Voluntary Delisting Timing: A Real Option Model and Empirical Evidence

Thursday 1st February, 2018

Izidin El Kalak[†], *Alcino Azevedo*[‡] *and Radu Tunaru*[§]

[†]*Kent Business School, Kent University*

[‡]*Aston Business School, Aston University*

[§]*Kent Business School, Kent University.*

Abstract

We develop a real options model which determines the optimal delisting time and provide a sensitivity analysis regarding the effect of the model parameters on our results. We test our results empirically using a data sample that comprises information on 2,577 US firms, of which 219 were delisted voluntarily over the time period between 1980 and 2016. Specifically, we estimate the probability of voluntary delisting using a survival analysis and find that both access to capital and financial visibility are good predictors for the delisting decision. Our empirical evidence also supports the asymmetric information hypothesis. We do not find conclusive empirical evidence suggesting that the stock liquidity affects the optimal voluntary delisting time.

Keywords: Delisting; Hazard Model; Voluntary Delisting Timing.

JEL codes: G34, D81.

1 Introduction

The decision to list a firm on a stock exchange is usually associated with the possibility of having access to a wider range of cheaper financial resources, enhancing market visibility, draw the attention of market makers, or using stocks or stock options programs to attract talented managers. But it also carries disadvantages such as those related to the ongoing listing fees and the expenses related to the exchange regulation. Thus, the expected advantages from being a listed firm often do not materialize, and the disappointment can lead to voluntary delisting.

Whilst the decision to list a firm on the exchange is normally perceived as a sign of the firm's confidence in its financial viability and the management willingness to operate in the future under tighter regulations and public scrutiny, the decision to delist voluntarily a firm from the exchange is usually seen as an indication that a business strategy failed and, therefore, a less ambitious one will have to be followed in the future.[1] Firms can also be delisted involuntarily by the exchange if they are unable to meet the regulatory standards, for instance, when they do not obey to the exchange rules on debt obligations, stock liquidity, accounting practices or ethical standards, or they are liquidated, or there is a merger and acquisition after which the firm identity ceases.

For instance, Toshiba was recently in the verge of being delisted by the Tokyo Stock Exchange because of doubts on whether "its internal management controls are of a standard befitting a large listed company" (Financial Times, articles published on 10th and 16th August, 2017, by Peter Wells). According to Nielsson (2013) and Pour and Lasfer (2013), the causes of the delistings from the UK AIM market can be classified as follows: i) breach of market regulations, ii) takeovers where the listed firm takes over a private firm and becomes private, changing thereafter its name, iii) firms which request to be transferred to the main market, iv) voluntary delisting, where firms request to be delisted from the exchange. For the US market, Chaplinsky and Ramchand (2012) uses a very similar classification.

To our best knowledge, there is not yet available in the literature a theoretical model on the optimal voluntary delist timing, although the empirical literature on the determinants of voluntary delisting is relatively extensive.[2] We develop a real options model which determines

[1]See Ashta et al. (2007) for descriptions of voluntary delistings in the French wine industry.

[2]The empirical literature is organized into two main branches: one branch which studies the determinants of voluntary delisting of foreign firms from local stock exchanges (Chaplinsky and Ramchand 2012, Liu et al. 2012), another, which investigates the determinants of voluntary delisting of local firms from their home stock exchanges (Bharath and Dittmar 2010, Pour and Lasfer 2013).

the optimal time to delist voluntarily a firm from the exchange, considering market uncertainty. When applied to the voluntary delisting decision, the real options theory asserts that listed firms hold the *option to delist* which has value if there is uncertainty. Thus, it should be exercised only if it is optimal to do so. We provide an analytical solution for the optimal voluntary delisting time and test our theoretical model using a data sample that comprises information on 2,577 US firms, of which 219 were delisted voluntarily over the time period between 1986 and 2016. Specifically, we estimate the probability of delisting relying on a discrete-time duration-dependent hazard model and our results show that revenue uncertainty is a key driver of the optimal delisting time. We also find that when revenues are relatively low or are expected to decline significantly in the future, voluntary delisting is more likely, and conclude that voluntary delistings tend to be clustered around the optimal delisting time that is suggested by our model.

We use firm's revenue as the underlying variable of model, but other variables could also be used, such as stock returns, earnings or cash flows. Our rationale for the use of revenue is that, typically, firms are relatively small when they are listed the first time and, usually, justify their listing decision with the idea of pursuing a more ambitious growth strategy. Moreover, we rarely see a relatively large and growing revenue firm to be delisted voluntarily. Our empirical data also shows that voluntary delisting is more likely when the firm's revenue is small or the revenue growth is low or declining.

The empirical section of this paper is based on five research hypotheses regarding the effect of some market variables on the probability of voluntary delisting. We conclude that access to capital (proxied by the market to book ratio, net equity issuance and leverage) and financial visibility (proxied by stock return and volatility) are good predictors for the probability of voluntary delisting, and that the free cash flow ratio is negatively related to the probability of delisting.

There is a relatively extensive empirical literature on delistings. Specifically, there are works which study voluntary delistings (Sanger and Peterson 1990, Clyde et al. 1997, You et al. 2012, Chaplinsky and Ramchand 2012, Bessler et al. 2012, Pour and Lasfer 2013), researches which examine delistings without distinguishing voluntary from involuntary delistings (Beaver et al. 2007, Jiang and Wang 2008, Li and Zhou 2006, Dewenter et al. 2010, Bakke et al. 2012), and studies which study both voluntary and involuntary delistings (Shumway 1997, Chaplinsky and Ramchand 2008, 2012, Pour and Lasfer 2013). Typically, within the involuntary delisting literature, the cause of the delisting is neglected.[3] A review the delisting literature, with a summary of the main reasons why listed firms become private again, is provided by Djama et al. (2012).

From the above literature, we acknowledge that: i) delisting affects negatively the stock price (Sanger and Peterson 1990, You et al. 2012), ii) the quality of the soon-to-be listed firm determines whether the firm benefits in the future from the listing decision (Chaplinsky and Ramchand 2008), iii) delisting affects negatively the long term stock trading volume (You et al. 2012), iv) regulation changes and corporate governance determines the delisting decision of foreign firms from home exchanges (Chaplinsky and Ramchand 2012, Bessler et al. 2012, Bortolon and da Silva 2015), and v) often the goal of the listing decision is to re-balance leverage rather than to increase the flexibility of raising capital (Pour and Lasfer 2013).

The voluntary delisting can also be seen as the reversal of the IPO (Bharath and Dittmar 2010). Hence, some of the variables which are known as determinants of the timing of the IPO may also affect the timing of the voluntary delisting. We note that the theoretical literature on IPO timing is relatively extensive (Draho 2000, Benninga et al. 2005, Busaba 2006, Jiang and Wang 2008, Casassus and Villalon 2010, Çolak and Günay 2011, Bustamante 2011, de Castro Ferreira 2014). In this rich literature various assumptions have been made regarding the main variables which drive the IPO timing. More specifically, Draho (2000) uses industry profits, Benninga et al. (2005), Bustamante (2011) and de Castro Ferreira (2014) use cash flows, Busaba (2006) considers after-market stock price, Jiang and Wang (2008) use earnings, and Casassus and Villalon (2010) use dividends and IPO-transaction costs.[4] There is also empirical evidence showing that very often IPOs occur in waves being the information spillover hypothesis usually used to explain these waves (Altı 2005).

Some of the above literature are real option models which determine the optimal IPO timing, for instance those of Bustamante (2011) and Grenadier and Malenko (2011), which captures the effect of signaling on both the timing of the IPO and the IPO announcement and where the exercise of the IPO option is seen as a signal of private information to outsiders, respectively. Pástor and Veronesi (2005) also develop a theoretical IPO timing model and conclude that IPO waves are related to favorable periods of stock market conditions. Benninga et al. (2005) concludes that the trade-off between private benefits of control and diversification affects the

[3]Two of the few exceptions to this rule are the works of Eisdorfer (2008) and Pour and Lasfer (2013).

[4]We should note that Jiang and Wang (2008) suggest that earnings thresholds should not be used as a delisting criteria.

IPO timing, Pástor et al. (2008) extends Benninga et al. (2005) by incorporating the possibility of learning about the average profitability of the private firm, and de Castro Ferreira (2014) concludes that the market sentiment can play an important role in the IPO timing.

This paper is organized as follows. Section 2 presents our real option model for the optimal delisting time. Section 3 introduces both our research hypotheses regarding the determinants of voluntary delisting and the hazard model variables. Section 4 describes the data sample and the methodology underlying our empirical analysis, and presents our results. Section 5 shows our robustness tests. Section 6 concludes the work.

2 The Model

2.1 Optimal Delisting Timing

We assume that $\{S_t\}_{t\geq 0}$ is a GBM with the dynamics:

$$dS_t = S_t(\alpha dt + \sigma dW_t)$$

so the analytical solution is known $S_t = S_0 \exp[\sigma W_t + \nu t]$, where $\nu = \alpha - \frac{\sigma^2}{2}$.

A very important variable in our real options study is:

$$A_T^{\nu} = \int_0^T \exp[2(W_t + \nu t)]dt \tag{1}$$

Using the properties of the Brownian motion one can express the solution of the GBM as:

$$S_t = S_0 \exp(\sigma \nu t) \exp\left(2\tilde{W}_{\frac{\sigma^2 t}{4}}\right)$$

where $\tilde{W}_t := \frac{\sigma}{2} W_{\frac{4t}{\sigma^2}}$ for any $t \geq 0$ is also a Brownian motion.

Therefore,

$$\int_0^T S_t dt = \frac{4}{\sigma^2} S_0 \int_0^{\frac{\sigma^2 T}{4}} \exp[2(\tilde{W}_t + \mu t)]dt \tag{2}$$

$$\stackrel{law}{=} \frac{4}{\sigma^2} S_0 A^{\mu}_{\frac{\sigma^2 T}{4}} \tag{3}$$

with $\mu = \frac{2\nu}{\sigma}$. Hence, if we know the law of A_t^{ν} we can calculate all we need on the $\int_0^T S_t dt$.

(**?**, corollary 6.6.2.4) provides a closed-form for the probability density of A_t^{ν} as follows

Corollary 2.1 *The law of A_t^ν is $P(A_t^\nu \in du) = \varphi(t,u)du$ where*

$$\varphi(t,u) = \frac{u^{\nu-1}}{\sqrt{2\pi^3 t}} \exp\left[\frac{\pi^2}{2t} - \frac{1}{2u} - \frac{\nu^2 t}{2}\right] \int_0^\infty \exp[-\frac{1}{2}uy^2] y^\nu \Psi_y(t) dt$$

where

$$\Psi_y(t) = \int_0^\infty \exp\left[-\frac{y^2}{2t} - r\cosh(y)\right] \sinh(y) \sin\left(\frac{\pi y}{t}\right)$$

When the focus is only on using the expectation of A_t^ν we can take the advantage of having an analytical formula for this quantity. Consequently,

Proposition 2.2 *The mean of A_t^ν is given by:*

$$E(A_t^\nu) = \frac{1}{4}\left(1 + c^{\nu/2} \exp[2(1+\nu)t]\right) \tag{4}$$

where $c^a = \frac{2}{2a+1}$.

For our purposes we denote by S_t^j the turnover process value at time t for either $j = 1$ the listed company or for $j = 2$ for the company after delisting. Each process is driven by a geometric Brownian motion process:

$$dS_t^j = \alpha_j S_t^j dt + \sigma_j S_t^j dW_t^i \tag{5}$$

with $E(dW_t^1 dW_t^2) = \rho dt$. If $\rho = 1$ that means the turnover processes will be considered under the same information filtration.

The reference point of decision making is fixed at time $t = 0$, that is today. The calculations will depend on the current value of turnover $S_0^j, \;\; j = 1, 2$ so they can be developed recursively as an ongoing decision process reflecting the arrival of new information on the company at the end of each year. We are searching for the decision action period defined by the end of the period $\tau \in \{t_1, t_2, \ldots, t_n, \ldots\}$ where the event $\{\tau = t_i\}$ means that the decision to delist is going to become effective in the period $(t_{i-1}, t_i]$ such that delisting becomes operational from time t_i.

