Delisting Timing: A Theoretical Model and Empirical Evidence*

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Abstract

We develop a theoretical real options model that can be used by executives to take a decision on the timing of voluntary delistings. The model is applied to 2358 US listed firms (1980-2016) to classify them into listed firms which should be listed and delisted firms which should be delisted (good decisions), and listed firms which should be delisted and delisted firms which should be listed (bad decisions). A survival model is then employed to examine the determinants of the delisting process for these two samples, such as agency costs, access to capital, stock liquidity, asymmetric information and financial visibility hypotheses. There are significant differences between the good and the bad decisions subsamples. We find that the role of some of the variables in the delisting of firms that made a bad decision differs from the role that these variables have in the delisting of firms that made a good decision. We also show that the turnover, turnover growth and turnover volatility are key determinants of voluntary delisting.

Keywords: Delisting; Corporate Information; Real Options; Survival Analysis; Voluntary Delisting.

JEL Codes: G12, G32, G34.

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1 Introduction

Perhaps a symptom that a less effusive sentiment regarding the public firm status still exists is the 8th August 2018 Elon Musk's tweet: "Am considering taking Tesla private at $420. Funding secured", after which Telas's share price went up 7.4% to $367.25, before being halted on Nasdaq at 2:08pm New York time.[2] Why did Elon Musk want to delist Tesla? Is it profitable to delist Tesla now? If the delisting of Tesla now is profitable, does a delay in the decision turn it even more profitable? These are legitimate questions, for which we do not have yet satisfactory answers.

We note that the listing decision is usually associated with the possibility of having access to a wider range of (cheaper) financial resources, enhancing market visibility, drawing the attention of market makers, or using stocks or stock options programs to attract talented managers. However, it may also carry disadvantages, such as those related to the ongoing listing fee and the expenses associated with the compliance with regulations. Therefore, if the net benefits of being listed are sufficiently low, it might be optimal to delist. Whilst "listing" is usually seen as a sign of the firm's confidence on its future financial viability and the managers' willingness to work under tighter regulation rules and public scrutiny, "delisting" can be perceived as a sign that the current business strategy failed and a new one will have to be followed in the future, which may lead firms to delay the decision beyond the optimal time.

We develop a theoretical model that can be used by firms to decide when to delist voluntarily. It is based on the real options theory (McDonald and Siegel, 1986; Dixit and Pindyck, 1994) which, if applied to a voluntary delisting, asserts that listed firms hold the *option to delist*. This new type of real option gathers its value from the uncertainty about the future gains resulting from the delisting. The exercise of this option is a financial decision process that is not automatic and it requires a complex analysis when (if) it is optimal to do so. Our empirical analysis shows that the turnover is a key determinant of the delisting, so we used it as the underlying variable of our real option model. We apply this model to a data sample that comprises information on 2358 US listed firms, of which 219 were delisted voluntarily, and classify the firms' ongoing listing and delisting decisions as "good" or "bad".

Then, we study the differences between the good and the bad decisions subsamples, considering

[2]See Financial Times, article published on 9th August 2018, by Peter Wells, "Tesla shares give up post-Musk take-private tweet gains": https://www.ft.com/content/3087d9d4-9bff-11e8-ab77-f854c65a4465.

variables commonly used in the finance literature as proxies for Asymmetric Information, Access to Capital, Financial Visibility, Agency Costs and Stock Liquidity hypotheses. Starting with an univariate analysis, we show that the differences are statistically significant and then progress to analyse these proxy variables in a discrete-time duration-dependent hazard model, to examine their effect on the likelihood of delisting and to estimate how close each firm is to the "time to delist".

Our hazard rate model has been used for bankruptcy predictions (Ongena and Smith, 2001; Campbell et al., 2008; Mehran and Peristiani, 2010). In this context, Heckman and Singer (1984) asserts that the heterogeneity across observations biases non-parametric estimates in favor of negative duration dependence. To mitigate this bias, Mehran and Peristiani (2010) suggest the use of a parametric survival model with random effects. Ongena and Smith (2001) also control for heterogeneity through firm-specific characteristics. Hence, in this paper, we opt for a discrete-time firm-level random effects model (Rabe-Hesketh and Skrondal, 2008).[3] In the hazard model, the dependent variable is the time duration between the IPO date and the time of the delisting.[4]

Amongst other results, we find that the turnover and the turnover growth are both negatively related to the likelihood of delisting, and the turnover volatility is positively related to the likelihood of delisting. We also conclude that firms that make good ongoing listing or delisting decisions exhibit different characteristics from those that make bad decisions. Specifically, our findings regarding the effect of the turnover growth on the likelihood of delisting are not conclusive for firms that make a good decision, but show a negative relationship for firms that make a bad decision. Regarding the effect of the turnover volatility on the likelihood of delisting, our results are not conclusive for firms that make a bad decision, but show a positive relationship for firms that make a good decision. Concerning the relationship between the turnover and the likelihood of delisting, our findings reveal that it is negative for both subsamples. These are important results because they show that firms which are more prone to make bad ongoing listing or delisting decisions tend to exhibit different characteristics from those that are more prone to make good decisions.

Two recent studies highlight that the number of US public firms has decreased significantly since the middle of the 1990s. Specifically, Doidge et al. (2017) show that it increased significantly until 1996 and decreased afterwards, almost every year, so there are today much less public firms. Kahle

[3] Notice that the delistings are recorded annually, without reporting the day, hour, minute and second.

[4] For the cases where the IPO date was not available, we used the date the firm first appears in the CRSP database.

and Stulz (2017) also report a decline in the number of public firms, as well as that today's public firms are less profitable and significantly larger and older than before. This listing trend leads us to Jensen (1989), who advocates that the private firms' ownership financed by debt and equity is more efficient in resolving agency problems between managers and investors than the public firms' ownership.

Doidge et al. (2017) also conclude that the high delisting rate is a consequence of an uncommonly high rate of acquisitions of publicly listed firms, a finding that is also reported by Gao et al. (2013), who investigate why there are fewer firms going public, or being listed, based on the idea that the ongoing listing costs are higher than the benefits, or that the benefits for smaller firms, after the 1996 listing peak, are smaller than before. Their findings support the view that a decrease in the net benefits of being listed is the main cause for the lower listing rate, and reject the hypothesis that, over time, firms delayed more the listing decision in order to achieve a larger size. It is also shown that the propensity to be listed decreased to less than half of what it used to be.

There is as relatively extensive literature which studies the timing of the Initial Public Offerings (IPO) (Benninga et al., 2005; Busaba, 2006; Jiang and Wang, 2008; Casassus and Villalon, 2010; Çolak and Günay, 2011, among others). But the frameworks used in these studies have not yet been applied to study the timing of voluntary delistings, which is a surprise given that, as it is stated by Bharath and Dittmar (2010), the delisting can be seen as the reversal of the IPO, although the motivations underlying it are quite different from those underlying the IPO. For the use of the real options models on IPO decisions, we refer the readers to Draho (2000), Bustamante (2011), and Grenadier and Malenko (2011).

We study voluntary delistings only, but firms can also be delisted involuntarily by the exchange if they are unable to meet the regulatory standards, such as when they do not obey to the regulations on the debt obligations, stock liquidity, accounting practices, or ethical standards.[5] There are also delistings when firms are liquidated, or there is a merger or acquisition, or when firms decide to delist from one exchange only, if they are listed in more than one, or to switch from one exchange to another.

The delisting empirical literature is relatively extensive, from which we acknowledge that the

[5] For instance, Toshiba was recently on 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 of 2017, by Peter Wells).

delisting affects negatively the stock price (Sanger and Peterson, 1990; You et al., 2012) and the long-term stock trading volume (You et al., 2012), corporate governance and regulation changes affect the delisting decision of foreign firms from home exchanges (Chaplinsky and Ramchand, 2012; Bessler et al., 2012), the quality of the soon-to-be listed firm has an impact on whether the firm will be able to benefit from the listing decision (Chaplinsky and Ramchand, 2008), and firms may decide to become listed because they want to re-balance their leverage rather than increase their flexibility to raise capital (Pour and Lasfer, 2013). There are also works which focus on voluntary delistings only (Sanger and Peterson, 1990; Clyde et al., 1997), studies which do not distinguish voluntary delistings from involuntary delistings (Dewenter et al., 2010; Bakke et al., 2012), and researches which investigate both voluntary and involuntary delistings (Shumway, 1997; Pour and Lasfer, 2013).

