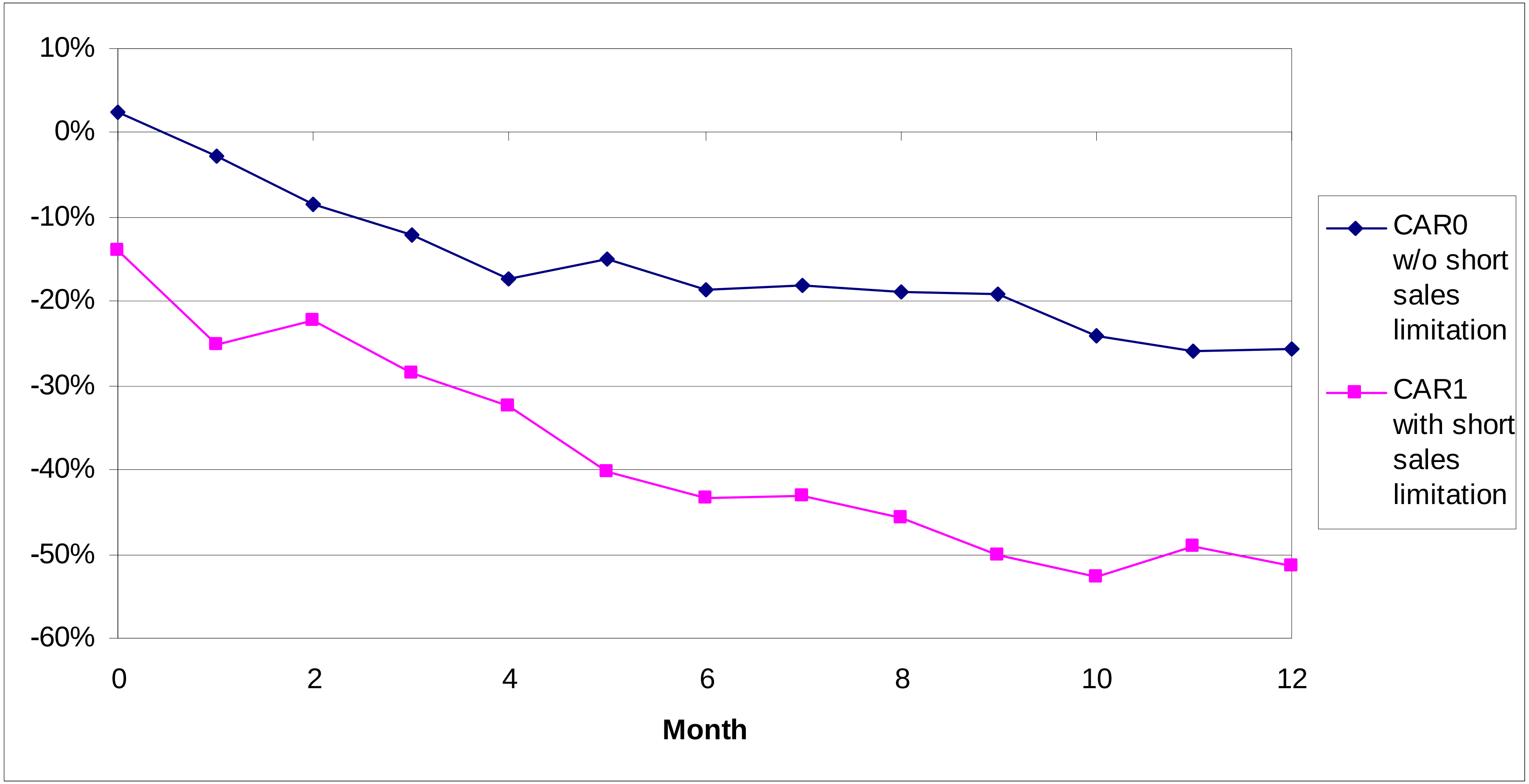

Figure 8D. Long-run Performance of Convertible Preferred Issuers; Conditioning Variable: Short-sale Restrictions

Cumulative average monthly returns (in %) from the announcement month until 12 months after. We employ the RATS Procedure and use the Fama-French Three-factor Model.