2.2 A Simplified Framework

One simple way to identify the optimal period for delisting is to consider the difference between the expected value of the total turnover generated up to the potential delisting time t_i if the company is listed and the total turnover if the company is not listed, plus any savings costs that would be made by not paying listing fees. Thus, we can find out the maximum:

$$\Delta_{t_i} = E\left(\int_0^{t_i} S_t^2 dt - \int_0^{t_i} S_t^1 dt + K(t_i)\right) \tag{6}$$

Following Benninga et al. (2005) one can assume that the cost of being listed is roughly equal to 10% of the turnover generated under the listed regime at any moment in time. Thus, we need to determine:

$$\Delta_{t_i} = E\left(\int_0^{t_i} S_t^2\right) dt - 0.9E\left(\int_0^{t_i} S_t^1 dt\right) \tag{7}$$

Denoting by m_2^i the first expectation by m_1^i the second expectation in (7) , using the result in Proposition 2.2 we find that:

$$m_j^i = \frac{S_0^j}{\sigma_j^2}\left[1 + \frac{2\sigma_j}{2\alpha_j - \sigma_j^2 + 2\sigma_j}\exp\left(\frac{\sigma_j t_i}{2}(2\alpha_j - \sigma_j^2 + \sigma_j)\right)\right] \tag{8}$$

for any given i and $j = 1, 2$. Thus, we have an analytical formula for each $\Delta_{t_i} = m_2^i - 0.9m_1^i$ that can be calculated for all $i = 1, 2, \ldots$ and see where is the maximum. Notice that if the sequence $\{\Delta_{t_i}\}_{i=1,2,\ldots}$ is increasing, it is never optimal to delist. This methodology can also be expanded to consider recursive listing and delisting events, although this direction of research is outside the scope of this paper.

2.3 Model Parameter Estimation

Using our data sample, which includes 2,577 firms with either the listed or the delisted status, we estimate the parameters of the geometric Brownian motion process of our model, specifically, the revenue volatility and growth rate. Table **??** shows our parameters estimations, from which we conclude that, for the full sample, $\sigma = 0.319$ and $\alpha = 0.239$. We also estimate the values of these parameters for two sub-samples, listed firms and delisted firms, and conclude that, for the former group, $\sigma = 0.316$ and $\alpha = 0.240$, whereas for the latter, $\sigma = 0.352$ and $\alpha = 0.240$. The mean difference between the revenue volatility of the two sub-samples is 0.036 and statistically significant (the revenue volatility of the delisted firms is about 11.4% higher than that of the listed firms). We find however that the mean difference between the revenue growth of the two sub-samples is very small and not statistically significant. These findings suggest that the listing decision may increase the revenue uncertainty. Notice that the delisted firms may suffer from selection bias, therefore, we should expect that their post-delisting operations to be more volatile.

[Insert Table **??** here]

Figure 1 shows the yearly evolution of the delisting profit over a future time period of 25 years. More specifically, we show eight scenarios. The first scenario (figure at the top on the left-hand side) studies the case where the parameters of the GBM process of the revenue for the two states (1-listed firms and 2-delisted firms) are the same: $\alpha_1 = \alpha_2 = 0.24$ and $\sigma_1 = \sigma_2 = 0.32$. It shows that it is profitable to exercise the delisting option now or at any given time over the next 25 years. In the second scenario (figure at the top of the page on the right-hand side) we examine the case where we decrease the revenue growth rate of the scenario above to $\alpha = 0.10$. Our results show that it is profitable to exercise the delisting option now or in the first five years (the profits from the delisting are negative for $t > 5$).

The third scenario (the second figure on the left-hand side, starting from the top of the page) investigates the case where we increase the revenue volatility of the state 2 to $\sigma_2 = 0.40$. Our results show that the firm should not delist during the first two years. It is profitable however to exercise the option to delist from the third year onwards. Nevertheless, notice that although the profits from delisting are negative until year two, they increase monotonically. Therefore, the firm should delay the delisting indefinitely (it is not optimal to exercise the option to delist the first time the profits from delisting become positive). For the fourth scenario (the second figure on the right-hand side, starting from the top of the page) studies the case where we decrease the revenue volatility of the state 2 to $\sigma_2 = 0.10$. Our results show that the firm should exercise the option to delist in the first year, because the delisting profits in this year reach a maximum. However, the option to delist stays in the money until year 12 when it turns out of the money.

In the last four scenarios we vary both α and σ at the same time, for instance, decreasing both to 0.10 (the third figure on the left-hand side, starting from the top of the page), or decreasing decreasing α to 0.10 and increasing σ to 0.40 (the third figure on the right-hand side, starting from the top of the page), or increasing α to 0.30 and decreasing σ to 0.20 (the fourth figure on the left-hand side, starting from the top of the page), or increasing α to 0.30 and σ to 0.40 (the fourth figure on the right-hand side, starting from the top of the page). The fifth scenario leads to the same decision outcome as the fourth, although the gains from delisting over the years where it is profitable to delist are slightly higher. The comparison of the above two findings is interesting because it shows that a significantly high decrease of the expected revenue growth rate in the delisting state, does not change the optimal time of the delisting but makes it slightly more profitable over the time period where it is profitable to delist. The comparison of the fifth and the sixth scenarios is also interesting because it shows that if we increase the volatility of the revenues in delisting state to $\sigma = 0.40$, the delisting profit gains from a decrease in the the revenue growth rate (which we can see when we compare scenario fourth with scenario fifth) are more than offset, making now the delisting decision profitable only in first two years. Specifically, the delisting option is in the money only in the first two years with a delisting profit equal to 0.2076 (or 20.76%) in the first year and 0.0930 (or 9.30%) in the second year.

In the seventh scenario we increase α_2 to 0.30 and decrease σ_2 to 0.20. Our results show that the firm has twelve years over which it is profitable to delist. Nevertheless, the highest delisting option value is still in year one (equal to 2.5203 (or 252.03%) and decreasing to 0.1467 (or 14.67%) in year 12. In the eighth scenario, we increase α_2 to 0.30 and σ_2 to 0.40. Our results show that delisting is profitable from year 2 onwards. Furthermore, because after the second the profit from delisting increases significantly, the firm should delay indefinitely since it is not optimal to delist the time the option to delist becomes profitable.

[Insert Figure 1 here]

2.4 A More General Case

A more general view is that the company will think to delist at the period for which Δ_τ is positive and maximum. For a fixed maturity T the option to delist at future time T can be conceptualized as

$$C_{delist}(S_0^1, S_0^2, K, T) = E\left[\max\left(\int_0^T S_t^2 dt - \int_0^T S_t^1 dt - K, 0\right)\right] \tag{9}$$

The option in (9) is a European spread option on the difference in cumulated turnover. Given the lack of analytical solutions in this case we should resort to Monte Carlo simulation making use of the identity (3). From a computational point of view we can generate a sample of values for $\{A_t^\nu\}_{t\geq 0}$ utilizing the fact that A_t^ν has the same law as Y_t^ν that is defined by the SDE

$$dY_t^\nu = [2(\nu+1)Y_t^\nu + 1]dt + 2Y_t^\nu dW_t \tag{10}$$

For further details and a proof see Carmona et al. (1997) and Dufresne (1989).

2.5 Listing Expenses

The decision to become a public firm is usually based on a cost-benefit analysis (DeAngelo et al. 1984, Bharath and Shumway 2008, Martinez and Serve 2011). Hence, if we consider uncertainty and the option value to become a public firm, the IPO decision is triggered when the financial benefits from being a public firm exceed the IPO option value. According to Ritter (1987) firms pay an equivalent of 7% of gross proceeds of the IPO to cover the variable costs related to costs such as auditing, certification, dissemination of accounting information, stock exchange fees. Benninga et al. (2005) estimate the financial benefits from being a private firm ("private benefits"), defined as the costs which are avoided when firms are not listed. For their data sample, they show that on average there is an increase of $62 million in the *selling, general, and administrative* costs between pre-IPO year and the post IPO year, accounting for about 10% of the firms' annual profit.

Furthermore, PWC published in 2012 and 2015 further information on the average cost of IPOs, categorizing these costs into two types: *going public costs*, which include all expenses related to the IPO process such as the legal advisors, external auditors and the underwriter fees, being these costs further classified into direct costs (costs that are attributable to the offering, netted against proceeds adding up to $3.7 million in average) and other incremental organizational costs, expensed as incurred (adding up to $1 million in average), another category of costs encompasses those costs related to the creation and maintenance of the organizational structure to support the ongoing public status, for instance, the one off cost related to the conversion of the firm into a public firm (costs related to the implementation of a new financial reporting system, document internal controls, and recruitment of a new board of director) which are estimated to add up to about $1 million in average, and recurring incremental costs associated with being a public firm (fees and legal accounting advice; incremental internal staff costs) where in average companies incur $1.5 million.

In our delisting option model, we consider the saving costs associated with the delisting, $K(t)$. We follow the above PWC (2012, 2015) reports to obtain $K(t)$. A first cost associated with the ongoing listing is the annual exchange fee, which differ across exchanges. A second type of fee is that related to the fees paid to comply with the Sarbanes-Oxley act (SOX), introduced in 2002 but only fully effective from 2004 onwards. In 2016, Protiviti consulting and professional services company has published the Sarbanes-Oxley compliance survey where they compute the average annual SOX compliance costs for firms according to their size. We rely on their findings to obtain the SOX compliance cost for each firm. A third cost indicator is based on the average annual auditing fees paid by firms. This indicator is calculated based on the dollar amount of the average auditing fees value for US public companies by revenue categorization which was estimated by PWC. Taking the average of these three main costs for each firm-year observation, we find that the average total cost is \$3.7367 million or taking this value as a percentage of revenue to be 3.61% which is lower than the 10% cost of listing found by Benninga et al. (2005). One possible explanation for this difference is the different sampling period to that of Benninga et al. (2005), which covers the period between 1982 and 2000, whereas our data sample covers the period between 1980 and 2014. However, it worth mentioning that when breaking down the value of average total costs as a percentage of revenue according to the listing status, we find that this low ratio compared to the one found by Benninga et al. (2005) is driven by the low ratio of listed firms which is 3.18%, while it is close to 7% for delisted firms.

Furthermore, we calculate the dollar amount of the SGA costs and found it to have a statistically significant correlation with the average listing costs with a coefficient value of 0.8173. In addition, the SGA value as a percentage of the firms' revenue also have a statistically significant correlation coefficient of 0.6779 with the ratio of total listing fees to revenues.

Table 11 explains the definition for the main variables used to construct the direct cost of being listed, whereas Table 6 lists the correlation coefficient values between each pair of variables, and panel C in Table 7 provides the descriptive statistics for these variables.

3 Empirical Analysis

3.1 Data Sample

Our data sample comprises information on 219 firms which were delisted from the NYSE, NASDAQ or OTCBB, over the time period between 1980 and 2016. To identify the delisted firms, we follow Chaplinsky and Ramchand (2012), who use CRSP shares delisting code (DLSTCD). According to this item, we further classify delisted firms according to three categories: (i) Merger and acquisition (DLSTCD codes 200-400), (ii) involuntary delisted firm which are removed from the exchange due to bankruptcy or liquidation (DLSTCD codes >=400 excluding 570 and 573), and (iii) voluntary delisted firms which have become private firms or trading as Pink Sheet (DLSTCD codes 332 and 570). Our study focuses on voluntary delisting only. We screen all sample firms in Compustat to verify that these delisted firms are no longer listed on any major stock exchange or trading under a new name. Firms that delist to the Pink Sheets are considered to be delisted, whereas firms which move from one exchange to another are not treated as delisted.

Our dataset is extracted from annual and quarterly Compustat databases and the daily share prices dataset of CRSP for the period 1980 to 2016. All the financial variables are computed using the Compustat annual database, whereas the stock market variables are computed using the daily CRSP database. Given that no daily or monthly observations are available in Compustat for Revenues values, we compute the revenues and revenue's volatility using quarterly observations. Furthermore, in line with other studies (e.g. Bharath and Dittmar (2010); Pour and Lasfer (2013)), we exclude financial, insurance, and utility firms from our sample. Moreover, firms are required to have positive values of common equity, total assets, stock price at the end of the fiscal year, and a number of shares outstanding. Furthermore, while using the monthly data to construct the market variables we limit our sample to only common stocks according to the issue type code item TPCI. In order to avoid any survivor-ship bias in the data we identify and keep all firms listed on the stock exchanges regardless of their status (active or inactive)[5]. Finally, to acquire a consistent and accurate estimation for some of the variables/parameters used in empirical tests and sensitivity analyses, we condition on any firm to have at least nine consecutive observations to enter our sample; hence, firms with eight consecutive observations or less are entirely removed from our sample.

The initial sample set we have after applying all the above conditions consists of 8,251 firms categorized as 2,358 listed firms, 3,497 delisted firms due to M&A, 2,086 involuntary delisted firms, and 219 delisted firms.