The rest of the paper is organized as follows. Section 2 describes our data sample, which is used to calibrate our theoretical delisting model and in the empirical analyses. Section 3 develops our real options delisting timing model. Section 4 presents the discrete-time duration-dependent hazard model and reports the first part of our empirical findings. Section 5 provides the robustness tests on our empirical analysis. Section 6 shows the empirical findings for both the *good* and the *bad* decisions samples. Section 7 concludes the work and discusses its practical implications.

2 Data Sample

This section describes our data sample, which is used in Sections 3, 4 and 6. Following previous literature (Bharath and Dittmar, 2010; Pour and Lasfer, 2013), we exclude financial, insurance and utility firms. The initial sample comprises information on 2,577 firms, of which 2358 are listed on the Amex, NYSE or NASDAQ and 219 were delisted voluntarily. It covers the time period between 1980 and 2016. To be included in our sample, firms have to be listed for at least nine consecutive years. This duration condition is important because it enhances the reliably of the parameters' estimation used in the calibration of our delisting model.

We follow Doidge et al. (2017) and identify the delisted firms based on the CRSP shares delisting code (DLSTCD), according to which firms are organized into three categories: mergers and acquisitions (DLSTCD codes 200-399), involuntary delistings due to bankruptcy or liquidation (DLSTCD codes >=400 excluding 570 and 573), and voluntary delistings that account for firms that became private or are traded on the Pink Sheet (DLSTCD codes 570 and 570). Notice that, firms that are delisted from the main exchanges and are traded on the "Pink Sheets" are also considered delisted. We use Compustat to retrieve quarterly and yearly financial data and CRSP to get the daily share prices data, which we use for the regression models, developed in Section 4, We ensure that the delisted firms are not listed elsewhere.

Column 1 of Table 1 provides the number of listed firms on Amex, Nasdaq, or NYSE during a particular year of our sample period, whereas column 2 provides the number of delisted firms that voluntarily delisted from the exchange in that particular year. We note that the number of voluntary delisting changes significantly near well-known economic, financial, or regulatory events. For instance, they increased after the 2002 Sarbanes-Oxley Act, decreased after the 2008-09 financial crisis, and increased in 2015 (see also Marosi and Massoud, 2007). Notice that the first delisting starts in 1988 as we consider the firms that entered the data sample in 1980 and were listed for at least nine consecutive years.

[Insert Table 1 here]

3 A Theoretical Model

We use the *turnover* as the underlying variable of our real option model. Typically, firms are relatively small when they are listed the first time and they tend to justify the "listing" decision with the idea that they would like to pursue a more ambitious sales growth strategy, for which being public may help. Moreover, we rarely see a firm with a relatively large and growing turnover being delisted voluntarily. The relevance of the turnover size on firms' decision of continuing to be listed or becoming delisted is supported, among others, by Weir and Laing (2002), who show that firms which become private again have lower growth opportunities, and by Kahle and Stulz (2017), who report that today's public firms are significantly larger. In Sections 4 and 6, we present empirical evidence supporting this modeling assumption.

Let us assume that $\{S_t\}_{t\geq 0}$ stands for the firm's turnover and follows a geometric Brownian motion (GBM) given by:

$$dS_t = S_t(\alpha dt + \sigma dW_t) \tag{1}$$

The solution for Equation (1) is $S_t = S_0 \exp[\sigma W_t + \nu t]$, with $\nu = \alpha - \frac{\sigma^2}{2}$. Using the properties of the Brownian motion, the solution for Equation (1) can be rewritten as:

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

where $\tilde{W}_t = \frac{\sigma}{2} W_{\frac{4t}{\sigma^2}}$. A very important variable in this framework that may help computationally is

$$A_T^\nu = \int_0^T \exp[2(W_t + \nu t)]dt. \tag{3}$$

For $t \geq 0$, $\tilde{W}_t$ is also a Brownian motion, and so

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

$$\stackrel{law}{=} \frac{4}{\sigma^2} S_0 A^\mu_{\frac{\sigma^2 T}{4}} \tag{5}$$

where $\mu = \frac{2\nu}{\sigma}$. Knowing the distribution law of A_t^ν enables us to compute $\int_0^T S_t dt$ - see Corollary 6.6.2.4 of Jeanblanc et al. (2009) which provides a closed-form solution for the probability density of A_t^ν.

Proposition 3.1 *The law of A_t^ν is $P(A_t^\nu \in du) = \varphi(t,u)du$, where:*

$$\varphi(t,u) = \frac{u^{\nu-1}}{\sqrt{2\pi^3 t}} \exp\left[\frac{\pi^2}{2t} - \frac{1}{2u} - \frac{\nu^2 t}{2}\right] \int_0^\infty \exp[-\frac{1}{2}uy^2] y^\nu \Psi_y(t)dt \tag{6}$$

where,

$$\Psi_y(t) = \int_0^\infty \exp\left[-\frac{y^2}{2t} - r\cosh(y)\right] \sinh(y) \sin\left(\frac{\pi y}{t}\right) \tag{7}$$

If the focus of the analysis is on the use of the expectation A_t^ν only, one can take advantage of the existence of an analytical solution for this quantity, described in the following proposition.

Proposition 3.2 *The mean of A_t^ν is given by:*

$$E(A_t^\nu) = \frac{1}{4}\left(1 + c^{\nu/2} \exp[2(1+\nu)t]\right) \tag{8}$$

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

In our case, S_t^j is the turnover value at time t for the state $j = 1$, if the firm is listed, and the state $j = 2$, if the firm is delisted, which is driven by the following GBM process:

$$dS_t^j = \alpha_j S_t^j dt + \sigma_j S_t^j dW_t^i \tag{9}$$

with $E(dW_t^1 dW_t^2) = \rho dt$.

We note that the turnover processes is considered under the same information filtration if $\rho = 1$. This is a relevant assumption for the delisting decision process since the executive has the same information with the company being listed or delisted. The proofs of the above propositions are provided in the Appendix B.

Figure 1 shows a time line that illustrates the two stages of our delisting option timing game. The reference point of decision making is fixed at time $t = 0$, that is today. Our calculations depend on the current value of the turnover S_0^j, with $j = 1, 2$. Thus, calculations can be done recursively, as an ongoing decision process, reflecting the arrival of new information at the end of each year.

Notice that we are searching for the delisting decision (action) period defined by the end of the period $\tau^* \in \{t_1, t_2, \ldots, t_n, \ldots\}$ in which the event $\{\tau^* = t_i\}$ occurs. The decision to delist the firm becomes effective in the period $(t_{i-1}, t_i]$ such that the firm is delisted from time t_i onwards.

[Insert Figure 1 here]

3.1 A Simplified Framework

One simple way to identify an 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 firm is listed and the total turnover the firm would generate if the company would be delisted, plus the savings costs associated with the delisting decision. Thus, we are searching for the month when the quantity in (10) is maximum.

$$\Delta_{t_i} = E\left(\int_0^{t_i} S_t^2 dt - \int_0^{t_i} S_t^1 dt + K(t_i)\right) \tag{10}$$

where K represents the ongoing listing expenses when the firm is listed and it switches to a saving cost if the firm becomes delisted.

We collected empirical data in order to estimate these costs, and concluded that they are about 3.61% of the annual turnover. Further details on this parameter estimation are provided in Section 3.3. Therefore, based on (10) we get:

$$\Delta_{t_i} = E\left(\int_0^{t_i} S_t^2\right) dt - 0.9639E\left(\int_0^{t_i} S_t^1 dt\right) \tag{11}$$

Denoting by m_2^i and m_1^i the first and the second expectation in Equation (11), respectively. Using this result in the above Proposition 3.2, we obtain:

$$m_j^i = \frac{S_0^j}{\sigma_j^2}\left[1 + \frac{2\sigma_j}{2\alpha_j - \sigma_j^2 + 2\sigma_j} \exp\left(\frac{\sigma_j t_i}{2}(2\alpha_j - \sigma_j^2 + \sigma_j)\right)\right] \tag{12}$$

for any given i and $j = 1, 2$.