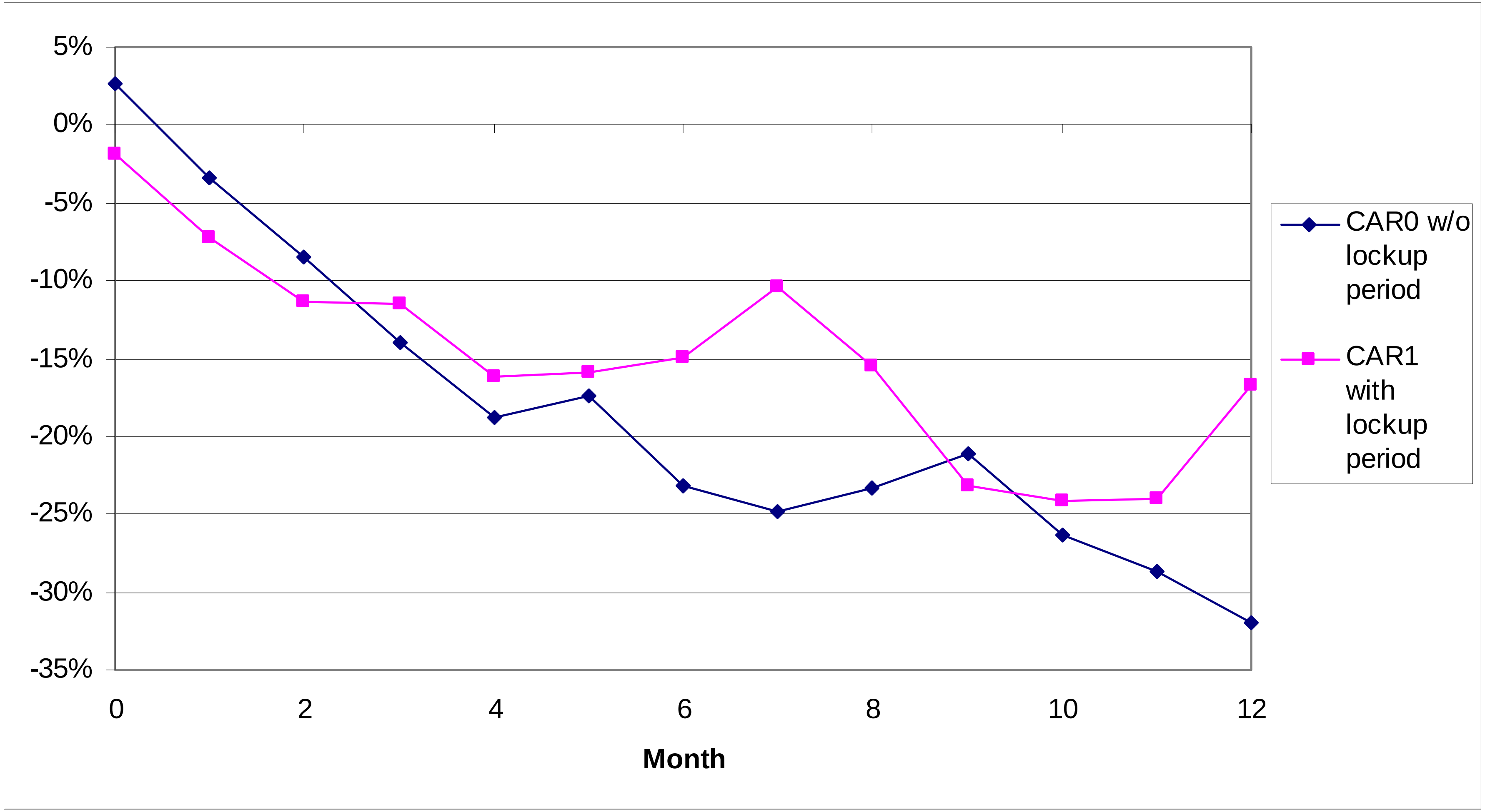

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Figure 8E. Long-run Performance of Convertible Preferred Issuers; Conditioning Variable : Lock-up Period

Cumulative average monthly returns (in %) from the announcement month until 12 months after. We employ the RATS Procedure and use the Fama-French Three-factor Model.