Table **??** presents the time-series distribution for the number of firms entering our sample each year, for listed and delisted firms (M&A, involuntary, voluntary). The M&A firms represents the highest portion of our initial sample with 42.86% of the sample, followed by listed firms 28.90%, involuntary delisted firms 25.56% and finally the voluntary delisted firms representing only 2.68% of the entire sample. As per the table, the last entry year in the sample

[Insert Table **??** here]

Table 3 reports the number of firms exiting our sample each year due to M&A, involuntary, or voluntary delisting. There is a higher number of voluntary delisted firms around some

[5]This can be achieved through the status alert item STALT

economic/financial events - e.g., the number of delisted firms increases after the 2002 Sarbenes-Oxley Act, in line Marosi and Massoud (2007a)who suggest that the Sarbones-Oxley Act is one of the main factors affecting firm's decision to go delist. Our dataset shows that the recent financial crisis affected the number of delisted firms - in 2006, 2007, and 2008 there were eleven, fourteen and nine voluntary delisted firms, respectively. In addition, there is a slight increase in the number of voluntary delisted firms during the technology bubbles in the early 2000s - the number of voluntary delisted firms increased significantly in the early 2000s as compared with the early and mid-1990s.

[Insert Table 3 here]

Table 4 reports the distribution of the listed and delisted firms across industry sectors as per Fama and French classification. The top sector experiencing the delisting behavior is the business equipment sector with 28.6% and 23.35% of the delisting incidences for the M&A and involuntary delisting, respectively, while manufacturing industries experience the highest percentage of voluntary delisting with 27.85% of the voluntary delisted sample. Then, followed by the business equipments, others, and shops with 18.72%, 14.61%, and 13.24% respectively. On the other hand, Consumer durables and chemicals industries are the least to voluntary delist with 0.91% and 2.28%, respectively.

[Insert Table 4 here]

Table 5 reports the number of firms in each exchange namely, NYSE, NASDAQ, and OTCBB. The highest number of firms are listed at the NYSE 48.22% followed by NASDAQ 44.15% then OTCBB 7.63%, whereas the highest number of voluntary delisted firms are reported at the OTCBB with 79% of the total voluntary delisted firms.

[Insert Table 5 5 here]

In order to start our analyses, we restrict our sample to only listed and voluntary delisted firms and remove all the M&A and involuntary firms. Therefore, the final number of firms in our sample is 2,668 (55,352 firm-year observations) where the number of listed and voluntary delisted firms are 2,429 and 239, respectively. Table 12 defines the variables used in our empirical analysis.

3.2 Methodology

Bharath and Shumway (2008) and Pour and Lasfer (2013) study the factors that determine the delisting decision using logit model and also examine the variables that affect the length of time it takes to be delisted using Cox hazard model. To empirically test the predictions of the real options model, we follow these previous studies by, first, using the logit model to examine the factors affecting the voluntary delisting decision. The dependent variable equals 1 for voluntary delisted firms and zero otherwise. Second, we use the hazard modelling approach (survival analysis) to examine the factors which affect the decision to delist, considering the length of time the delisting procedure takes. Specifically, we develop a discrete-time duration-dependent hazard model[6] for the firms on the delisting category, a method is widely used in bankruptcy prediction models (see Campbell et al. 2008, El Kalak and Hudson 2016). The dependent variable is the duration between the IPO year of the firm (or the first appearance in CRSP if IPO date was not available) and the time it voluntary delist.

The Cox proportional hazard model is a continuous-time semi-parametric technique which determines the survival probability over time, for instance, the probability of delisting, merger, acquisition and bankruptcy. The main advantage of the semi-parametric Cox method is that it is easier to estimate survival probabilities without the need to define a baseline harzad rate (Cleves et al. (2016)). Yet, it is based on a proportional hazard assumption which states that time-dependent covariates must have hazard functions that are proportional to time; hence, Cox model assumes that the hazard function is correctly specified to describe all the covariate effects across different firms and therefore ignores the unobserved heterogeneity (Mehran and Peristiani 2010). To take into account the heterogeneity problem, Mehran and Peristiani (2010) propsoe the use of a parametric survival model with random effects. In addition, if the delisting event is recorded annually, without specifying the exact time (day, hour, minute, second), a discrete-time model with random effects is used instead of the continuous-time framework (Rabe-Hesketh and Skrondal 2008).

Therefore, we use the following hazard model with heterogeneity, on a panel data structure, which takes the functional form:

$$h(t|X_{i,t-1}) = h(t|0).\omega_{i,t}.exp(X_{i,t-1}\beta) \tag{11}$$

[6]Shumway (2001) advocates that hazard models provide better predictions for bankruptcies than static models such as multiple discriminant analysis and ordinary single-period logit techniques.

where, $h(t|0)$ is the baseline hazard rate when all the covariates equal zero, $h(t|X_{i,t-1})$ is the individual hazard rate of firm i at time $t-1$ and $X_{i,t-1}$ is the vector of covariates of each firm i at time $t-1$. $\upsilon_{i,t}$ is the unobserved heterogeneity with random effects and $\omega_{i,t} = exp(\upsilon_{i,t})$. The time to voluntary delisting is assumed to follow a Weibull distribution. The hazard rate captures the change in the hazard for a unit increase in the independent variable. A hazard ratio higher than one means that the delisted firm has a shorter time to the event than the listed firms.

The discrete hazard model technique enjoys both time-series and cross-sectional characteristics, and it is flexible to handle any variation over time for the covariates under investigation, and take into account the right censoring of our dataset. To control for unobserved heterogeneity, we estimate the hazard models using random effects [7]. We lag all explanatory variables by one year to reduce regression endogeneity problem (Mehran and Peristiani, 2010).

we further estimate the survival and the hazard curves based on the Kaplan-Meier estimator. As per Figure 2, it can be noticed that the survival curve gradually declines with the passage of time, where most of the firms in our sample exit around the age of 60 years. On the other hand, the hazard curve shows non-constant hazard rates for any defined age group where the hazard curve increases sharply in the early life of the firm and afterwards experiences a steady decline until the average life of firms is around 45 years then it takes another peak between 45 and 55 years.

[Insert Figure 2 here]

3.3 Control Variables

The use of real options theory on the IPO timing is still sparse, being the works of Draho (2000), Benninga et al. (2005), Chen and Chen (2011) and Bustamante (2011), and Pástor and Veronesi (2005) among the few exceptions.

In particular, Draho (2000) analyses the timing of the IPO by treating the going-public decision as a real option, where outside investors value the private firm using publicly observed market prices of firms from the same industry. Firms never go public in a down market because the value of the waiting (option) is high, which may justify the clustering of IPOs near market peaks. Bustamante (2011) offers a real options model where firms may use the timing of the IPO

[7] As a robustness test in section 3.5, following (Mehran and Peristiani 2010), we re-estimate the hazard models assuming two other unobserved heterogeneity assumptios:(i) firm-level frailty, and (ii) shared frailty effects at the two-digit SIC level.

to signal the quality of their investment prospects to outside investors. Her results shows that firms with better investment prospects accelerate their IPO relative to their perfect information benchmark in order to reveal their type to outside investors. Chen and Chen (2011) also use real-options models to determine closed form solutions for the optimal timing and equilibrium pricing of IPOs.

There are also important works by Zingales (1995) and Benninga et al. (2005) studying the IPO dynamics. Specifically, the former analyses the role of the IPO in maximizing the proceeds the initial owner obtains from selling his firm, whereas the latter investigates the trade-off between an entrepreneur's private benefits which are lost when the firm becomes public and the gains from diversifying the financing sources.

A limited but increasing number of studies attempt to investigate the reasons behind the firms' delisting. First, the value gain of leverage buyouts transactions in the 1980s were suggested as a main motivator (see DeAngelo et al. 1984, Kaplan 1991) with agency problems and tax benefits as the main drivers for these transactions. Bharath and Dittmar (2010) assess whether firms trade off the costs and benefits of being listed in the stock market when they decide to go private. They find that information, liquidity, access to capital are the factors which determine the firm's probability to go private.

The literature focused on the U.S. market clearly differentiate between the voluntary delisting decision, which is based on the firm's management choice, and the going private decision, which is imposed through leverage buyouts (Leuz et al. (2008); Marosi and Massoud (2007a)). The U.K. market has different institutional setting than the U.S. market as pointed out by Pour and Lasfer (2013). They find that firms voluntarily delist from the market when they generate negative returns, have low growth opportunity and profitability, unable to raise equity, and have high leverage.

Building on our theoretical real options model and taken into account previous empirical findings in the literature, we develop an empirical model to test the theoretical model's prediction while controlling for several variables found to be important determinants for the delisting decision.

The first set of variables are related to the asymmetric information hypothesis.Pagano et al. (1998) and Bharath and Dittmar (2010) suggest that firms are more likely to go private if there is asymmetric information between the managers and the investors. Smaller firms with high intangible assets value have higher adverse selection costs leading to higher probability of delisting (Pour and Lasfer 2013). However, Marosi and Massoud (2007b) find that asymmetric information does not affect the decision to delist. We use three proxies for the adverse selection cost: (i) the size of the firm; (ii) the intangible assets ratio; and (iii) firm's age.

The second set of variables tests the access to capital prediction. Public firms have a wider range of sources of financing allowing for lower cost of capital as compared to private firms. Pickens Jr (1987) advocate that the higher the visibility of public firms, as compared with private firms, the higher is the firm's ability to raise capital. The status of public firms enable them to benefit from higher competition among the capital suppliers and therefore from lower bank loans interest rates (Röell 1996). Thus, financially constrained firms should prefer to be public (Bharath and Dittmar 2010, Pagano et al. 1998). Consequently, private firms which expect to grow significantly in the future are more likely to go public (Fischer 2000, Kim and Weisbach 2005), although there are also firms that decide to go public in order to rebalance their leverage (Pagano et al. 1998).

The IPO literature shows mixed results regarding the effect of debt financing on the decision to go public. Brau (n.d.) reveals that firms decide to be public primarily to create public shares that can be used in future acquisition, whereas Bancel and Mittoo (2009) find that the main reason why European firms become public is to increase bargaining power with the banks and reduce leverage. There is also empirical evidence that some firms switch back to private when they realize that leverage re-balancing is not possible as a public firm (Bancel and Mittoo 2009, Aslan and Kumar 2011).

We measure the level of financial constraints using the KZ index (see Bharath and Dittmar 2010, Baker and Gompers 2003) and monitor whether firms pay dividends. We consider the leverage, growth opportunities and firms' ability to raise capital using the market to book ratio, growth rate, capital expenditure intensity and net equity issuance variables.

The agency costs between the managers and the shareholders are more acute in public firms (see Jensen n.d.). Hence, a motivation for reverting back to private can be the possibility of reducing the agency costs. Lehn and Poulsen (1989) argue that firms with low growth opportunities and large free cash flows are more likely to become private again, although these results are contradicted by those of Aslan and Kumar (2011). Therefore, we use free cash-flows and the return on assets as proxies for the agency costs, following Lehn and Poulsen (1989) and Bharath and Dittmar (2010).

The current literature suggests that the liquidity improves significantly after the IPO and is one of the reasons why firms decide to becoming public. Bharath and Dittmar (2010) show that firms with lower stock liquid have a higher probability delisting. We measure the stock liquidity using two proxies: trade volume and stock turnover.

The lack of financial visibility, proxied by stock price uncertainty, stock return, and analysts forecasts, leads to low interest of the investors by the firm that is positively related to the probability of delisting (see Brealey et al. 1977, Mehran and Peristiani 2010, Bharath and Dittmar 2010). The decision to go public is often largely affected by the possibility of getting the investors recognition (Bancel and Mittoo 2009, Pour and Lasfer 2013).

We use stock return volatility and stock return as proxies for the financial visibility, following Gregoriou and Nguyen (2010), which suggest that higher stock price volatility and lower stock turnover leads to lower financial visibility and, therefore, higher probability of delisting.

3.4 Results

3.4.1 Descriptive Statistics

First, we conduct a multicollinearity test among the control variables selected. If any pair of variables shows a high level of correlation then we conduct a univariate analysis for these variables and the variable that enjoys the highest Wald chi-square value obtained from the univariate test is kept in the multivariate model and the other variable is dropped. Panel A, in table 6 reports the Pearson correlation coefficients among the proxy variables used in testing the hypotheses developed. We find that two pairs of variables have significantly high correlation levels namely: Size-TVR and FCF-ROA with correlation levels of -0.7522* and 0.9188*, respectively. Therefore, after conducting the univariate analysis for these variables and comparing the Wald Chi-square we keep Size and FCF in the multivariate model and drop the TVR and ROA. In addition to the correlation between the proxy variables included in the multivariate models, we find significantly positive high correlation of 0.8173 between the selling, general, and administrative expenses provided by Compustat (XSGA) and the manually constructed variable "total fees" which includes the annual listing fees, auditing fees, and SOX compliance costs.