Hence, we have an analytical solution for each $\Delta_{t_i} = m_2^i - 0.9639m_1^i$ that can be calculated for $i = 1, 2, \ldots$, which enables us to determine where is the maximum over a given decision horizon. Notice that, if the sequence $\{\Delta_{t_i}\}_{i=1,2,\ldots}$ is increasing, it implies that it is never optimal to delist, or in other words the firm should stay listed. With the ebbs and flows of new information on the market, the parameters of the underlying GBM process assumed to generate the turnover values may change. Then the decision is revalued using the new parameter values. This methodology can be extended to consider recursive listing and delisting events, or to calculate the value of the option to delist with Monte Carlo simulation as described in the Appendix A.

Our model relies on two sets of parameters. One set relates to the GBM process, namely the turnover trend for each state, α_1 if the firm is listed and α_2 if the firm is delisted, and the turnover volatility, σ_1 if the firm is listed and σ_2 if the firm is delisted, another relates to the ongoing listing expenses (K), which exists only when the firm is listed and is a saving cost if the firm is delisted.

3.2 GBM Parameters

We estimate the turnover growth rate and volatility using the sample described in Section 2. Table 2 shows our results for the full sample, and for the listed and the delisted firms samples, as well as for the t-test on the mean difference between the above latter two samples. The mean turnover volatility of the delisted firms is about 11% higher than that of the listed firms (35.2% against 31.6%) and this mean difference is statistically significant at 10% level. Notice that, although the study of the determinants of the higher volatility of the delisted firms is out of the scope of this research, this mean difference supports our modeling choice of using two independent GBM processes for the turnover states.[6] Finally, the turnover growth rates of the listed and the delisted firms samples are very similar (23.9% against 24.0%) and the mean difference is not statistically significant.

[Insert Table 2 here]

3.3 Listing Expenses

There is no public data available on the expenses associated with the ongoing listing status. However, Ritter (1987) estimates that firms pay about 7% of the IPO gross proceeds to cover the variable costs related to the auditing, certification and dissemination of accounting information, and the ongoing listing fee, and Benninga et al. (2005) show that there is an average increase of \$62 million in the *SGA (selling, general, and administrative)* costs between the pre-IPO and the post-IPO year, which means that the "private benefits" (the saving costs if the firm is delisted) are about 10% of the firms' annual profit. Additionally, PwC released in 2012 and 2015 data on the average US IPO cost, with information on the expenses associated with the *ongoing public status*, classified as ongoing listing exchange fee, auditing fee, and compliance fee.[7]

We estimate the dollar amount of the average auditing fee paid by the US public firms. For the compliance fee, we determine the firms' average annual SOX compliance costs based on the information released in 2006 and 2017 by the Protiviti consulting and professional services (Sarbanes-Oxley compliance survey).[8] We find that the average total annual ongoing listing cost is \$3.7367 million (3.61% of the annual turnover).[9] We also estimate the dollar amount of the *selling, general, and*

[6] Perhaps the higher turnover volatility of the delisted firms is because these firms are smaller and, therefore, more innovative and prone to engage with higher risk projects.

[7] The PwC's report is available at: https://www.PwC.com/us/en/deals/publications/cost-of-an-ipo.html.

[8] Information available at: https://www.protiviti.com/US-en/insights/sox-compliance-survey

[9] Notice that our estimation is not too far away from the 10% of gross profits of Benninga et al. (2005), despite the fact that the data used by Benninga et al. (2005) is from 1982-2000. Also, the small difference between these two estimations might be because the sample of Benninga et al. (2005) comprises listed firms only, whereas ours incorporates both listed and delisted firms. We note that the mean of the ongoing listing costs, expressed as a percentage of the annual turnover, differs significantly across the listed and the delisted firms (3.53% against 6.79%).

administrative (SGA) expenses, and the correlation coefficient between the SGA and the average ongoing listing expenses, which is 0.8173 and statistically significant. The correlation coefficient between the SGA expenses and the ongoing listing fee is 0.6779, and it is also statistically significant. Table 10 in the Appendix D defines the variables used in these estimations.

3.4 Theoretical Findings

Figure 2 illustrates our main theoretical findings. Notice that, because there is no information available on the firms' turnover after they become delisted, we use a Monte Carlo simulation to estimates the future turnover for a time period of 25 years, based on the last available turnover value. The figure at the top reveals that it is profitable to delist now (time zero) but not yet optimal, because the delisting profit increases if the decision is delayed. For the figure at the bottom, we changed the turnover volatility of the delisting state (State 2) from 32% to 10%, and conclude that it makes the "delisting now" optimal and more profitable. Notice that, the delisting profit decreases if the decision is delayed. We can also see that at year 12 the listed firm is indifferent between continuing to be listed or to becoming delisted. Notice that, the delisting profit curve crosses the zero profit threshold line. Therefore, a lower turnover volatility in the delisted state accelerates the delisting decision, as it was expected.

[Insert Figure 2 here]

Figure 5 in the Appendix B provides a complementary sensitivity analysis, where we also study the effect of changes in the turnover growth rate on the delisting profit and timing. Comparing Figure 2, the figure at the top, with Figure 5, the figure at the top in the left-hand side, we conclude that a decrease in the turnover growth rate of the delisted state (State 2), from 24% to 10%, makes the delisting now optimal. Notice that a decrease in the turnover growth rate in state 2 may produce "optimal" time to delist only in the very near future, since the incentive is the saving on the exchange fee only. As the time elapses, the lower growth rate enhances no delisting decisions. This result also highlights that, although the numerical calculation indicates delisting, the profit from the delisting is very small, as it is projected on the vertical axis.

4 Empirical Evidence

In this section, we study the determinants of the delistings decision, using a hazard model (survival analysis) that considers the length of time it takes the delisting event to occur. We start this section by justifying the use of our control variables then we discuss the methodology, and end with providing our main results. Table 11, in the Appendix D, defines the regression variables.

4.1 Control Variables

Our hazard model uses the following set of firm (and market) specific control variables:

Asymmetric Information: according to Pagano et al. (1998) and Bharath and Dittmar (2010), firms with high asymmetric information between managers and investors are more likely to become private. On the other hand, Pour and Lasfer (2013) advocates that smaller firms with high intangible assets value have higher adverse selection costs, and that this increases the probability of delisting, although this finding is contradicted by Marosi and Massoud (2007). We use the turnover size, intangible assets and age as proxies for the adverse selection cost.

Access to Capital: it is well-documented that becoming public gives firms access to a wider range of cheaper financial sources. We use the KZ index to measure the financial constraints, following Baker and Gompers (2003) and Bharath and Dittmar (2010), and take into account whether the firm pays dividends. There is also evidence that firms often become public to rebalancing their leverage (Pagano et al., 1998), and also mixed results on the effect of debt financing on the decision to go public. Specifically, Brau (2012) shows that firms decide to become public because they want to have public shares to be used in future acquisitions, and Bancel and Mittoo (2009) reports that European firms become public because they may want to increase their bargaining power with the banks, or to reduce leverage.[10] We use as proxies to the access to capital, leverage, growth opportunities and firms' ability to raise capital, the leverage, market-to-book ratio, capital expenditure intensity, dividend payments and net equity issuance.

Financial Visibility: financial visibility is enhanced after a firm becomes public, and this may facilitate access to cheaper capital (Röell, 1996). Thus, his might be one of the reasons why financially constrained private firms may want to become public (Bharath and Dittmar, 2010;

[10] There is also evidence that there are firms which become private again after realizing that the rebalancing of the leverage is not possible (Bancel and Mittoo, 2009; Aslan and Kumar, 2011).

Pagano et al., 1998). However, the lack of financial visibility for a listed firm (proxied by stock price volatility), stock return, and analysts forecasts, leads to lower interest from investors, which may enhance the likelihood of delisting (Brealey et al., 1977; Mehran and Peristiani, 2010; Bharath and Dittmar, 2010). We consider stock return and stock return volatility as proxies for the financial visibility, following Gregoriou and Nguyen (2010).

Agency Costs: these are more acute for public firms than for private firms (Jensen, 1986), which may affect the delisting decision. Lehn and Poulsen (1989) argue that firms with low growth opportunities and large free cash flows are more likely to become private again, a finding which is however contradicted by Aslan and Kumar (2011). We use free cash-flows as a proxy for the agency costs, following Lehn and Poulsen (1989) and Bharath and Dittmar (2010).