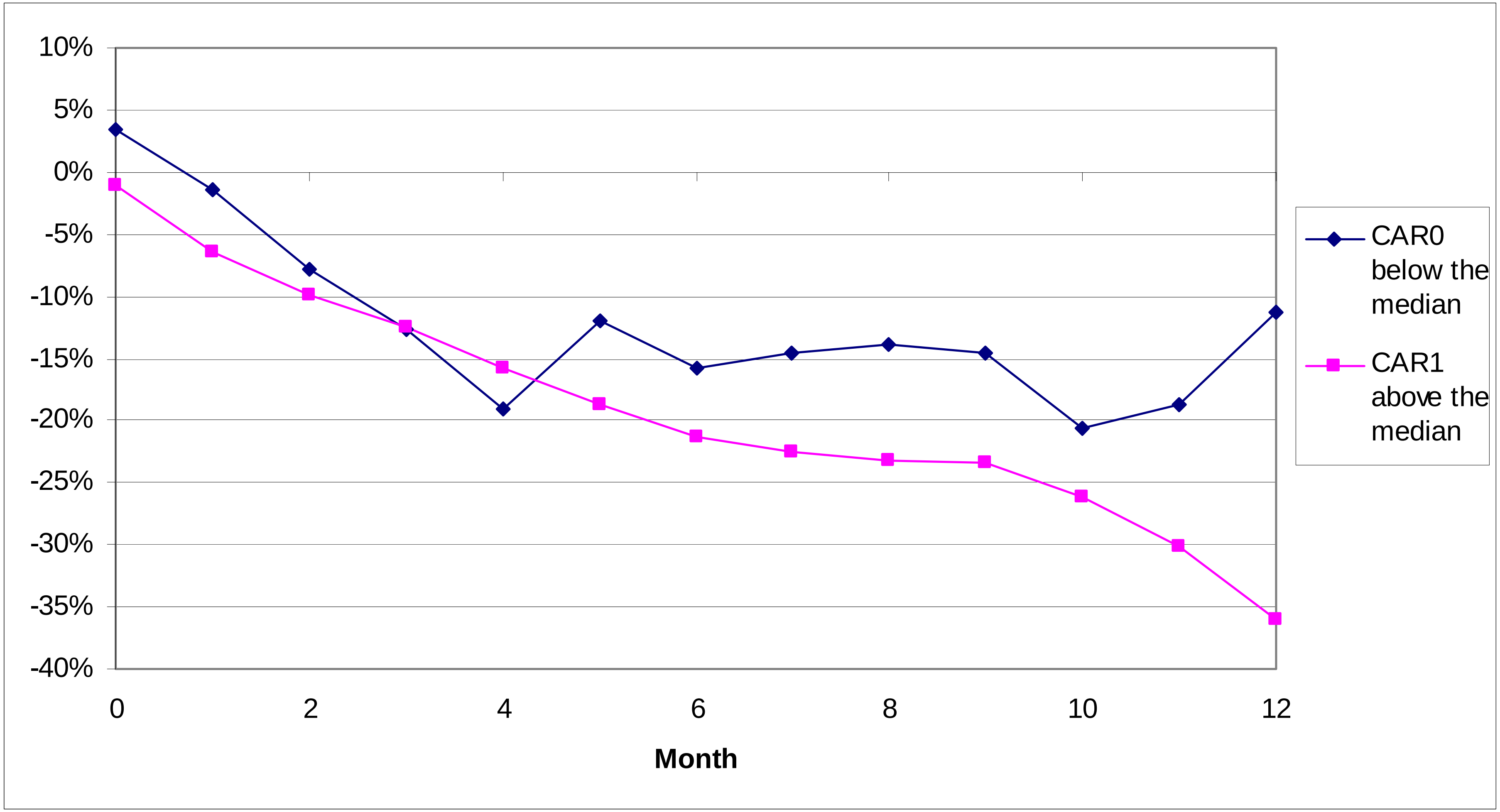

Figure 8F. Long-run Performance of Convertible Preferred Issuers; Conditioning Variable : Initial Discount

Cumulative average monthly returns (in %) from the announcement month until 12 months after. We employ the RATS Procedure and use the Fama-French Three-factor Model.