[Insert Table 6 here]

Table 7 provides the descriptive statistics of the proxy variables used in the final multivariate analyses. We report three types of descriptive statistics. The first is based on the quotation sample which is the average of the period from the IPO date of the firm to the delisting date. The second type of descriptive statistics is based on the average values of variables one year before the delisting decision. Finally, we report the descriptive statistics for the entire sample combining both listed and delisted firms.

[Insert Table 7 here]

In terms of asymmetric information proxies, the results suggest that delisted firms are significantly smaller in size with a mean value of 4.5542 compared to listed firms with a mean value of 5.1242 for the quotation sample and 4.5873 and 6.8219 for delisted and listed firms one year before delisting. In addition, delisted firms have lower intangible assets 0.0707 compared to listed firms 0.1303 for the quotation period which provides an initial result refuting the possibility of a higher adverse selection problem between insiders and outsiders within the delisted sample. In line with the findings of Marosi and Massoud (2007b) for the U.S. market and Pour and Lasfer (2013) for the U.K. market, we find that firm's age for delisted firms to be significantly lower 2.4075 compared to that of listed firms 2.7271. These results also holds for the one year before delisting.

Regarding access to capital, the results from the quotation sample show that by comparison with listed firms the delisted companies are over-levered, suggesting that they rely on debt to finance their investment. In addition, delisted firms have a significantly lower market-to-book ratio, suggesting that their growth opportunities are lower. Moreover, there is a statistically significant difference between the net equity issuance mean between listed and delisted firms, where the mean value of net equity issuance ratio of delisted firms is 0.0460 compared to 0.0333 for listed firms. Financial visibility measured by stock return volatility reports a mean value of 0.0796 and 0.777 for listed and delisted firms, respectively. These results are in line with the argument that firms with higher volatility are more inclined to delist from the exchange. The difference between stock returns for delisted and listed firms is not statistically significant for the quotation sample.

In terms of agency costs hypothesis, delisted firms have lower free cash flows ratio of -0.0037 compared to listed firms with a reported mean of 0.0419. This contradicts Jensen's (1986) argument that the larger is a firm's cash flow, the stronger the incentive to take that firm private. The stock turnover ratio, measuring firm's liquidity, highlights that delisted firms are significantly more liquid 0.1196 compared to their listed counterparts 0.0625 for the quotation sample. Finally, a mean comparison between the two samples shows that listed firms enjoy statistically significant higher revenue's growth when compared to the delisted firms. where the mean revenue's growth values are 15.63% and 13.56% for listed and delisted firms, respectively. The mean value of the revenue's volatility for delisted firms is also significantly higher 27.11% compared to that of listed firms 21.08%.

3.4.2 Regression Results

For each method used (logit and hazard model) we construct two models namely: (i) the base model which includes only the control variables; (ii) we add to the base model the growth revenue and revenue uncertainty to identify whether these two main variables in our theoretical model can empirically predict the firm's voluntary decision.

Panel A in table 9 reports the results from the logit model. The dependent variable is a binary variable equals one when the firm is delisted. Overall, the results are quantitatively similar between the two models. We find that size

From panel B in 8, we use the discrete-time hazard model where the dependent variable is the time to voluntarily delist. In line with our descriptive statistics reported in table 8, these results reveal that firms have a greater hazard rate of delisting if they have higher leverage, return volatility and revenue volatility. On the contrary, the hazard rate of delisting increases if firms are smaller in size, have lower market to book ratio (MB), dividends payment (Dividend), net equity issuance, stock return, and revenue growth. These results support the asymmetric information, access to capital, and financial visibility hypotheses.

The asymmetric information argument is partially supported as intangible assets proxy which measures the adverse selection problem between insiders and outsiders is not statistically significant in model (4). However, the firm size is significantly negative showing that firms who voluntary delist are smaller in size with a hazard ratio of 0.7772.

Our results support the access to capital hypotheses, the hazard rate of voluntary delisting is higher if firms have the lower market to book ratio and higher leverage ratio. A unit increase in leverage increases the hazard rate of delisting by 2.7440, whereas a unit decrease in the market to book increases the hazard rate of delisting by 0.7503.

We find evidence in support with the financial visibility hypotheses where the increased stock return volatility leads to higher probability of firms to delist, This supports the findings of Pour and Lasfer (2013) who report a positive but insignificant result between stock volatility (ReturnVol) and delisting decision, where we find the hazard ratio to be 1.0910. [8] In addition, we find that stock return increase is negatively related with the delisting probability as the hazard ratio suggests that a unit increase in stock return leads to a reduction in the probability of delisting by 0.7686.

The liquidity hypothesis is not supported as an indicator for the firm's decision to delist from the exchange, where the stock turnover ratio does not enjoy a statistically significant value. Our results are not in line with Liu et al. (2012) who show that liquidity is the main driver for US firms to delist from the Tokyo Stock Exchange.

In addition, the agency cost prediction, which argues that firms with high free cash flow and low growth opportunities tend to go private in order to reduce the agency costs between managers and shareholder, is not supported by our results given that free cash flow is statistically significant and enjoys a negative relationship with the probabilities of voluntary delisting. The hazard ratio suggests that a unit increase in free cash flow leads to a decrease in the probability of delisting by 0.4833. This finding is line with Aslan and Kumar (2011) who report similar results to ours.

Finally, as per the real options model, the Revenue's volatility variable represents an uncertainty regarding the firms generated revenues, hence, it should be positively related to delisting since higher levels of volatility increase the firm's uncertainty about generating stable and predictable revenues which in turn increase the firm's probability of delisting. Therefore, we have re-estimated our model (3) by including both revenues' growth and volatility while estimating the probability of voluntary delisting. From model (4), we find that our empirical findings are in line with the theoretical real options model where this revenue uncertainty has a significantly positive relationship with the probability to delist, suggesting that when the firms revenues are more uncertain its probability to delist increases, whereas the probability of delisting decrease when the firm's revenue growth increases.

[Insert Table 8 here]

[8] In contradiction to our findings,Mehran and Peristiani (2010) report a significantly negative relation between uncertainty and delisting suggesting that firms with a higher probability of failure are less likely to delist voluntarily.

3.5 Robustness Tests

3.5.1 Receiver Operating Curve

The receiver operating characteristics curve (ROC) is a widely used measure for evaluating the accuracy of the predictive power of a model. ROC curves identify the true positive rate against the false positive rate as the threshold to discriminate changes between listed and delisted firms. The area under the ROC curve (AUROC) indicates the accuracy of the predictive power of the model, where 1 means a perfect model (Anderson 2007). Figure 2 plots the ROC curves for both within sample period 1980-2011 and the out of sample period 2012-2016 for the two hazard models developed (Model 3 and 4) in 8. Both ROC curves enjoy a high predictive power of 85.63% and 83.08% for out of and within the sample periods for the first model, respectively. This means that varying the cut off that predicts who will go private, on average, the hazard model will accurately predict the firms that go private 83.08% 85.63% of the time for within the sample period (out of the sample period). Similarly, the predictive power of the second model developed is accurate where the ROC curves indicate a value of 86.05% and 84.10% for the out of sample and within sample periods, respectively.

[Insert Figure 2 here]

3.5.2 Unobserved Heterogeneity

In order to investigate the impact of the unobserved heterogeneity in our previous hazard model (Model 4), we re-estimate the hazard model under two unobserved heterogeneity assumptions as indicated byMehran and Peristiani (2010) namely: (i) firm-level frailty, and(ii) shared frailty effects at the industry level using the two-digit SIC codes. From 9, we find that the results reported when including the firm-level frailty and the shared frailty effects at the industry level are quantitatively similar to that of the base model.

[Insert Table 9 here]

3.5.3 Different Matching Samples

Previous studies, such as Bharath and Dittmar (2010) and Pour and Lasfer (2013), compare their findings between the delisted sample and a matched sample of listed firms by using several matching criteria. We explore the robustness of our hazard model by reporting the analysis conducted in 8 model (4) using several matching criteria for the control group of the listed firms. First, we match the control group based on firm characteristics such as Market to Book ratio (MB) and size. Then, we match based on Fama-French 2-digit industry classification. Further, we impose a matching based on two types of screens:(i) size and industry classification, and (ii) MB and industry classification. Finally, we pick the control group based on three variables namely: MB, size, and industry classification. After these sampling procedures, the results are reported in 10 which show similar results to the base model for most of the matched groups.

[Insert Table 10 here]

4 Conclusions

We develop a real options model which determines the optimal delisting time. We provide a sensitivity analysis for the effect of some of our model parameters on the optimal delisting time. Furthermore, we test empirically our model using a dataset that comprises information on 2,577 US firms, of which 219 were delisted voluntarily over the time period between 1980 and 2016. More specifically, we estimate the probability of voluntary delisting using a survival analysis, and conclude that access to capital and financial visibility are good predictors for delisting. We also find that there is partial evidence supporting the asymmetric information hypothesis, and no evidence that the stock liquidity affects the probability of delisting.

References

Altı, A.: 2005, Ipo market timing, *The Review of Financial Studies* **18**(3), 1105–1138.

Anderson, R.: 2007, *The credit scoring toolkit: Theory and practice for retail credit risk management and decision automation*, Oxford University Press.

Ashta, A., Patil, S. and Seguin, G.: 2007, Behavioral finance issues in listing and delisting in the french wine industry: Lessons from the case of grands vins boisset, *Decision* **34**(2), 304–941.

Aslan, H. and Kumar, P.: 2011, Lemons or cherries? growth opportunities and market temptations in going public and private, *Journal of Financial and Quantitative Analysis* **46**(02), 489–526.

Baker, M. and Gompers, P.: 2003, The determinants of board structure at the initial public offering, *Journal of Law and Economics* **46**(2), 569–598.

Bakke, T.-E., Jens, C. and Whited, T.: 2012, The real effects of delisting: Evidence from a regression discontinuity design, *Finance Research Letters* **9**(4), 183–193.

Bancel, F. and Mittoo, U.: 2009, Why do european firms go public?, *European Financial Management* **15**(4), 844–884.

Beaver, W., McNichols, M. and Price, R.: 2007, Delisting returns and their effect on accounting-based market anomalies, *Journal of Accounting and Economics* **43**(2), 341–368.

Benninga, S., Helmantel, M. and Sarig, O.: 2005, The timing of initial public offerings, *Journal of Financial Economics* **75**(1), 115–132.

Bessler, W., Kaen, F., Kurmann, P. and Zimmermann, J.: 2012, The listing and delisting of german firms on nyse and nasdaq: Were there any benefits?, *Journal of International Financial Markets, Institutions and Money* **22**(4), 1024–1053.

Bharath, S. and Dittmar, A.: 2010, Why do firms use private equity to opt out of public markets?, *Review of Financial Studies* **23**(5), 1771–1818.

Bharath, S. and Shumway, T.: 2008, Forecasting default with the merton distance to default model, *Review of Financial Studies* **21**(3), 1339–1369.

Bortolon, P. M. and da Silva, A.: 2015, Delisting brazilian public companies: Empirical evidence about corporate governance issues, *BBR-Brazilian Business Review* .

Brau, J.: n.d., Why do firms go public?

Brealey, R., Leland, H. and Pyle, D.: 1977, Informational asymmetries, financial structure, and financial intermediation, *The Journal of Finance* **32**(2), 371–387.

Busaba, W.: 2006, Bookbuilding, the option to withdraw, and the timing of ipos, *Journal of Corporate Finance* **12**(2), 159–186.

Bustamante, C.: 2011, The dynamics of going public, *Review of Finance* **16**(2), 577–618.

Campbell, J., Hilscher, J. and Szilagyi, J.: 2008, In search of distress risk, *The Journal of Finance* **63**(6), 2899–2939.

Carmona, P., Petit, F. and Yor, M.: 1997, *Exponential functionals and Principal Values Related to Brownian Motion*, chapter On the distribution and asymptotic results for exponential functionals of Lévy processes, pp. 73–126.

Casassus, J. and Villalon, M.: 2010, Optimal ipo timing in an exchange economy.

Chaplinsky, S. and Ramchand, L.: 2008, From listing to delisting: foreign firms entry and exit from the us, *Unpublished working paper, University of Virginia, Charlottesville, VA* .

Chaplinsky, S. and Ramchand, L.: 2012, What drives delistings of foreign firms from us exchanges?, *Journal of International Financial Markets, Institutions and Money* **22**(5), 1126–1148.