Stock Liquidity: it improves significantly once firms become public. Bharath and Dittmar (2010) show that firms with less liquid stocks are more likely to be delisted. We use stock turnover as a proxy for the stock liquidity, following Amihud and Mendelson (1988). Several models have been proposed to examine the effect of stock liquidity, where there is a particular focus on the trade-off between liquidity and control ownership to in order to identify the effect of ownership structure (Amihud and Mendelson, 1988; Bolton and Von Thadden, 1998). The decision to go public is often also affected by the possibility of getting the investors recognition (Bancel and Mittoo, 2009; Pour and Lasfer, 2013).

4.2 The Hazard Model

The initial model we use to estimate the firm's delisting decision is the following: Pr(Firm i Voluntarily Delist at Time t) = f(Turnover Growth, Turnover Volatility, Controls). However, the dependent variable and some of the independent variables are time-varying, therefore, it cannot be estimated using standard logit or probit models. We have to use a duration analysis, which is widely used in the finance literature, particularly in bankruptcy estimation (Ongena and Smith, 2001; Campbell et al., 2008; Mehran and Peristiani, 2010, among others). The duration analysis shares characteristics of both the time-series and the cross-sectional analysis, and is flexible enough to handle any variation of the covariates under investigation over time and allows us to model the voluntarily delisting decisions explicitly as a function of our main explanatory variables (i.e., turnover growth and turnover volatility).

A particularly useful function of duration analysis is the hazard function. This function, $h(t)$, is the instantaneous rate of an event (voluntary delisting) occurring at time t. Specifically, it is the limiting probability that the firm will delist in a given time interval conditional on it not yet being delisted by the beginning of the interval as the width of the interval goes to zero. This can be parametrized as a function of a set of determinants X_t (i.e., turnover growth, turnover volatility) which can be expressed as: $h_i(t) = m(t, X_{i,t}\beta)$. One issue in this estimation is that we need to identify a functional form for the relation between hazard, time, and X_t covariates.

The most widely used survival regression specification is to allow a hazard function $h(t|0)$, which is also known as the baseline hazard that captures how the probability of delisting changes over time for when all the covariates are equal to zero, to be multiplied by $e^{X_{i,t}\beta}$. This regression formulation is called the proportional hazards (PH) model. Any paramteric hazard function can be used for the baseline hazard $h(t|0)$ (such as weibull, exponential, Gompertz, ...etc.) or it can be left completely unspecified, by the use of Cox's semi-parametric PH model.[11] The choice among these different models to specify $h(t|0)$ is not arbitrary. To determine the appropriate model, we estimate the hazard curve based on the Kaplan-Meier estimator.

As per Figure 3, the hazard curve provides us with an initial idea that the hazard rate is non-constant over time (hump-shaped curve) as it shows a fairly different functional relationship with firm's age. The hazard rate shows a positive duration dependency with the firm's age until a certain point in time (around year 17) then it shows a negative duration with the passage of time. Given this hump-shaped curve, the Cox semi-parametric PH model is used as our estimation method (Cox, 1972).[12] The benefit of using this model is that we do not need to assign any functional form for the baseline hazard function.

[Insert Figure 3 here]

Given the above, our semi-parametric PH cox model, on a panel data structure, is defined as follows:

$$h(t|X_{i,t}) = h(t|0).e^{X'_{i,t}.\beta} \tag{13}$$

[11]The use of a parametric model to specify the baseline hazard rate provides more efficient estimates of β at the expense of specification bias if the model is not correctly specified.

[12]In Section 5, we re-estimate the hazard function assuming the baseline hazard follows a log-logistic distribution (fully parametric model) while addressing heterogeneity concerns

In Equation (13), $h(t|X_{i,t})$ is the hazard rate of firm i conditional on it not being delisted until time t, $h(t|0)$ is the baseline hazard rate for when all the covariates are equal to zero, $X_{i,t}$ is a vector of covariates of firm i at time t, the βs are estimated using the partial maximum likelihood. Standard errors of the coefficients are corrected for possible firm-level clustering using a robust-variance estimation method. The models include time fixed effects using year dummy controls.

The sign of the estimated coefficient β on a covariate X in the hazard model should be interpreted as follows: a positive (negative) β estimate represents a shorter (longer) duration to the delisting. Alternatively, we can interpret the estimated β as an indication of the partial impact of a given characteristic of the firm on the likelihood of delisting, holding the duration constant. The hazard ratio is determined by computing the e^{β}, which shows how much the hazard of the delisting event increases for a unit change in the independent covariate.

As all of the active firms remain listed on the exchange at or after the end of our sample period, so we cannot observe the true duration until they eventually delist (right censoring). This aspect of our data sample must be taken into account, otherwise our model parameters could suffer from biased and inconsistent estimates (Ongena and Smith, 2001). In order to correct for this right censoring issue, we express the log-likelihood function as a weighted average of the sample density of completed duration spells (delisting) and the survivor function of uncompleted spells (remain listed) (see, e.g., Kiefer, 1988).[13]

4.3 Main Results

4.3.1 Descriptive Statistics

Table 3 shows the descriptive statistics of the variables used in our multivariate analysis. Panels A and B show the statistics for the Quotation and the Year Before Delisting (YBD) samples, respectively. For these samples, we also report the t-test. Panels C and D provide the statistics for the Full sample and the variables used in our estimation for the ongoing listing expenses (variable "k" of our delisting option model).

For the *Asymmetric Information* proxy variables, we find that the turnover size of the delisted firms is, for the Quotation and the YBD samples respectively, about 35% and 49% smaller than

[13] In Section 5.4, we provide a robustness study where we also correct for left-censoring problem in our data.

that of the listed firms. For the Quotation sample, the delisted firms have also a lower intangible assets ratio than that of the listed firms (0.07 against 0.13). We also conclude that one year before being delisted, the mean age of the delisted firms is lower than that of the firms which decide to continue to be listed (2.8 against 3.1), which is in line with Marosi and Massoud (2007) and Pour and Lasfer (2013) findings.

Regarding the *Access to Capital* proxy variables, for the Quotation sample, we find that the mean of the leverage ratio of the listed firms is higher than that of the delisted firms (0.24 against 0.21), which may suggest that listed firms have indeed more aggressive turnover growth strategies for which they rely more on debt. But the mean of the MB ratio of the delisted firms is lower than that of the listed firms (1.7 against 2.1), which shows that there are less growth opportunities for the soon-to-be delisted firms. Additionally, the NEI of the delisted firms is higher than that of the listed firms (0.05 vs. 0.03). Qualitatively, the above results, for the Quotation sample, also hold for the YBD sample.

Regarding the *Financial Visibility* proxy variables, for the quotation sample, we conclude that the mean of the stock return of the listed firms is more or less the same as that of the delisted firms, and that the difference is not statistically significant. But the mean of the stock return volatility of the listed firms is significantly lower than that of the delisted firms (0.0298 against 0.038). This return volatility mean difference is more extreme for the YBD sample (0.265 against 0.482). Concerning the *Agency Costs* proxy variables, for the Quotation sample, we conclude that the delisted firms have a lower FCFR than the listed firms (-0.004 against 0.042). Regarding the *Stock Liquidity* proxy variables, for the Quotation sample, we find that the delisted firms have a higher STR than the listed firms (0.12 against 0.06).

For the Quotation sample, all the mean differences discussed above are statistically significant at 1% level, with the exception of that of the Stock Return, which we use as a proxy for the "Financial Visibility". Qualitatively, the above results also hold for the YBD sample, although for some variables the mean difference is not statistically significant.

[Insert Table 3 here]

4.3.2 Determinants of Delisting

In Panel A of Table 4, we start our analysis by considering only the control variables in section 4.2 (model 1). Then, we added to this base model the turnover growth and the turnover volatility (model 2) so as to examine whether these two key variables of our theoretical delisting model affect the delisting decision. We also report the hazard ratio for each variable in both models.

Our findings show that both models (1 and 2) lead to the same qualitative results. Specifically, the hazard rate decreases with the firms' turnover size, intangible assets, market to book and NEI, and increases with the leverage and stock return volatility. From model 2, we also acknowledge that the hazard rate decreases with the turnover growth rate and increases with the turnover volatility.