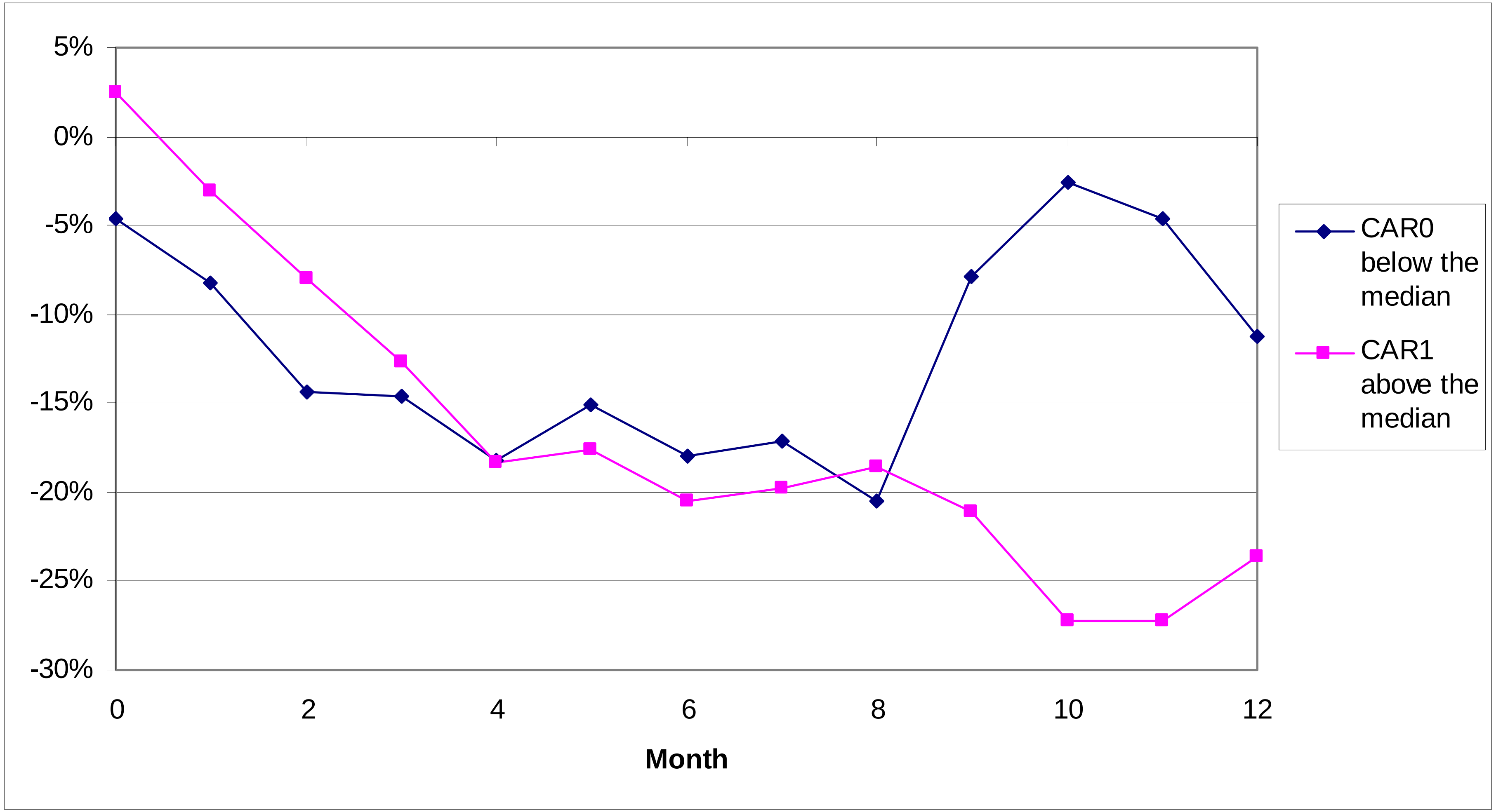

Figure 8G. Long-run Performance of Convertible Preferred Issuers; Conditioning Variable: the Lookback Ratio

Cumulative average monthly returns (in %) from the announcement month until 12 months after. We employ the RATS Procedure and use the Fama-French Three-factor Model.