Chen, C. and Chen, Z.: 2011, Optimal timing and equilibrium pricing for ipos, SSRN working paper.

Cleves, M., Gould, W. and Marchenko, Y.: 2016, *An introduction to survival analysis using Stata, Revised third edition*, Stata Press.

Clyde, P., Schultz, P. and Zaman, M.: 1997, Trading costs and exchange delisting: The case of firms that voluntarily move from the american stock exchange to the nasdaq, *The Journal of Finance* **52**(5), 2103–2112.

Çolak, G. and Günay, H.: 2011, Strategic waiting in the ipo markets, *Journal of Corporate Finance* **17**(3), 555–583.

de Castro Ferreira, J. D. O.: 2014, Optimal timing for an ipo with market sentimentapos.

DeAngelo, H., DeAngelo, L. and Rice, E.: 1984, Going private: The effects of a change in corporate ownership structurel, *Midland Corporate Finance Journal* **2**, 35–43.

Dewenter, K., Kim, C.-S. and Novaes, W.: 2010, Anatomy of a regulatory race to the top: Changes in delisting rules at korea's two stock exchanges, 1999–2002, *Journal of Corporate Finance* **16**(4), 456–468.

Djama, C., Martinez, I. and Serve, S.: 2012, What do we know about delistings? a survey of the literature, *Comptabilités et innovation*, pp. cd–rom.

Draho, J.: 2000, The timing of initial public offerings: A real option approach, *Available at SSRN 271351* .

Dufresne, D.: 1989, Weak convergence of random growth processes with applications to insurance, *Insurance: Mathematics and Economics* **8**, 187–201.

Eisdorfer, A.: 2008, Delisted firms and momentum profits, *Journal of Financial Markets* **11**(2), 160–179.

El Kalak, I. and Hudson, R.: 2016, The effect of size on the failure probabilities of smes: An empirical study on the us market using discrete hazard model, *International Review of Financial Analysis* **43**, 135–145.

Fischer, C.: 2000, Why do companies go public? empirical evidence from germany's neuer markt, *Empirical Evidence from Germany's Neuer Markt (May 2000)* .

Gregoriou, A. and Nguyen, N. D.: 2010, Stock liquidity and investment opportunities: New evidence from ftse 100 index deletions, *Journal of International Financial Markets, Institutions and Money* **20**(3), 267–274.

Grenadier, S. R. and Malenko, A.: 2011, Real options signaling games with applications to corporate finance, *The Review of Financial Studies* **24**(12), 3993–4036.

Jensen, M.: n.d., Agency cost of free cash flow, corporate finance, and takeovers, *American Economic Review* **76**(2), 323–329.

Jiang, G. and Wang, H.: 2008, Should earnings thresholds be used as delisting criteria in stock market?, *Journal of Accounting and Public Policy* **27**(5), 409–419.

Kaplan, S.: 1991, The staying power of leveraged buyoutsl, *Journal of Financial Economics* **29**, 287–314.

Kim, W. and Weisbach, M.: 2005, Do firms go public to raise capital?, *Technical report*, National Bureau of Economic Research.

Lehn, K. and Poulsen, A.: 1989, Free cash flow and stockholder gains in going private transactions, *The Journal of Finance* **44**(3), 771–787.

Leuz, C., Triantis, A. and Wang, T. Y.: 2008, Why do firms go dark? causes and economic consequences of voluntary sec deregistration, *Journal of Accounting and Economics* **45**, 181–208.

Li, J. and Zhou, J.: 2006, Earnings management and delisting risk of initial public offerings.

Liu, S., Stowe, J. and Hung, K.: 2012, Why us firms delist from the tokyo stock exchange: An empirical analysis, *International Review of Economics and Finance* **24**, 62–70.

Marosi, A. and Massoud, N.: 2007a, Why do firms go dark?, *Journal of Financial and Quantitative Analysis* **42**, 421–442.

Marosi, A. and Massoud, N.: 2007b, Why do firms go dark?, *Journal of Financial and Quantitative Analysis* **42**(02), 421–442.

Martinez, I. and Serve, S.: 2011, The delisting decision: the case of buyout offer with squeeze-out (boso), *International Review of Law and Economics* **31**(4), 228–239.

Mehran, H. and Peristiani, S.: 2010, Financial visibility and the decision to go private, *Review of Financial Studies* **23**(2), 519–547.

Nielsson, U.: 2013, Do less regulated markets attract lower quality firms? evidence from the london aim market, *Journal of Financial Intermediation* **22**(3), 335–352.

Pagano, M., Panetta, F. and Zingales, L.: 1998, Why do companies go public? an empirical analysis, *The Journal of Finance* **53**(1), 27–64.

Pástor, L., Taylor, L. A. and Veronesi, P.: 2008, Entrepreneurial learning, the ipo decision, and the post-ipo drop in firm profitability, *The Review of Financial Studies* **22**(8), 3005–3046.

Pástor, L. and Veronesi, P.: 2005, Rational ipo waves, *The Journal of Finance* **60**(4), 1713–1757.

Pickens Jr, T. B.: 1987, Boone.

Pour, E. K. and Lasfer, M.: 2013, Why do companies delist voluntarily from the stock market?, *Journal of Banking and Finance* **37**(12), 4850–4860.

Rabe-Hesketh, S. and Skrondal, A.: 2008, *Multilevel and longitudinal modeling using Stata*, STATA press.

Ritter, J. R.: 1987, The costs of going public, *Journal of Financial Economics* **19**(2), 269–281.

Röell, A.: 1996, The decision to go public: An overview, *European Economic Review* **40**(3), 1071–1081.

Sanger, G. and Peterson, J.: 1990, An empirical analysis of common stock delistings, *Journal of Financial and Quantitative Analysis* **25**(2), 261–272.

Shumway, T.: 1997, The delisting bias in crsp data, *The Journal of Finance* **52**(1), 327–340.

Shumway, T.: 2001, Forecasting bankruptcy more accurately: A simple hazard model*, *The Journal of Business* **74**(1), 101–124.

You, L., Parhizgari, A. and Srivastava, S.: 2012, Cross-listing and subsequent delisting in foreign markets, *Journal of Empirical Finance* **19**(2), 200–216.

Zingales, L.: 1995, Insider ownership and the decision to go public, *The Review of Economic Studies* **62**(3), 425–448.

5 Figures

6 Tables

Table 1: Descriptive statistics of parameter estimates of the geometric Brownian motion for all companies in the study.

	Listed Firms	
	σ	α
Mean	0.316	0.239
SD	0.31	0.32
percentile 10%	0.0922	0.0537
percentile 90%	0.667	0.507
	Delisted Firms	
Mean	0.352	0.24
SD	0.355	0.399
percentile 10%	0.106	0.036
percentile 90%	0.777	0.493
t-value	-1.6385^{*}	-0.0367
	Full sample	
Mean	0.319	0.239
SD	0.314	0.328
percentile 10%	0.0937	0.0516
percentile 90%	0.667	0.505

Table 2: Time-series distribution of firms entering the sample

This table shows the number of firms entering our sample over the time period from 1980 to 2016. The last entry year in the sample is 2009 as we restrict firms to have at least 8 years of consecutive observations in order to be included into our sample. Columns (2),(4),(6),(8) and (10) show for each year the number of listed, M&A, involuntary, voluntary and total firms, respectively. Columns (3),(5),(7), and (9) show for each year the percentages of fimrs entering the sample which are for listed, M&A, involuntary, voluntary and total firms, respectively.

Year	Listed		Delisted						Total
		%	M&A	%	Involuntary	%	Voluntary	%	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1980	465	23.66	968	49.26	472	24.02	60	3.05	1965
1981	15	9.87	66	43.42	68	44.74	3	1.97	152
1982	22	9.28	123	51.90	89	37.55	3	1.27	237
1983	34	14.05	116	47.93	87	35.95	5	2.07	242
1984	17	8.17	101	48.56	87	41.83	3	1.44	208
1985	42	13.82	161	52.96	96	31.58	5	1.64	304
1986	48	15.89	153	50.66	98	32.45	3	0.99	302
1987	62	22.55	126	45.82	73	26.55	14	5.09	275
1988	26	11.71	121	54.50	64	28.83	11	4.95	222
1989	35	15.84	131	59.28	50	22.62	5	2.26	221
1990	23	8.52	155	57.41	89	32.96	3	1.11	270
1991	56	19.65	132	46.32	95	33.33	2	0.70	285
1992	72	21.88	130	39.51	119	36.17	8	2.43	329
1993	96	29.63	119	36.73	100	30.86	9	2.78	324
1994	78	27.86	118	42.14	76	27.14	8	2.86	280
1995	131	30.25	196	45.27	98	22.63	8	1.85	433
1996	111	35.92	111	35.92	74	23.95	13	4.21	309
1997	93	44.29	74	35.24	33	15.71	10	4.76	210
1998	116	40.56	104	36.36	58	20.28	8	2.80	286
1999	101	50.75	52	26.13	34	17.09	12	6.03	199
2000	99	62.66	34	21.52	17	10.76	8	5.06	158
2001	45	47.87	32	34.04	14	14.89	3	3.19	94
2002	47	42.34	41	36.94	23	20.72	0	0	111
2003	44	43.14	44	43.14	12	11.76	2	1.96	102
2004	78	63.93	27	22.13	16	13.11	1	0.82	122
2005	92	64.34	31	21.68	17	11.89	3	2.10	143
2006	159	77.56	23	11.22	20	9.76	3	1.46	205
2007	107	85.60	8	6.40	7	5.60	3	2.40	125
2008	44	93.62	0	0	0	0	3	6.38	47
Total	2,358	28.90	3,497	42.86	2,086	25.56	219	2.68	8,160

Table 3: Time-series distribution of firms exiting the sample

This table shows the sample distribution over the time indicating the number of firms existing the sample each year due to M&A, involuntary delisting, or voluntary delisting.

Year	M&A	Involuntary	Voluntary	Year	M&A	Involuntary	Voluntary
1980	0	0	0	2000	167	120	7
1981	0	0	1	2001	97	123	10
1982	0	0	0	2002	96	112	11
1983	0	0	2	2003	111	87	12
1984	0	0	5	2004	147	83	14
1985	0	0	4	2005	160	59	10
1986	0	0	0	2006	194	72	5
1987	0	0	2	2007	128	96	10
1988	101	3	3	2008	100	84	12
1989	75	51	3	2009	127	48	8
1990	53	74	2	2010	138	55	5
1991	40	77	5	2011	107	64	11
1992	56	58	3	2012	108	42	5
1993	91	63	4	2013	100	35	7
1994	105	48	4	2014	118	55	4
1995	120	56	2	2015	102	177	29
1996	174	49	1	2016	11	24	7
1997	199	72	1				
1998	236	75	6	Total	3,497	2,086	219
1999	236	98	4				

Figure 1: Several simulated scenarios for the delisting option calculus.