From model (2), we find that the coefficient of the firm's turnover growth is negative, therefore, firms of lower turnover growth are more prone to be delisted voluntarily. Additionally, the hazard ratio is 0.522, which means that the hazard rate of delisting decreases by (0.5734 - 1) 47.8% for each unit increase in the firm's turnover growth. In addition, we find that the higher the turnover volatility, the more likely is the delisting, which is in line with the literature which studies the effect of uncertainty on the timing of option exercising decision. The hazard ratio suggests that a unit increase in turnover volatility increases the probability of delisting by 59.8%.

As per the control variables, we notice that the asymmetric information argument provides contradicting results. Specifically, the coefficient of the firm's turnover size is negative, therefore, firms of smaller turnover size are more prone to be delisted voluntarily. Additionally, the hazard ratio is 0.747, which means that the hazard rate decreases by (0.747 - 1) 25.3% for each unit increase in the firm's turnover size. This finding is supported by Pagano et al. (1998). Regarding the intangible assets, which is a proxy for the adverse selection problem between insiders and outsiders, we find a significantly negative effect on the probability of delisting, which does not support the asymmetric information hypothesis. Previous literature provides inconclusive evidence on the effect of intangible assets on the delisting probabilities. Notice that Bharath and Shumway (2008) and Pour and Lasfer (2013) find a positive and statistically significant relationship between intangible assets and delisting, although Marosi and Massoud (2008) conclude that the information asymmetry has no affect on the delisting decision.

Our findings also support the access to capital hypothesis. Specifically, the hazard rate increases with the leverage and decreases with market to book ratio. Notice that a unit decrease in the market to book ratio increases the hazard rate of delisting by 25.4%, whereas a unit increase in leverage increases the hazard rate of delisting by 251.3%. We also find evidence which supports the financial visibility hypotheses. Specifically, the probability of delisting increases with the increased stock return volatility. This result supports that of Pour and Lasfer (2013), who show that there is a positive (although not statistically significant) relationship between delisting and stock volatility. Our hazard ratio is equal to 1.129 which implies that a unit increase in stock volatility increases the hazard rate of delisting by 12.9%.

We did not find support for the liquidity hypothesis, since the coefficient of the stock turnover ratio (STR) is not statistically significant, which 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. Additionally, the agency cost prediction, which advocates that firms with high free cash flow and low growth opportunities are more prone to go private again to reduce the agency costs between managers and shareholder, is not supported by our findings, since the coefficient of the free cash flow is statistically insignificant.

[Insert Table 4 here]

5 Robustness Tests

5.1 Left Censoring

Our data sample also suffers from the left censoring problem, because when the IPO date is not available, we use the first record date in Compustat as the duration start date. We note that The earliest record date available in Compustat is 1950. Ongena and Smith (2001) highlight the fact that accounting for the left censored observations is not as straightforward as for the right censored observations. But ignoring these left censored observations can bias our parameters estimations. Therefore, we follow Heckman and Singer (1984) and take out of our sample all the left censored observations, and run two models and compare their results with those of our baseline model (Panel B, in Table 4).

We also apply another robustness check strategy, following Ongena and Smith (2001), who advocate that, if our results are sensitive to the left censoring problem, then a change in the first observed year of the sample would create instability in the parameter estimates. Hence, we changed the start date of our sample period from 1980 to 1985, and run again our baseline hazard model. We repeat the above methodologies considering 9 consecutive observations as the minimum number of time periods to qualify a firm for our sample. For instance, after eliminating the left censored observations, if a firm's total number of firm-year observations drop to below 9 consecutive periods, we remove all the firm-year observations for this particular firm. However, these (untabulated) analyses lead to very similar qualitative results as those of our baseline model (Model 2, in Table 4). One exception to note, after applying Heckman and Singe's (1984) method, is that CAPEX and Stock return coefficients become statistically significant with a negative sign which further confirms our access to capital and financial visibility hypotheses.

[Insert Table 4 here]

5.2 Initial Matching Samples

Previous studies, such as those of Bharath and Dittmar (2010) and Pour and Lasfer (2013), use an initial matched sample approach between the listed and the delisted firms, following several matching criteria, for instance the IPO year, industry group, and firm's characteristics. Following these studies, we examine the robustness of our baseline hazard model estimations by re-estimating the results provided in Model 2 of Table 4, using a similar initial matching method where we first match firms based on starting date and the industry classification. This type of matching provides a better understanding on how the delisted firms compare to their matched sample of the listed firms since the starting date, and how the determinants of the delisting evolve as compared to matched listed firms.

To identify a sample of listed firms (the control group) that exhibits no significant differences in observable characteristics, other than turnover and the turnover volatility, compared to those of the delisted firms (the treatment group), in addition to the initial matching criteria of the same starting date and Fama-French 2-digit industry classification, we match firms in both groups using variables which are found to differentiate between the listing and the delisting status based on both our data base and the prior literature.

To check the variables (confounders[14]) with the largest differences between the treated (delisted) and control (listed) groups, we identify the explanatory variables used in our baseline hazard model (Model 2, in Table 4) with the largest statistically significant mean difference, as per the t-test of Table 3, Panel A.

Our findings reported in Table 3, Panel A, show that the listed and the delisted firms differ significantly in terms of turnover size. Indeed, turnover size has the largest mean difference. We also concluded that it is a key determinant of the delisting, in the sense that smaller firms are more likely to be delisted Witmer (2005). We also match on stock turnover (STR) as the mean difference between listed and delisted firms is high and statistically significantly, following Bharath and Dittmar (2010) who also used STR as a key matching variable between listed and going private firms. Finally, we also use market to book ratio as a matching variable between listed and delisted firms, following Bharath and Dittmar (2010). In Table 5 we report our findings, and conclude that they are very similar to those we obtained from our baseline model.

[Insert Table 5 here]

5.3 Receiver Operating Curve

The receiver operating characteristics curve (ROC) is a widely used measure to evaluate the accuracy of the predictive power of a model. 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 4 shows the ROC curves for both the within sample period (1980-2011) and the out of sample period (2012-2016) for the two hazard models (1) and (2), whose results are in Table 4. The ROC curves show a high predictive power of 85.63% and 83.08%, respectively for the out of sample and the within the sample periods for Model 1, which means that varying the cut off that predicts which firms will be delisted, on average in 83.08% and 85.63% of the times, the hazard model will be able to predict accurately the firms which will be delisted, for the within the sample period and the out of the sample period, respectively. Similarly for the predictive power of Model 2, where the ROC curves indicate that on average, in 86.05% and 84.10% of the times, the hazard model will be able to predict accurately the firms which will be delisted, for the out of sample and

[14] Confounding is a variable which influences both the dependent and the independent variables of our model, causing a spurious association.

the within sample periods, respectively.

[Insert Figure 4 here]

5.4 Unobserved Heterogeneity

According to Figure 3, we find the hazard rate to follow a hump-shaped curve with its relation to firm's age. Given the changing nature of hazard curve and favouring accurate specification on the expense of efficient β estimates,we used the Cox semi-parametric model which does not specify a functional form for the baseline hazard. To verify the robustness of our estimation, we use a parametric model to estimate the hazard rates assuming the time to delist follows a Weibull distribution. Furthermore, in studies of survival analysis it is assumed that the population is homogeneous. This assumption, if applied to this paper, would mean that, each firm has the same risk of experiencing the delisting event, conditional on a set of covariates. Additionally, the delisting times of the firms in the sample are assumed to be independent. But this assumption may not hold for all the firms in the sample, because different firms may have different risks and hazards. Consequently, an association between the event times (the delisting, or the end of the sample period for active firms) of some sample subgroups (firms, clusters within years, or industries) could exist if these share a common characteristic that cannot be observed. Failure to control for unobserved heterogneity can produce sever bias in the nature of duration dependence and the estimates of the covariates (Heckman and Singer, 1984). To overcome this problem, Vaupel et al. (1979) coined the term “Frailty”, normally defined as an unobserved random factor, $v_{i,t}$, to account for the unobserved heterogeneity due to unobserved covariates. This factor modifies multiplicatively the firms' hazard function of firms, or cluster or groups of firms as per Equation (16) below. These frailties can be firm-specific or group-specific, being referred to as individual frailty or shared frailty, respectively.

$$h(t|X_{i,t}) = h(t|0).\omega_{i,t}.e^{X'_{i,t}\beta} \tag{14}$$

where $\omega_{i,t} = e^{v_{i,t}}$.