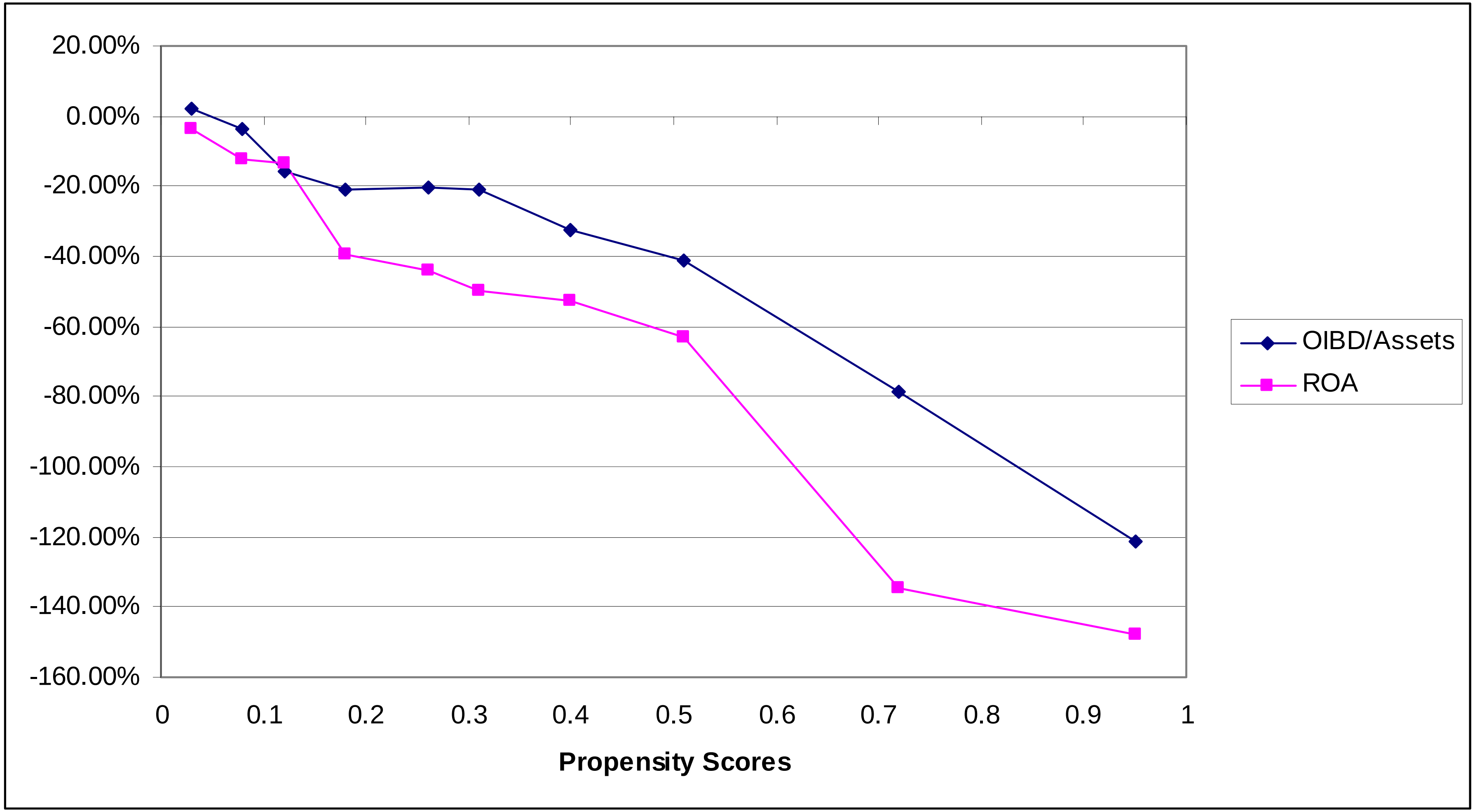

Figure 9. Probability of issuing a death spiral (measured by the propensity score) and operating performance 1 year before the issue