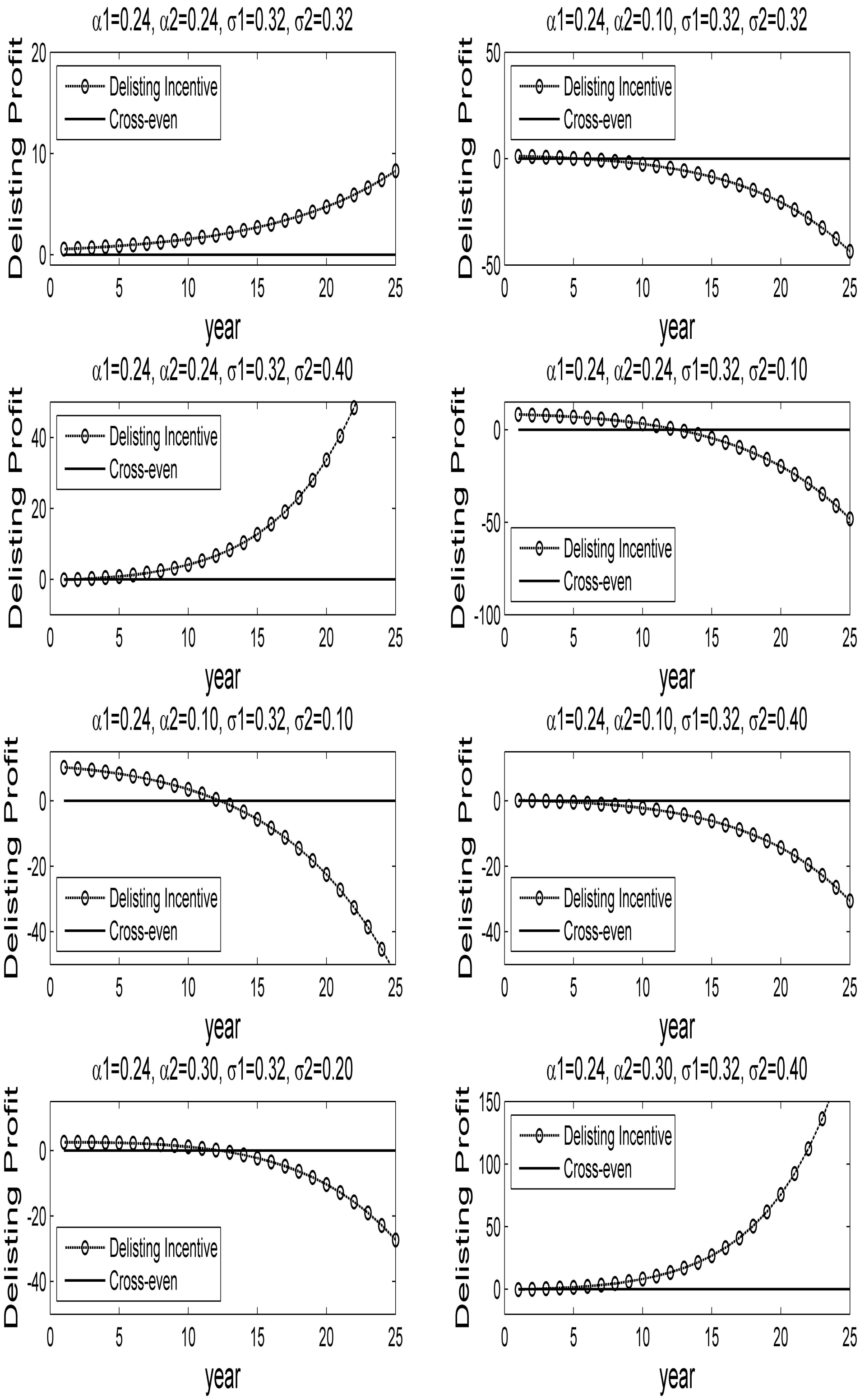

Figure 2: Survival and Hazard Curves.

This figure shows the estimated curves based on the Kaplan-Meier estimator, where the left-hand side figure (1A) represents the survival curve and the right-hand side represents the hazard curve (1B), whereas the age of firms in years is represented by the Age.

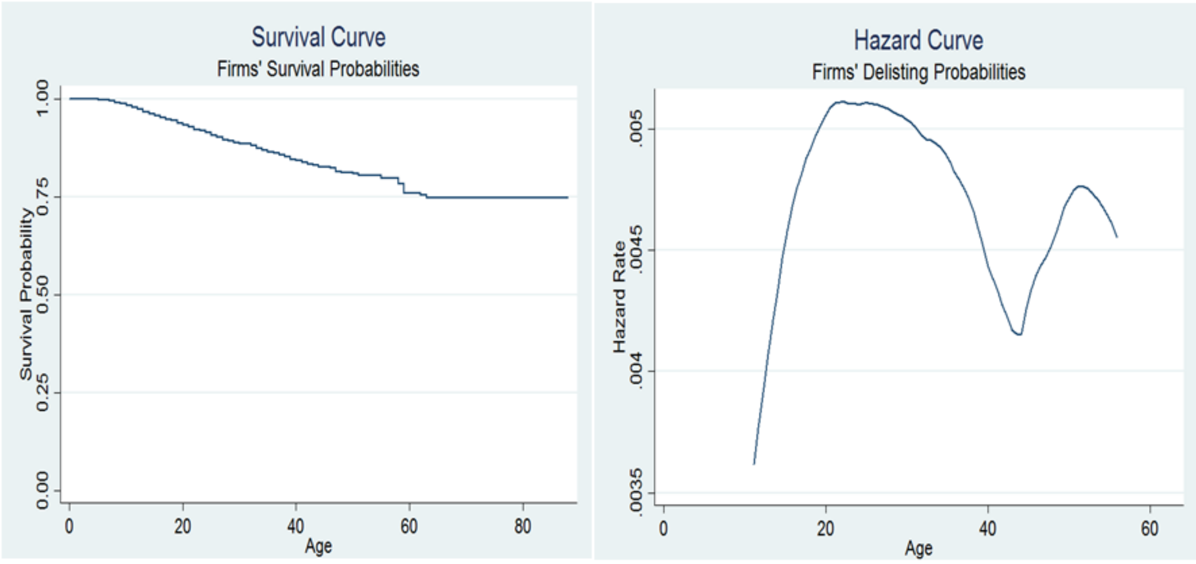

Table 4: Distribution of listed and delisted firms across industry

This table shows our industry-code construction as per Fama-French classification. The SIC codes are provided in column (1) and the respective industry names are given in column (2). In columns (3) and (5) we provide the number of listed and delisted firms in each industry, while in column (4) and (6) we provide the percentage of these firms in each industry for each listing/delisting status over the sample time period (1980 - 2016).

IND Code	Industry Name	Listed	%	M&A	%
1	Consumer Nondurables	111	4.71	146	4.18
2	Consumer Durables	11	0.47	10	0.29
3	Manufacturing	410	17.39	612	17.5
4	Energy	153	6.49	209	5.98
5	Chemicals	82	3.48	94	2.69
6	Business Equipment	556	23.58	1,000	28.6
7	Telecom	0	0	0	0
8	Utilities	0	0	0	0
9	Shops	285	12.09	419	11.98
10	Healthcare	343	14.55	517	14.78
11	Money	0	0	0	0
12	Others	407	17.26	490	14.01
	Total Firms	2,358	100	3,497	100
IND Code	Industry Name	Involuntary	%	Voluntary	%
1	Consumer Nondurables	94	4.51	19	8.68
2	Consumer Durables	9	0.43	2	0.91
3	Manufacturing	391	18.74	61	27.85
4	Energy	156	5.99	12	5.48
5	Chemicals	50	2.4	5	2.28
6	Business Equipment	487	23.35	41	18.72
7	Telecom	0	0	0	0
8	Utilities	0	0.0000	0	0
9	Shops	284	13.61	29	13.24
10	Healthcare	230	11.03	18	8.22
11	Money	0	0	0	0
12	Others	416	19.94	32	14.61
	Total Firms	2,086	100	219	100

Figure 3: ROC Curves

This figure shows the Area Under the Receiver Operating Characteristics Curve (AUROC) for the three discrete-time duration-dependent models. In the Y-axis we plot the true positive rate (sensitivity), i.e. the proportion of actual delisting transactions correctly classified by the model. In the X-axis we plot the false positive rate (1-specificity), (i.e.) the proportion of not delisting transactions, incorrectly classified as delisting transactions by the model. Points above the diagonal (random guess) indicate good classification results. The area under the curve measures the accuracy of the model. The left-hand side figures show the out of sample AUROC from 2012 to 2016 and the right-hand side figures show the within sample AUROC from 1980 to 2011.

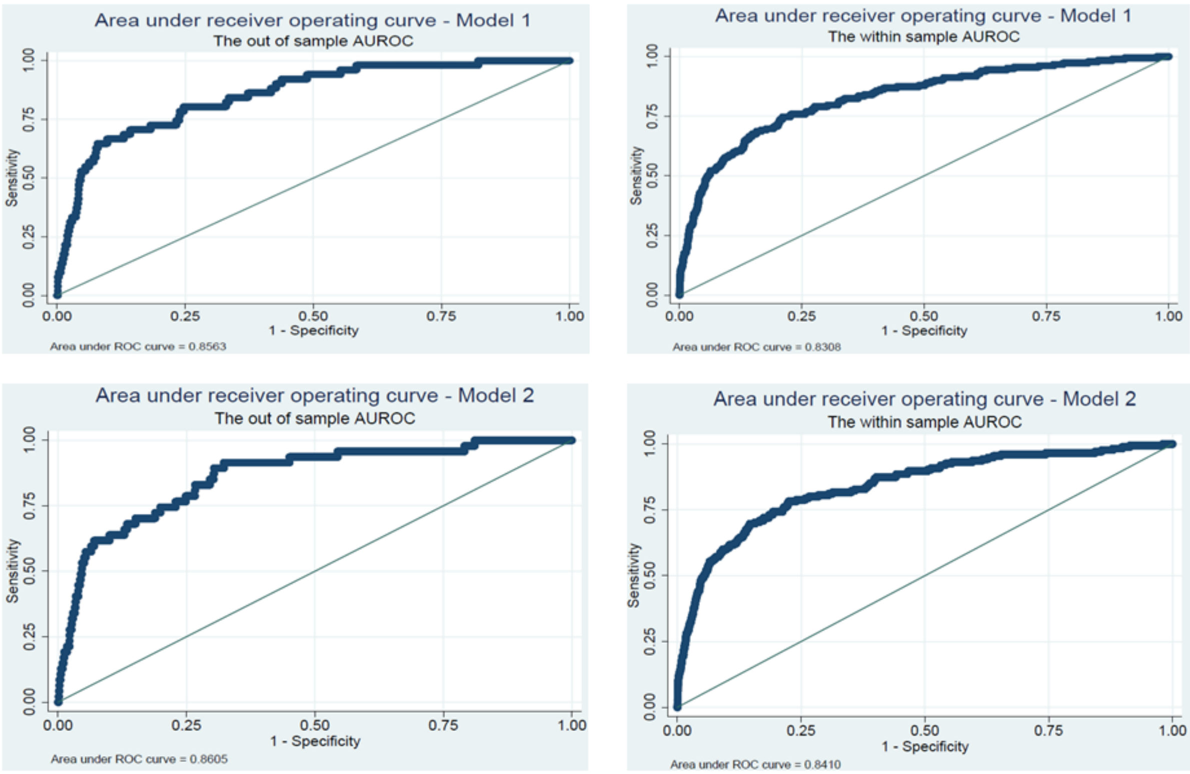

Table 5: Distribution of listed and delisted firms across exchanges

This table shows the distribution of firms across each of the three exchanges namely, New York Stock Exchange (NYSE), NASDAQ, and Over the Counter Bulletin Board (OTCBB). The exchanges names are given in column (1). In columns (2), (4), (6), and (8) we provide the number of listed and delisted firms in each industry, while in column (3), (5), (7), and (9) we provide the percentage of these firms in each exchange for each listing/delisting status over the sample time period (1980 - 2016).

Exchange	Listed	%	M&A	%	Involuntary	%	Voluntary	%	total
NYSE	1,137	48.22	1,306	37.35	32	1.53	23	10.5023	2,585
NASDAQ	1,041	44.15	2,022	57.82	38	1.82	23	10.50	3,124
OTCBB	180	7.63	169	4.83	2,016	96.64	173	79	2,538
Total	2,358	100	3,497	100	2,086	100	219	100	8,160