In order to test the validity of our results, while controlling for the unobserved heterogeneity, it is computationally easier to specify heterogeneity in a parametric model (i.e., Weibull) compared to semi-parametric model (Mehran and Peristiani, 2010). To test our parametric model with heterogeneity we use the following equation:

$$h(t|X_{i,t}\beta;\gamma,\theta) = \gamma e^{X'_{i,t}\beta+\upsilon_{i,t}}.[te^{X'_{i,t}\beta+\upsilon_{i,t}}]^{\gamma-1} \tag{15}$$

where $\upsilon_{i,t}$ is an unobserved heterogeneity factor which is assumed to be normally distributed with mean zero and variance θ. θ is the frailty variance that is estimated from the data and measures the variability of the frailty across groups. The unobserved heterogeneity is included in the model using gamma distribution.

Table 4 provides the results. In model (1) we report the baseline parametric model without taking into consideration the effect of unobserved heterogeneity $\upsilon_{i,t} = 0$. Models (2), (3), and (4) report the results from the parametric model under three unobserved heterogeneity assumptions: (i) year and firm random effects $\upsilon_{i,t}$; (ii) firm-level frailty $\upsilon_{i,t} = \upsilon_i$; (iii) shared frailty at the industry level $\upsilon_{i,t} = \upsilon_j$ (j = 2-digit SIC), respectively. The variances θ of $\upsilon_{i,t}$ are estimated to be 0.223, 0.313, and 0.043; the likelihood ratio test of H_0: $\theta = 0$ are 2.61, 2.21, and 1.97 for model (2), (3), and (4), respectively. Therefore, the likelihood ratio test of H_0: $\theta = 0$ would be rejected. Thus, the results indicate the presence of factors other than those included in the model that impact delisting times and controlling for unobserved heterogeneity is justified. The ρ of the Weibull model is significantly greater than one for all hazard models which means that the delisting decision exhibits positive duration dependence. The use of parametric model provides statistically stronger results for our main variables of interest compared to those of the Cox model (i.e., Turnover Growth and Turnover Volatility). However, our main variables remain to be statistically significant and with the expected sign for both parametric and semi-parametric models.

[Insert Table 6 here]

6 Good *vs.* Bad decisions samples

In Table 7, we show our results which are driven by the classification provided by our theoretical delisting model. Our results show that of the 219 firms that were delisted voluntarily between 1980 and 2016, 62 made a good decision and 157 made a bad decision. Additionally, of the 157 firms which made a bad decision, we conclude that 88 were delisted but should have remained listed and

69 were delisted but should have delayed more the decision, although the delisting now is profitable. We also find that 1676 listed firms made a good decision in having remained listed although for 585 of these firms the delisting now is profitable (but not optimal). We also conclude that there are 682 listed firms which should be delisted immediately.

[Insert Table 7 here]

In order to test empirically the robustness of our theoretical classification, we split our initial sample into two groups, the group of firms which made a "good" decision and the group of firms which made a bad decision (Table 7) and test whether the mean differences between the two samples, regarding the Asymmetric Information, Access to Capital, Financial Visibility, Agency Costs, and Liquidity proxy variables are statistically significant. In Table 8, we provide our results, which show that the listed firms that made a bad decision by remaining listed are on average smaller and younger, have lower intangible assets and FCF ratios, and higher market to book ratios, returns and return volatility than the listed firms which made a good decision by remaining listed.

Regarding the delisted firms which made a bad decision by remaining listed, we concluded that these are on average larger and older, and have lower intangible assets and market to book MB ratios, as well as net equity investment, returns and return volatility, and higher FCF ratios than the delisted firms that made a good decision by delisting. We conclude that most of the mean differences are statistically significant at 1% or 5% level, for both the listed and the delisted samples. These findings show that the firms which are identified by our model as firms which made good and bad decisions exhibit different characteristics. This is a relevant result because our delisting model enables us to identify the firms' characteristics which may make them more prone to non optimally remaining listed or to delist.

[Insert Table 8]

Relying on the information above, we run again our semi-parametric Cox hazard model, whose results are provided in model 2 (Panel A) of Table 4, for both the firms which made a good decision and the firms which made a bad decision. Notice that we do not control for whether the good and the bad decisions are related to the decision to delist the firm from the exchange or to keep the firm listed.

In Table 9, model (1) is our baseline hazard model which we use for the full sample, whereas models (2) and (3) are used for the firms which made bad and good decisions, according to our theoretical delisting model, respectively. Comparing the coefficients across the three models, we conclude that there are relevant differences in terms of both the magnitude and the statistical significance of the regression coefficients, which reinforce our assertion, based on univariate findings (Table 8) according to which firms that make good decisions have some distinct features from those which make bad decisions. The Wald χ^2 test indicates that both models (2) and (3) have good fit ($p<0.001$).

In terms of differences, unlike model 2 (Bad decision), we find that turnover volatility significantly affects the delisting probability in model 3 (Good decisions). We find Turnover Growth to significantly affect the delisting probabilities for both samples of firms that took a good and bad decisions to delist or remain listed. As per the control variables, we find that the coefficient of Intangible to be statistically significant only for the model which applies to the bad decision sample (model 2), whereas it is insignificant for the model of the good decisions sample (model 3). On the contrary, the coefficient of Return Volatility is found to be insignificant for the model with bad decision and significant for the good decision model. As per the other variables such as Turnover Size, Leverage, MB ratio, and NEI, we find statistically significant results for both models (2 and 3). Furthermore, the coefficients of Age, CAPEX, Dividend, FCF, STR, and Stock return, are found to be insignificant for all three models.

For all significant covariates, the sign of the estimated coefficients are consistent with our main hypotheses. We find that firms (in model 2 and 3) have shorter period until delisting when they are smaller and have lower turnover Growth, higher leverage, lower MB ratio, and lower NEI.

[Insert Table 9 here]

7 Conclusion

We develop a theoretical real options model which optimizes the timing of a voluntary delisting. In order to test the reliability of this new model, we use it to classify the firms' "ongoing listing" and "delisting" decisions as *good* or *bad*, relying on a data sample that comprises information on 2358 US listed firms, over the time period between 1980 and 2016. Under our classification, a firm makes a good or a bad decision depending on whether it remains listed or is delisted optimally, following our model. Also, using the turnover as the underlying variable of our delisting real options model, a variable which is absent from most of the empirical delisting literature, we show that it is a key determinant of delisting, as well as the turnover growth and the turnover volatility. We performed appropriate robustness tests, which account for unobserved heterogeneity, left censoring and initial matching samples.

Our findings show that the role of some variables on the delisting of firms that made a bad decision differs from that these variables have on the delisting of firms that made a good decision. Specifically, for the bad decision subsample, the turnover, turnover growth and age affect negatively the likelihood of delisting, whereas, for the good decision subsample, we conclude that the turnover volatility has a positive effect on the likelihood of delisting. These are relevant findings because they show that our delisting model is capable of identifying firm-specific characteristics that make firms more prone to make wrong (or suboptimal) ongoing listing or delisting decisions.

Our theoretical delisting model can also be useful to investors and financial analysts following firms that are more prone to voluntary delisting. It enables them to determine when (if) it is optimal to delist, and monitor how far a listed firm is from its optimal voluntary delisting threshold.

It would be interesting to extend our theoretical delisting model to involuntary delistings, so as to determine the optimal delisting threshold from the perspective of the exchange, using for instance a model setting which could also incorporate a welfare analysis and the likelihood of the arrival of major economic shocks or financial crises. This welfare analysis could also be performed from the perspective of a central planner, so as to provide insights on the optimal involuntary delisting threshold which are helpful for financial regulators.

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Tables and Figures

Table 1: Listed and Delisted Firms

This table reports the number of listed and voluntary delisted firms over the sample time period (1980-2016). The "Listed Firms" column reports the number of firms that are listed on Amex, Nasdaq or NYSE over time. The "Delisted Firms" column reports the number of firms that are delisted voluntarily from the exchange over time. The "Delisting Rate" column shows the ratio of delisted firms over listed firms over time.