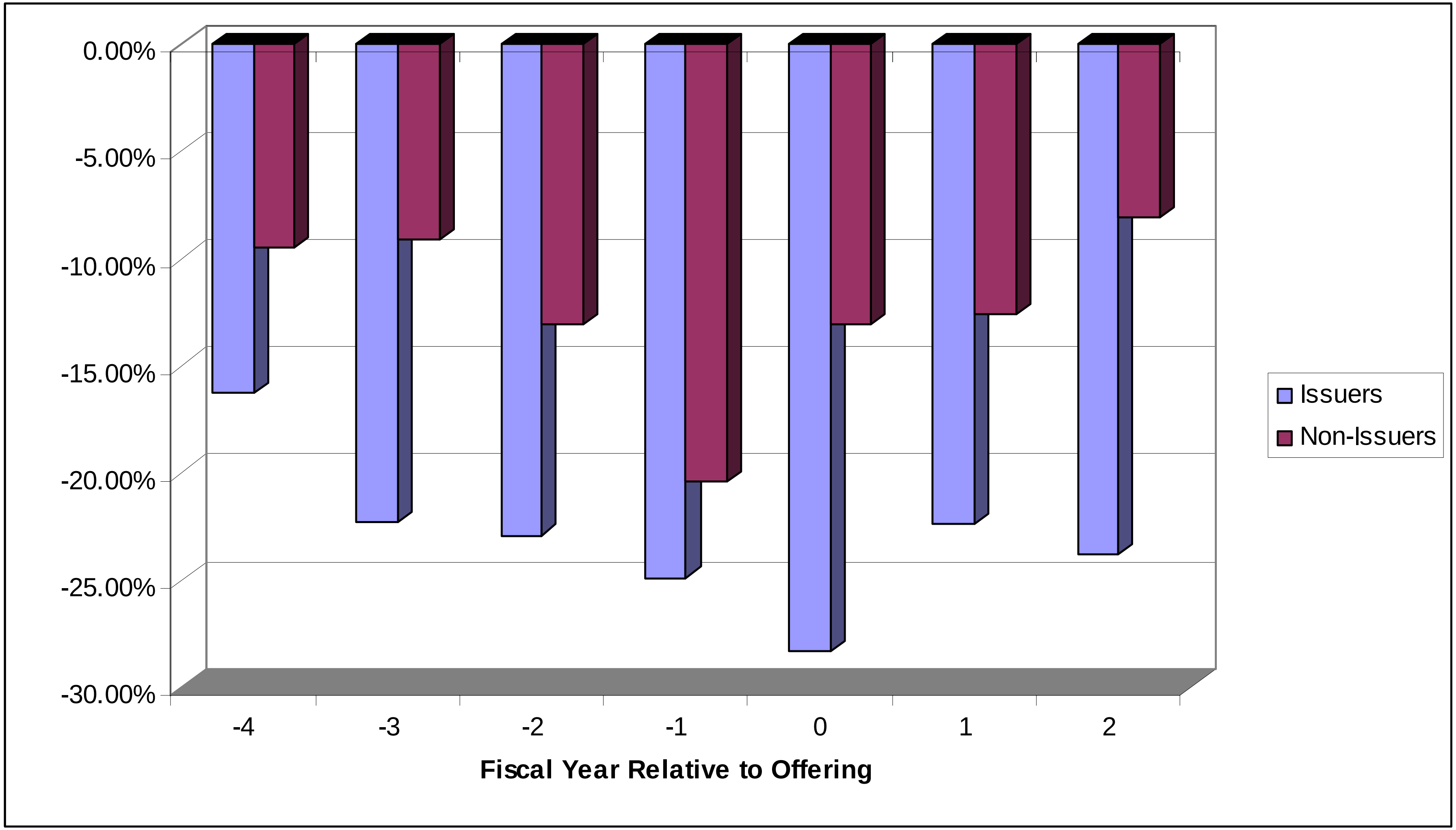

Fig. 10a Relative operating performance of death spiral issuers: OIBD/Assets

Median operating cash flow to asset ratio four years before the announcement until 2 years after the announcement for both floating-priced convertible issuers and matching firms. The results are based on Table 19 (panel A and B).