Table 6: Pearson correlation matrix

This table shows the correlation coefficients among the proxy variables used in testing the hypotheses developed, where * means that the correlation coefficient is significant at 1% level.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Panel A																						
VolDel(1)	1																					
Size(2)	-0.0088*	1																				
Intangible(3)	-0.0051	0.2551*	1																			
Age(4)	0.0183*	0.3994*	0.0975*	1																		
Leverage(5)	-0.0006	0.0572*	0.0893*	-0.1345*	1																	
MB(6)	-0.0117*	-0.2431*	-0.0486*	-0.1980*	-0.0643*	1																
CAPEX(7)	-0.0102*	0.0095*	-0.2317*	-0.1543*	0.0677*	0.0087*	1															
Dividend (8)	-0.0068	0.2038*	-0.0195*	0.1301*	-0.0534*	0.0175*	0.0160*	1														
NEI (9)	-0.0090*	-0.2860*	-0.0880*	-0.3270*	-0.0939*	0.4002*	0.0612*	-0.0862*	1													
KZ (10)	0.0015	-0.1588*	-0.0555*	-0.1400*	0.1179*	-0.0755*	0.0321*	-0.2509*	0.0052	1												
Return (11)	0.0017	-0.0879*	-0.0255*	-0.0322*	-0.0205*	0.1268*	-0.0427*	-0.0417*	0.0312*	0.0163*	1											
ReturnVol (12)	0.0209*	-0.4337*	-0.0851*	-0.2536*	0.0510*	0.0751*	-0.0582*	-0.2398*	0.1848*	0.1095*	0.3711*	1										
STR (13)	0.0051	-0.3047*	-0.1309*	-0.0563*	-0.0046	-0.0919*	0.006	-0.0509*	-0.0104*	0.0709*	0.0189*	0.0377*	1									
FCFR (14)	-0.0104*	0.3737*	0.0323*	0.1474*	-0.1389*	-0.3788*	0.0797*	0.1828*	-0.4222*	-0.0524*	0.0210*	-0.3825*	0.0262*	1								
ROA (15)	-0.0126*	0.4040*	0.0658*	0.1547*	-0.0870*	-0.3693*	0.0395*	0.2050*	-0.4420*	-0.0480*	0.0135*	-0.3914*	0.0205*	0.9188*	1							
TVR (16)	-0.0371*	0.7522*	0.1743*	0.2644*	-0.1381*	0.0597*	0.0738*	0.2491*	-0.1512*	-0.1826*	-0.0069	-0.5618*	-0.1459*	0.4299*	0.4598*	1						
Revenue (17)	-0.0100*	-0.0791*	0.0168*	-0.2320*	-0.0410*	0.2042*	0.1007*	-0.0614*	0.2470*	-0.0062	0.0314*	0.0480*	-0.0166*	-0.0316*	-0.0299*	0.0385*	1					
RevenueVol (18)	0.0053	-0.2813*	-0.0940*	-0.1946*	0.0288*	0.1797*	-0.0090*	-0.0717*	0.2574*	0.0311*	0.0206*	0.1933*	0.0154*	-0.3167*	-0.3405*	-0.2514*	0.2454*	1				
Panel B																						
SGA (19)	0.003	0.5611*	0.1477*	0.2575*	0.0140*	-0.0084*	-0.0381*	0.1645*	-0.1179*	-0.1589*	-0.0327*	-0.2063*	-0.1439*	0.1033*	0.1175*	0.3938*	-0.0629*	-0.1261*	1			
totalfees (20)	-0.0209*	0.7607*	0.1460*	0.3087*	0.1090*	-0.0992*	0.0562*	0.1780*	-0.1865*	-0.1713*	-0.0472*	-0.3312*	-0.2429*	0.2365*	0.2599*	0.5602*	-0.0495*	-0.2120*	0.8173*	1		
SGAratio (21)	0.0027	-0.3072*	-0.0164*	-0.1693*	-0.0597*	0.3562*	-0.0335*	-0.1058*	0.4060*	-0.0044	0.0127*	0.2340*	-0.0249*	-0.5763*	-0.6227*	-0.2436*	0.1117*	0.3182*	-0.0724*	-0.2075*	1	
TFR (22)	0.0038	-0.3051*	-0.0815*	-0.0732*	0.0019	0.3206*	-0.0517*	-0.0676*	0.3998*	0.0139	0.0351*	0.1861*	-0.0005	-0.4752*	-0.5069*	-0.2645*	0.0011	0.2877*	-0.0744*	-0.1300*	0.6779*	1

Table 7: Descriptive statistics

This table reports the descriptive statistics of the variables used in the multivariate analysis for the delisted, listed and full sample firms. The full sample includes 2668 firms of which 239 firms that voluntarily delisted. Panel A presents the descriptive statistics (mean and standard deviation) for the quotation sample of the firms which is the average of the period from the IPO date of the firm (or the first entry into Compustat) to the delisted date (for delisted firms) or censoring date (for listed firms). Panel B, reports the descriptive statistics for the delisted and listed firms one day before the delisting event. We hypothetically assume that the last date of listed firms is the date of censoring. Panel C, reports the descriptive statistics for the entire sample. t-test is the t-statistics for the differences in means between the two groups. Money values are reported in millions of US dollars.

Variable	Panel A, Quotation sample					Panel B, One year before delisting					Full Sample	
	Listed Firms		Delisted Firms			Listed Firms		Delisted Firms				
	Mean	SD	Mean	SD	t-test	Mean	SD	Mean	SD	t-test	Mean	SD
Panel A												
Asymmetric information												
Size	6.1242	2.2658	4.5542	2.6916	37.6875***	6.8219	2.1762	4.5873	2.5597	14.3045***	6.0290	2.3243
Intangible	0.1303	0.1667	0.0707	0.1271	19.9083***	0.1939	0.2027	0.0833	0.1384	7.8884***	0.1267	0.1652
Age	2.7271	0.8571	2.4075	0.8157	20.5932***	3.1333	0.5603	2.8262	0.4905	7.8362***	2.7077	0.8581
Access to Capital												
Leverage	0.2132	0.2054	0.2441	0.2115	-8.2604***	0.2497	0.2277	0.2646	0.2463	-0.9174	0.2151	0.2059
MB	2.1111	1.7685	1.7311	1.8981	11.7780***	2.0447	1.6326	1.5510	1.8176	4.2381***	2.0880	1.7789
CAPEX	0.0610	0.0651	0.0536	0.0637	6.2023***	0.0481	0.0564	0.0467	0.0596	0.3616	0.0605	0.0651
Dividend	0.0132	0.0245	0.0084	0.0202	10.7058***	0.0148	0.0263	0.0062	0.0174	4.6642***	0.0129	0.0243
NEI	0.0333	0.1498	0.0460	0.1658	-4.6138***	0.0146	0.1420	0.0179	0.1046	-0.3347	0.0341	0.1509
KZ	-2.9898	11.0006	-0.6531	6.8568	-11.6986***	-5.7833	15.1808	-1.4904	9.9427	-3.8867***	-2.8504	10.8122
Financial Visibility												
Return	0.0796	0.2694	0.0777	0.3166	0.3905	-0.0132	0.2045	0.0866	0.4391	-6.0493***	0.0795	0.2725
ReturnVol	0.0298	0.0175	0.0380	0.0254	-22.4462***	0.0265	0.0139	0.0482	0.0395	-15.2507***	0.0302	0.0181
Agency Costs												
FCF	0.0419	0.2262	-0.0037	0.2634	11.0109***	0.0012	0.2576	-0.0741	0.3665	3.9716***	0.0391	0.2289
Liquidity												
Turnover	0.0625	0.0660	0.1196	0.1795	-40.4111***	0.0515	0.0315	0.0890	0.1272	-11.1152***	0.0659	.0789
Others												
Revenue	0.1563	0.3642	0.1356	0.3987	3.1127***	0.0499	0.3434	0.0358	0.3515	0.5797	0.1550	0.3664
RevenueVol	0.2108	0.2571	0.2711	0.2657	-12.8880***	0.2093	0.2679	0.2887	0.2957	-4.1567***	0.2144	0.2581
Panel B												
Direct Listing Expenses												
SGA	49.5207	110.2541	41.2945	119.0363	3.8945***	65.2220	123.5958	35.6725	108.568	3.253***	49.0233	110.8209
TLF	3.7472	4.0649	3.3190	4.4820	1.9132**	2.4143	1.4312	1.5845	2.2935	1.3779	3.7367	4.0760
SGAratio	0.2821	0.2458	0.2934	0.2542	-2.3964**	0.3064	0.2693	0.3379	0.2882	-1.5649	0.2828	0.2463
TLFratio	0.0353	0.2097	0.0679	0.2266	-2.8320***	0.0318	0.1000	0.0694	0.2389	-0.6242	0.0361	0.2102
Fee	0.1081	0.1709	0.0290	0.0416	26.2127***	0.1335	0.2027	0.0318	0.0550	7.3501***	0.1033	0.1671
SOX	0.8712	0.4898	0.6160	0.4440	27.8671***	0.9906	0.5141	0.5846	0.4209	11.0128***	0.8565	0.4909
Auditfee	0.7160	0.4509	0.5123	0.4999	24.6968***	0.7425	0.4373	0.5205	0.5007	7.0945***	0.7036	0.4566

Table 8: Determinants of voluntary delisting

This table reports results of the determinants of the voluntary delisting decision. The sample includes 2668 firms of which 239 have voluntarily delisted for the period from 1980 to 2016. Panel A reports the results from the logit regressions to determine the factors affecting the decision to voluntarily delist. The dependent variable is a binary variable equals one when the firm is delisted. Model (1) is the base model and includes all the control variables discussed in section (3). Model (2) adds the revenue and revenue's volatility to the model to be tested in line with the theoretical real options model. Marginal effects are computed for each model. Panel B reports the results from the hazard model. The dependent variable is the time to delist, which measures the time between the IPO (or, if the IPO date is not available, the first available observations in Compustat). Model (3) is the base model and includes all the control variables discussed in section (3). Model (4) adds the revenue and revenue's volatility to the model to be tested in line with the theoretical real options model. Hazard ratios are reported which indicates the marginal effect of a unit increase in the independent variable for increasing the delisting event. For the hazard models, the firm-year observations are considered as recurring censored events until the firm is voluntarily delisted. The table reports the coefficients and, in parentheses, the standard errors which are corrected for firm-level clustering effects using a robust-variance estimation methodology. ***, **, * means that the coefficients are significant at the 1%, 5%, and 10% level, respectively. Variables are defined in Append B. We control for year, industry, and stock exchange listing using dummies.

Variable	Logit model			Hazard model		
	(1)	(2)	Marginal effect	(3)	(4)	Hazard ratio
Size	-0.3248**	-0.3180***	6.0581	-0.2596***	-0.2521***	0.7772
	(0.1495)	(0.0714)		(0.0436)	(0.0432)	
Intangible	-1.6150**	-1.4721**	0.1298	-1.0736*	-0.9119	0.4017
	(0.6384)	(0.5995)		(0.5696)	(0.5615)	
Age	0.3773	0.3770**	2.7121	-1.2418***	-1.2253***	0.2937
	(0.4519)	(0.1918)		(0.1695)	(0.1707)	
Leverage	1.2323***	1.2347***	0.2141	0.9766***	1.0094***	2.7440
	(0.3282)	(0.2742)		(0.2629)	(0.2597)	
MB	-0.2918***	-0.2756***	2.1050	-0.3043***	-0.2872***	0.7503
	(0.1041)	(0.0993)		(0.1046)	(0.1017)	
CAPEX	-2.2096	-1.8942	0.0597	-2.5671*	-2.2377	0.1067
	(1.7483)	(1.5337)		(1.5508)	(1.4871)	
Dividend	-0.4658***	-0.4668***	0.4688	-0.7542***	-0.7483***	0.4732
	(0.1750)	(0.1748)		(0.1713)	(0.1716)	
NEI	-1.5384**	-1.5395**	0.0345	-1.8436**	-1.8560**	0.1563
	(0.7371)	(0.7103)		(0.7336)	(0.7293)	
FCFR	-0.7788***	-0.6212**	0.0377	-0.9197***	-0.7272***	0.4833
	(0.2590)	(0.2678)		(0.2175)	(0.2301)	
Turnover	-0.0120	-0.0631	0.0641	-0.5212	-0.5375	0.5842
	(1.7744)	(1.0209)		-0.5212	(0.7660)	
Return	-0.2375**	-0.2397**	0.0789	-0.2596***	-0.2631***	0.7686
	(0.1056)	(0.0976)		(0.0566)	(0.0572)	
ReturnVol	0.1052*	0.1033***	3.0739	0.0895***	0.0871***	1.0910
	(0.0567)	(0.0328)		(0.0137)	(0.0139)	
Revenue		-0.4705**	0.1564		-0.5561**	0.5734
		(0.2289)			(0.2293)	
RevenueVol		0.5530**	0.2151		0.6313***	1.8801
		0.5530**			(0.2148)	
Constant	-2.1800	-2.4886***		-5.7418***	-5.9280***	
	(1.6587)	(0.8502)		(0.3781)	(0.3790)	
Wald chi2	324.13***	330.72***		311.46***	329.94***	
Likelihood ratio test	-1223.6011	-1219.2425		-690.44982	-684.08054	
AIC	2557.202	2552.485		1408.9	1400.161	
BIC	3043.824	3056.801		1533.241	1542.265	
Firm-year observations	51,414	51,414		53,184	53,184	

Table 9: Unobserved heterogeneity

This table reports the results from the hazard model under two unobserved heterogneity assumptions namely: (i) firm-level frailty ($\upsilon_{i,t} = \upsilon_i$), and (ii) shared frailty efects at the industry level using the two-digit SIC codes ($\upsilon_{i,t} = \upsilon_j$ where j = SIC code). The table reports the coefficients and, in parentheses, the standard errors which are corrected for firm-level clustering effects using a robust-variance estimation methodology. ***, **, * means that the coefficients are significant at the 1%, 5%, and 10% level, respectively. Variables are defined in Appendix B. We control for year and stock exchange listing using dummies.