Year	Listed Firms	Delisted Firms	Delisting Rate
1980	525		
1981	541		
1982	560		
1983	599		
1984	614		
1985	655		
1986	688		
1987	759		
1988	789	4	0.51
1989	825	6	0.73
1990	848	2	0.24
1991	901	5	0.55
1992	978	3	0.31
1993	1082	4	0.37
1994	1158	4	0.35
1995	1243	2	0.16
1996	1370	1	0.07
1997	1473	1	0.07
1998	1550	6	0.39
1999	1655	4	0.24
2000	1764	7	0.40
2001	1802	10	0.55
2002	1838	14	0.76
2003	1869	12	0.64
2004	1926	14	0.73
2005	1984	10	0.50
2006	2086	5	0.24
2007	2192	11	0.50
2008	2228	17	0.76
2009	2247	14	0.62
2010	2285	7	0.31
2011	2334	7	0.3o
2012	2366	5	0.21
2013	2381	7	0.29
2014	2372	7	0.30
2015	2372	22	0.93
2016	388	8	2.06

Figure 1: Delisting Timeline

This figure shows a timeline regarding the delisting decision. At $t = 0$ the delisting option timing game starts - i.e., the firm becomes listed. At $t = \tau^*$ it is optimal for the firm to delist. From $t = \tau^*$ onwards, the firm is delisted and does not have the option to become listed again.

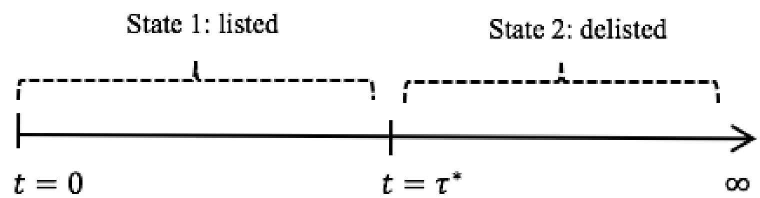


Table 2: Descriptive Statistics - GBM Process Parameter Estimation

This table provides information on the turnover volatility and growth rate for the full sample and the listed firms and delisted firms sub-samples. It also shows the t-values for mean difference between the turnover volatility and the growth rate of the listed firms and the delisted firms.

	Listed Firms	
Panel A	σ	α
Mean	0.316	0.239
SD	0.31	0.32
percentile 10%	0.0922	0.0537
percentile 90%	0.667	0.507
Panel B	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
Panel C	Full sample	
Mean	0.319	0.239
SD	0.314	0.328
percentile 10%	0.0937	0.0516
percentile 90%	0.667	0.505

Figure 2: Theoretical Findings

This figure shows the effect of changes in the value of the turnover volatility on the profitability of the delisting. The solid horizontal line represents the zero delisting profit threshold, and the convex or the concave curves represent the profit if the firm is delisted, as a function of time which is given in years. We assume that the delisting option has a maturity of 25 years.

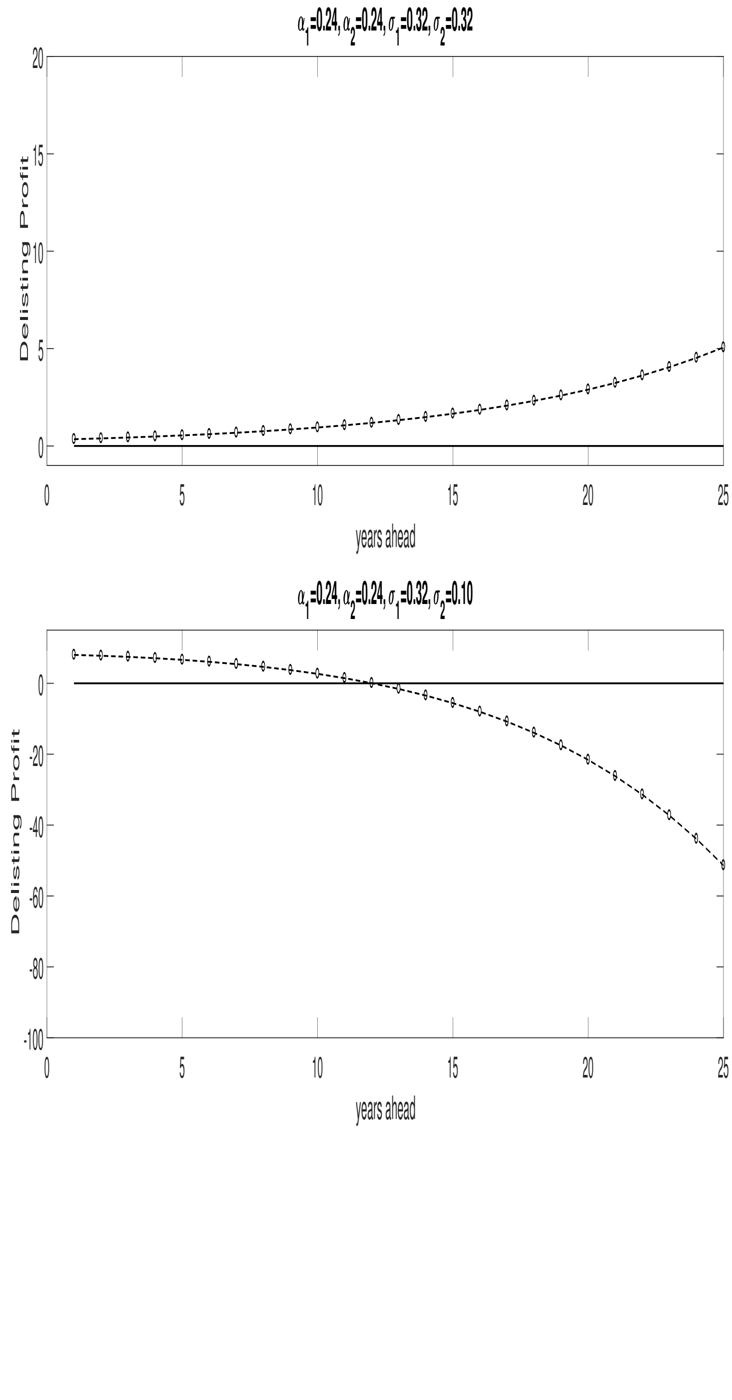


Figure 3: Smoothed Hazard Estimate

This figure reports the smoothed hazard curves non-parametrically estimated using the Kaplan Meier estimator.

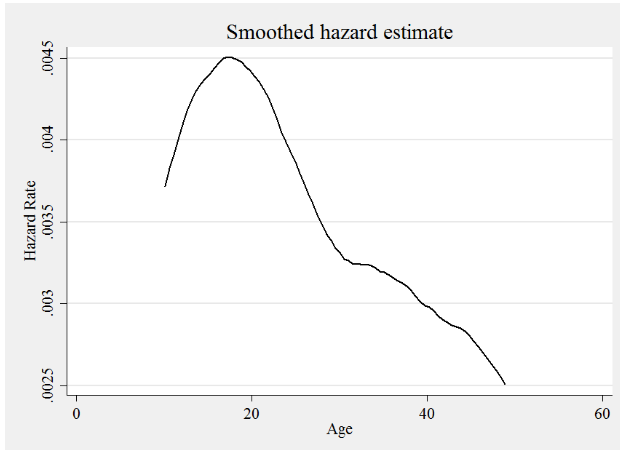


Table 3: Descriptive Statistics

This table reports the descriptive statistics of the variables used in our multivariate analysis, for the listed and the delisted firms of the "Quotation" sample (panel A) and the Year Before Delisting (panel B), as well as for the Full sample. The quotation sample considers the average of all observations for a specific sample for 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. Panel D reports information on the full sample, which includes 2,577 firms, 219 of which were voluntarily delisted. Monetary values are reported in millions of US dollars.