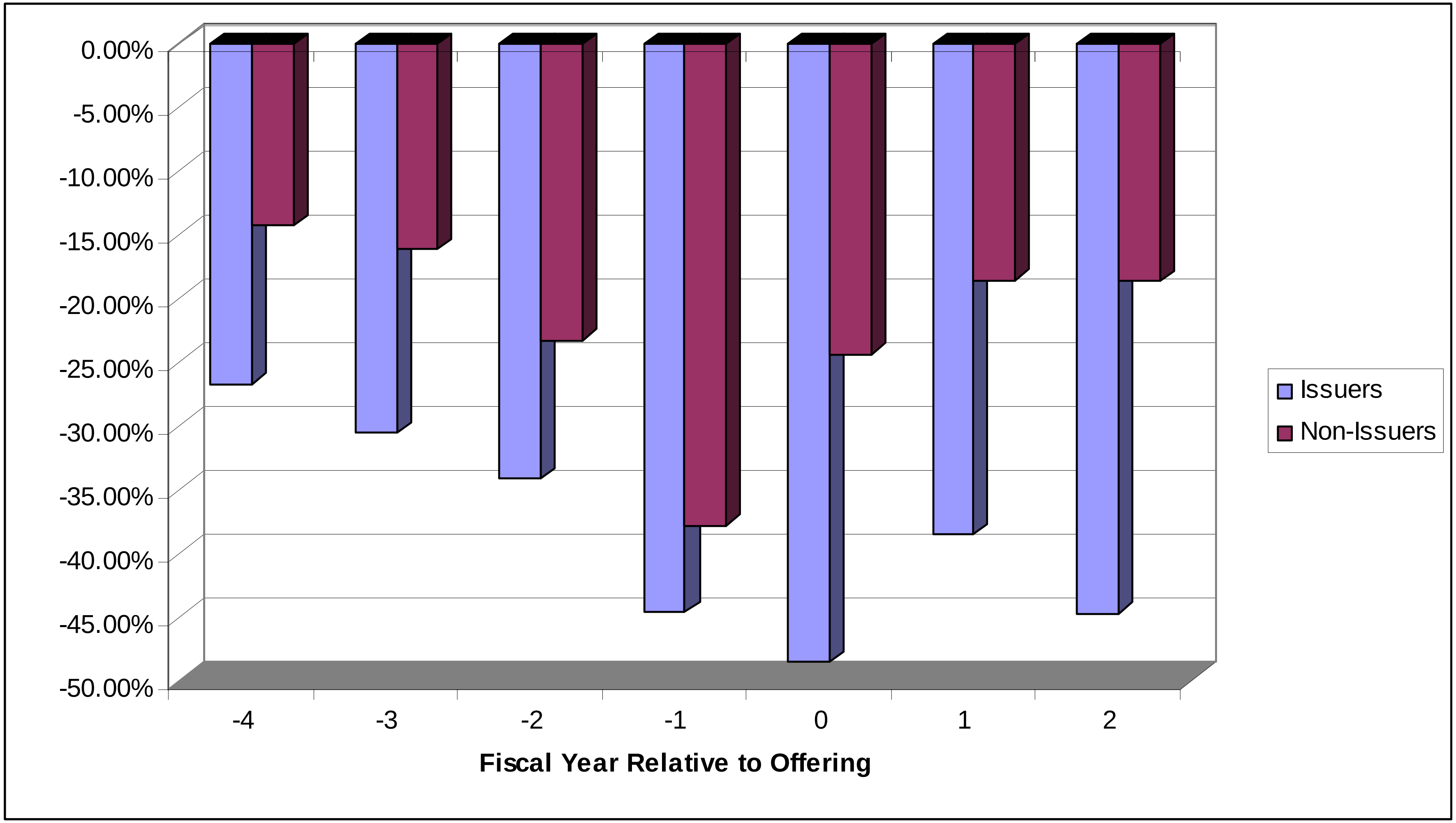

Fig. 10b Relative operating performance of death spiral issuers: ROA

Median return on assets for issuer and matching firms four years before the announcement until 2 years afterwards. The numbers are based on Table 19 (panel A and B).

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