Variable	Baseline model	Firm-level frailty	SIC-level shared frailty
Size	-0.2521***	-0.2321***	-0.2550***
	(0.0432)	(0.0463)	(0.0381)
Intangible	-0.9119	-0.9082	-0.8270
	(0.5615)	(0.5652)	(0.5428)
Age	-1.2253***	-1.2762***	-1.2009***
	(0.1707)	(0.2111)	(0.1026)
Leverage	1.0094***	1.0094***	0.9496***
	(0.2597)	(0.2664)	(0.2840)
MB	-0.2872***	-0.2633***	-0.2699***
	(0.1017)	(0.1012)	(0.0665)
CAPEX	-2.2377	-2.1782	-2.3565*
	(1.4871)	(1.4856)	(1.3536)
Dividend	-0.7483***	-0.7328***	-0.7971***
	(0.1716)	(0.1756)	(0.1791)
NEI	-1.8560**	-1.8793**	-1.7407**
	(0.7293)	(0.7464)	(0.7569)
FCFR	-0.7272***	-0.6107**	-0.7946***
	(0.2301)	(0.2453)	(0.2326)
Turnover	-0.5375	-0.4516	-0.6165
	(0.7660)	(0.7696)	(0.6893)
Return	-0.2631***	-0.3971	-0.2668***
	(0.0572)	(0.3234)	(0.0846)
ReturnVol	0.0871***	0.1429***	0.0887***
	(0.0139)	(0.0431)	(0.0170)
Revenue	-0.5561**	-0.5666**	-0.5493**
	(0.2293)	(0.2218)	(0.2173)
RevenueVol	0.6313***	0.6305***	0.6239***
	(0.2148)	(0.2201)	(0.2326)
Constant	-5.9280***	-6.3807***	-5.8735***
	(0.3790)	(0.4881)	(0.4312)
Wald chi2	311.46***	293.55***	307.13***
Log Likelihood	-690.44982	-682.77655	-683.09338
AIC	1408.9	1399.553	1400.187
BIC	1533.241	1550.539	1551.172
Observations	53,183	53,183	53,183
Number of groups			9

Table 10: Matching samples

This table reports the results of the hazard model for the entire sample of volunarilty delisted firms and a comparision sample of listed firms based on different matching criteria. Model (1) is the base model which is the hazard model reported in 8 Model (4). Models from (2) to (7) are the hazard models with matched control firms based on Market-to-Book (MB), Size, 2 digit SIC industry code, Industry and Size, Industry and MB, and Industry, Size, and MB combined, respectively. *The table reports the coefficients and, in parentheses, the standard errors which are corrected for firm-level clustering effects using a robust-variance estimation methodology. ***, **, * means that the coefficients are significant at the 1%, 5%, and 10% level, respectively. Variables are defined in Appendix B. We control for year and stock exchange listing using dummies.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size	-0.2521***	-0.2301***	-0.1068***	-0.0403	-0.0993**	-0.2214***	-0.0992**
	(0.0432)	(0.0447)	(0.0405)	(0.0398)	(0.0409)	(0.0418)	(0.0429)
Intangible	-0.9119	-0.1847	-0.1376	0.5133	-0.2868	-0.4805	-0.0839
	(0.5615)	(0.5581)	(0.5274)	(0.4854)	(0.5330)	(0.5601)	(0.5311)
Age	-1.2253***	-1.5006***	-1.3770***	-0.6192***	-1.3469***	-1.4422***	-1.3421***
	(0.1707)	(0.2149)	(0.2172)	(0.1875)	(0.2047)	(0.2068)	(0.2151)
Leverage	1.0094***	0.9830***	1.1274***	0.2277	0.9232***	0.7385***	1.1841***
	(0.2597)	(0.2838)	(0.2896)	(0.2972)	(0.3026)	(0.2797)	(0.2762)
MB	-0.2872***	-0.1246**	-0.2807**	-0.0956	-0.2433***	-0.1286**	-0.1553*
	(0.1017)	(0.0559)	(0.1092)	(0.0633)	(0.0902)	(0.0648)	(0.0876)
CAPEX	-2.2377	-0.9247	-0.4172	-1.2732	-1.1209	0.0102	-0.4020
	(1.4871)	(1.3287)	(1.3778)	(1.4112)	(1.4236)	(1.3932)	(1.4292)
Dividend	-0.7483***	-0.8740***	-0.9133***	-1.3317***	-1.0154***	-0.9468***	-0.9983***
	(0.1716)	(0.1972)	(0.2088)	(0.2069)	(0.1984)	(0.1984)	(0.1999)
NEI	-1.8560**	-1.7079**	-1.6477**	-1.1837	-1.4417*	-1.8612**	-1.2289
	(0.7293)	(0.8137)	(0.7942)	(0.7262)	(0.7614)	(0.7395)	(0.7945)
FCFR	-0.7272***	-0.7828***	-0.7174***	-0.8871***	-0.4112	-0.9538***	-0.6885***
	(0.2301)	(0.2756)	(0.2548)	(0.2022)	(0.2521)	(0.2322)	(0.2426)
Turnover	-0.5375	-0.5529	-0.8142	-1.6895**	-0.9223	-0.7680	-0.7793
	(0.7660)	(0.7461)	(0.7443)	(0.7991)	(0.8261)	(0.7417)	(0.8546)
Return	-0.2631***	-0.5285**	-0.1253	-0.1336**	-0.5212**	-0.3274**	-0.3109
	(0.0572)	(0.2146)	(0.1193)	(0.0557)	(0.2348)	(0.1366)	(0.1928)
ReturnVol	0.0871***	0.1385***	0.1089***	0.0857***	0.1655***	0.1327***	0.1163***
	(0.0139)	(0.0344)	(0.0287)	(0.0262)	(0.0354)	(0.0276)	(0.0311)
Revenue	-0.5561**	-0.2349	-0.4704**	-0.6463***	-0.4033*	-0.3623	-0.3886*
	(0.2293)	(0.2138)	(0.2145)	(0.2291)	(0.2260)	(0.2419)	(0.2338)
RevenueVol	0.6313***	0.5350**	0.6550***	0.5975***	0.7610***	0.5391**	0.6017**
	(0.2148)	(0.2244)	(0.2476)	(0.2236)	(0.2432)	(0.2384)	(0.2557)
Constant	-5.9280***	-5.5355***	-5.7648***	-4.3043***	-6.0034***	-5.4780***	-6.1867***
	(0.3790)	(0.4402)	(0.4580)	(0.3963)	(0.4565)	(0.4228)	(0.4449)
Wald chi2	311.46***	247.7***	174.83***	354.68***	190.83***	278.93***	206.22***
Log Likelihood	-690.44982	-307.62325	-300.54427	-294.25784	-296.48166	-302.54988	-306.11631
AIC	1408.9	647.2465	633.0885	620.5157	624.9633	637.0998	644.2326
BIC	1533.241	755.5636	741.4006	728.8352	733.2779	745.4144	752.5472
Observations	53,183	6,437	6,437	6,437	6,437	6,437	6,437

Appendix A

Proof of Proposition 1

Now we can prove that, for fixed uncertainties (σ_1, σ_2) the probability of delisting increases with the expected rate of return.

Proof of Proposition 2

The probability to delist a firm from the exchange is equal to:

$$\Phi \frac{K - \mu(Q)}{\sigma} \tag{12}$$

The first derivative of Equation (12) is:

$$\varphi\left(\frac{K - \mu(Q)}{\sigma}\right)\left(-\frac{1}{\sigma}\right)\mu'(Q) \tag{13}$$

where,

$$\mu(Q) = \frac{1}{\eta}\left(-Q - \frac{1}{2}(\sigma_1^2 - \sigma_2^2)\right) \tag{14}$$

Therefore,

$$\mu'(Q) = -\frac{1}{\eta} \tag{15}$$

Hence, the first derivative of (12) is:

$$\varphi\left(\frac{K - \mu(Q)}{\sigma}\right)\left(-\frac{1}{\sigma}\right)\left(-\frac{1}{\eta}\right) \tag{16}$$

After rearranging its terms, it yields:

$$\varphi\left(\frac{1}{\sigma\eta}\right)\left(\frac{K - \mu(Q)}{\sigma}\right) > 0 \tag{17}$$

Appendix B

Table 11: Variables Definition of the Firm's Direct Listing Expenses

This table defines the main variables used in constructing the listing expenses variable used in our real options model. Columns 1 and 2 indicate the variable's code and name; Column 3 defines each variable.

Code	Variable Name	Definition
FEES	Exchange Listing Fees	Fees paid to the exchange at which the firm is listed on. Constructed as per the details given in **NASDAQ**, **NYSE**, and **OTCBB** websites.
SOX	Compliance Fees	Sarbanes Oxley compliance fees: Average annual SOX compliance fees based on the firms size following **Protiviti** website.
AUDITFEES	Direct Auditing Fees	Average cost of annual auditing fees based on the firms annual revenues following PWC reports in 2009 and 2015.
TLF	Total Listing Fees	The sum of: Exchange listing fees, SOX compliance fees, and direct auditing fees. FEES + SOX + AuditFEE.
TLFratio	The ratio of TLF	The value of total listing fees as a percentage of revenues
SGA	Selling, General and Administraive	The value of Selling, General, and Administrative Expenses taken from Compustat
SGAratio	The ratio of SGA	The value of SGA as a percentage of revenues

Table 12: Variables Definition and the Hypotheses Tested

This table defines the proxy variables and list them according to the hypothesis tested. Panel C, provides the Compustat item codes for the constructed variables. Panel D, defines the proxy variables and Panel F lists the expected sign as per the hypotheses developed.

Code	Variable Name	Compustat/CRSP Item Code	Definition	A priori
Dependent Variable				
VolDel	Voluntary Delisting	dlstcd ==332 — dlstcd==570	Voluntary Delisting: Equals one when the firm is delisted on the year of delisting and zero otherwise	
Asymmetric information				
Size	Size	LOG (SALES)	Natural logarithm of total sales in 1962 dollars	(-)
Intangible	Intangible Assets	INTAN/AT	intangible assets/total assets	(+)
Age	Firm Age		The number of years since the firm's IPO date, if not available then the number of years since the firm's record first appears in Compustat	(-)
Access to Capital				
Leverage	Leverage	(DLTT+DLC)/AT	Total debt/ Total asset	(+)
MB	Market to Book Ratio	(AT-CEQ+(PRCC_F*CSHO))/AT	Market value of total assets divided by total assets	(-)
CAPEX	Capital Expenditure	CAPX/AT	capital expenditure scaled by total assets	(-)
Dividend	Dividend Dummy		Equals one if a firm paid out dividends during the fiscal year and zero otherwise	(-)
NEI	Net Equity Issuance	(SSTK-PRSTKC)/AT	Ratio of net equity issuance to total assets	(-)
KZ	KZ-Index	KZ = -0.0019*(CFT/KT-1) + 0.2826*(Q) + 3.139*(TD/TA) - 39.36*(DIV/KT-1) - 1.315*(CA/KT-1)	where (CFt/Kt-1) is the cash flow over the lagged property, plant and equipment. (Q) is [total asset(AT) = book value equity (CEQ) + market value equity (PRCC-F*CSHO) / total assets(AT)]. (TD/TA) is the total debt over total assets. (DIV/Kt-1) is the cash dividends over lagged property, plant and equipment. (CA/Kt-1) is cash balance over lagged property, plant and equipment. A firm with a high KZ index is considered to be more financially constrained.	(-)
Financial Visibility				
Return	Stock Price return	(prccd[_n] - prccd[_n-1])/prccd[_n-1]	Daily stock price return over the past year.	(-)
ReturnVol	Stock Return Volatility		The standard deviation of daily stock returns over the past year.	(+)
STR	Stock Turnover Ratio	ln(cshtr_f)/ln(csho)	log(Annual number of shares trader) / log(Number of shares outstanding)	(-)
Agency Costs				
FCFR	Free Cash Flow Ratio	(IBC+XIDOC+DPC+TXDC+ESUBC+SPPIV+ FOPO+FSRCO)/at we follow Frank and Goyal (2003) definition:	Free Cash Flow / Total Assets where Free Cash Flow = Income before extra items + Discontinued Operation + Depreciation and Amortization + Deferred Taxes + Equity in Net Loss + Gain/Loss from PPE + Other funds from operations + Other sources of funds	(+)
ROA	Return on Assets	EBIT/AT	EBIT / Total Assets	(+)
Liquidity				
TVR	Trade Volume Ratio	ln(cshtr_f)*ln(prcc_f)	log(Annual Number of Shares traded)*log(Closing price at the end of the year)	(-)
STR	Stock Turnover Ratio	ln(cshtr_f)/ln(csho)	log(Annual number of shares trader) / log(Number of shares outstanding)	(-)
Others				
Revenue	Firms revenue growth	(sale[_n] - sale[_n-1])/sale[_n-1]		(-)
RevenueVol	Revenues volatility		The standard deviation of quarterly revenue growth each year	(+)