Variable	**Panel A**: Quotation					**Panel B**: Year Before Delisting					**Panel C**: Full	
	Listed Firms		Delisted Firms			Listed Firms		Delisted Firms				
	Mean	SD	Mean	SD	t-test	Mean	SD	Mean	SD	t-test	Mean	SD
Theoretical Model												
TurnoverGr	0.1563	0.3642	0.1356	0.3987	3.1127***	0.0499	0.3434	0.0358	0.3515	0.5797	0.1550	0.3664
TurnoverVol	0.2108	0.2571	0.2711	0.2657	-12.8880***	0.2093	0.2679	0.2887	0.2957	-4.1567***	0.2144	0.2581
Asymmetric Information												
Turnover	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	0.4829	0.0022	0.3814	0.0086	11.2108***	0.4776	0.0021	0.2648	0.0298	6.2942***	0.4767	0.4994
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												
FCFR	0.0419	0.2262	-0.0037	0.2634	11.0109***	0.0012	0.2576	-0.0741	0.3665	3.9716***	0.0391	0.2289
Stock Liquidity												
STR	0.0625	0.0660	0.1196	0.1795	-40.4111***	0.0515	0.0315	0.0890	0.1272	-11.1152***	0.0659	.0789
Panel D												
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 4: Estimation Results: Semi-parametric Hazard Models

This table provides an estimates based on maximum likelihood estimation of the proportional hazard model using Cox (1972) partial likelihood function as per Equation (13). Our sample includes 2,577 firms, of which 219 were delisted voluntarily between 1980 and 2016. The coefficients measure the partial impact of each covariate on the likelihood of delisting, conditional on duration. The dependent variable is the time to delist, which measures the time between the IPO and the delisting event. If the IPO date is not available, we use the first available observations in Compustat. In Panel A, model 1 is the base hazard model which includes all the control variables discussed in Section 4. In Model 2, we add the turnover growth and volatility to Model 1, following the assumption underlying the delisting model developed in Section 3. For these models, we report the regression coefficients (columns 2 and 4) and the hazard ratios (columns 3 and 5). Panel B reports the coefficient estimates and the hazard ratios from Model 2 but takes into account the left censoring problem. Model 3 (columns 6 and 7)reports the results based on Heckman and Singer's (1984) estimation strategy, and Model 4 (columns 8 and 9) shows our results for when we change the first year of the sample from 1980 to 1985. All estimates are adjusted for right censoring. standard errors are corrected for firm-level clustering effects using a robust-variance estimation methodology, and are reported below the coefficients in between brackets. The models include time fixed effects using year dummy controls. The hazard ratio gives an estimate of how much the hazard of delisting increases for a unit change in the covariate. ***, **, * means that the coefficients are significant at the 1%, 5%, and 10% level, respectively. All the regression covariates are defined in Table 11, in the Appendix B.

Variable	**Panel A:** without Left Censoring				**Panel B:** with Left Censoring			
	Base model without turnover (1)		Base model with turnover (2)		Heckman and Singer 1984 (3)		Start Date: 1985 (4)	
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
TurnoverGr			-0.522**	0.593	-0.413*	0.662	-0.463**	0.629
			(0.211)		(0.223)		(0.205)	
TurnoverVol			0.469**	1.598	0.478*	1.612	0.472**	1.604
			(0.217)		(0.244)		(0.223)	
Turnover	-0.297***	0.743	-0.292***	0.747	-0.198***	0.821	-0.277***	0.758
	(0.050)		(0.050)		(0.063)		(0.051)	
Intangible	-1.662***	0.190	-1.499***	0.223	-1.094*	0.335	-1.535***	0.215
	(0.573)		(0.567)		(0.579)		(0.570)	
Age	-0.385	0.680	-0.313	0.731	0.206	1.229	-0.551*	0.577
	(0.321)		(0.341)		(0.431)		(0.286)	
Leverage	1.256***	3.510	1.257***	3.513	0.870***	2.386	1.326***	3.765
	(0.265)		(0.266)		(0.320)		(0.265)	
MB	-0.312***	0.732	-0.293***	0.746	-0.256**	0.774	-0.288***	0.749
	(0.109)		(0.107)		(0.118)		(0.108)	
CAPEX	-1.789	0.167	-1.556	0.211	-3.033*	0.048	-2.229	0.108
	(1.346)		(1.317)		(1.751)		(1.454)	
Dividend	-0.238	0.788	-0.240	0.787	-0.035	0.966	-0.185	0.831
	(0.170)		(0.171)		(0.189)		(0.173)	
NEI	-1.901**	0.149	-1.858**	0.156	-1.608**	0.200	-1.792**	0.167
	(0.751)		(0.742)		(0.740)		(0.736)	
FCF	-0.478**	0.620	-0.314	0.731	-0.296	0.744	-0.314	0.731
	(0.241)		(0.256)		(0.296)		(0.260)	
STR	0.125	1.134	0.053	1.054	-3.280	0.038	0.237	1.268
	(0.756)		(0.759)		(3.865)		(0.826)	
Return	-0.181	0.834	-0.194	0.823	-0.251**	0.778	-0.205	0.815
	(0.127)		(0.130)		(0.119)		(0.126)	
ReturnVol	0.122***	1.129	0.122***	1.129	0.164***	1.178	0.130***	1.139
	(0.030)		(0.030)		(0.026)		(0.029)	
Wald chi2	952.37***		945.89***		1,002.04***		411.04***	
Likelihood ratio test	-1,381.814		-1,376.916		-974.148		-1,317.798	
AIC	2,853.628		2,847.831		2,030.296		2,723.595	
BIC	3,253.296		3,265.262		2,376.464		3,111.871	
Firm-year observations	53,184		53,184		34,308		50,234	

Table 5: Estimation Results: Initial Matching Samples

This table reports the results based on initial matched samples between delisted firms (treatment groups) and listed firms (control groups) which uses several matching criteria at the IPO year and/or industry group. The results are based on maximum likelihood estimation of the proportional hazard model using Cox (1972) partial likelihood function as per Equation (13). Model (1) is the baseline model estimated (without matching). Models from (2) to (5) are estimated from the hazard models with matched control firms based on starting year and industry classification, firm's Turnover, stock's turnover, and Market to Book ratio, respectively. All estimates are adjusted for right censoring. 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. The models include time fixed effects using year dummy controls. ***, **, * means that the coefficients are significant at the 1%, 5%, and 10% level, respectively. All the regression covariates are defined in Table 11, in the Appendix B.

Variable	Base Model Model 1	IPO year and Industry Model 2	Turnover Model 3	Stock's turnover Model 4	MB Model 5
TurnoverGr	-0.522**	-0.548**	-0.621***	-0.430**	-0.246
	(0.211)	(0.239)	(0.238)	(0.214)	(0.190)
TurnoverVol	0.469**	0.447*	0.704***	0.473*	0.419*
	(0.217)	(0.244)	(0.250)	(0.253)	(0.223)
Turnover	-0.292***	-0.125***	-0.133***	-0.251***	-0.292***
	(0.050)	(0.044)	(0.045)	(0.045)	(0.052)
Intangible	-1.499***	-0.602	-0.974*	-0.971*	-0.875
	(0.567)	(0.483)	(0.540)	(0.535)	(0.572)
Age	-0.313	0.286	-1.739***	-1.709***	-1.935***
	(0.341)	(0.286)	(0.196)	(0.185)	(0.192)
Leverage	1.257***	0.680**	1.353***	1.433***	1.152***
	(0.266)	(0.315)	(0.314)	(0.286)	(0.308)
MB	-0.293***	-0.127**	-0.283***	-0.210***	-0.120**
	(0.107)	(0.063)	(0.098)	(0.079)	(0.061)
CAPEX	-1.556	0.859	0.044	-0.543	-0.540
	(1.317)	(1.353)	(1.331)	(1.296)	(1.240)
Dividend	-0.240	-0.688***	-0.502**	-0.512**	-0.500**
	(0.171)	(0.200)	(0.210)	(0.209)	(0.204)
NEI	-1.858**	-1.444*	-2.209**	-1.547*	-2.462**
	(0.742)	(0.753)	(0.923)	(0.796)	(1.019)
FCF	-0.314	-0.469*	-0.447*	-0.421	-0.386
	(0.256)	(0.248)	(0.271)	(0.265)	(0.303)
STR	0.053	-0.359	0.191	-1.607	0.091
	(0.759)	(0.727)	(0.694)	(1.210)	(0.728)
Return	-0.194	0.031	0.026	-0.407*	-0.411*
	(0.130)	(0.235)	(0.125)	(0.211)	(0.228)
ReturnVol	0.122***	0.010	0.106***	0.121***	0.139***
	(0.030)	(0.044)	(0.034)	(0.039)	(0.043)
Wald chi2	945.89***	275.95***	253.17***	350.29***	306.77***
Likelihood ratio test	-1376.9157	-1007.5777	-1239.8015	-1219.8933	-1246.4618
AIC	2847.831	2043.155	2507.603	2467.787	2520.924
BIC	3265.262	2137.935	2602.376	2562.542	2615.701
Firm-year observations	53,184	6,438	6,438	6,438	6,438

Figure 4: Receiver Operating Characteristics (ROC) Curves

This figure shows the area under the receiver operating characteristics curve (AUROC) for the two semi-parametric hazard 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.

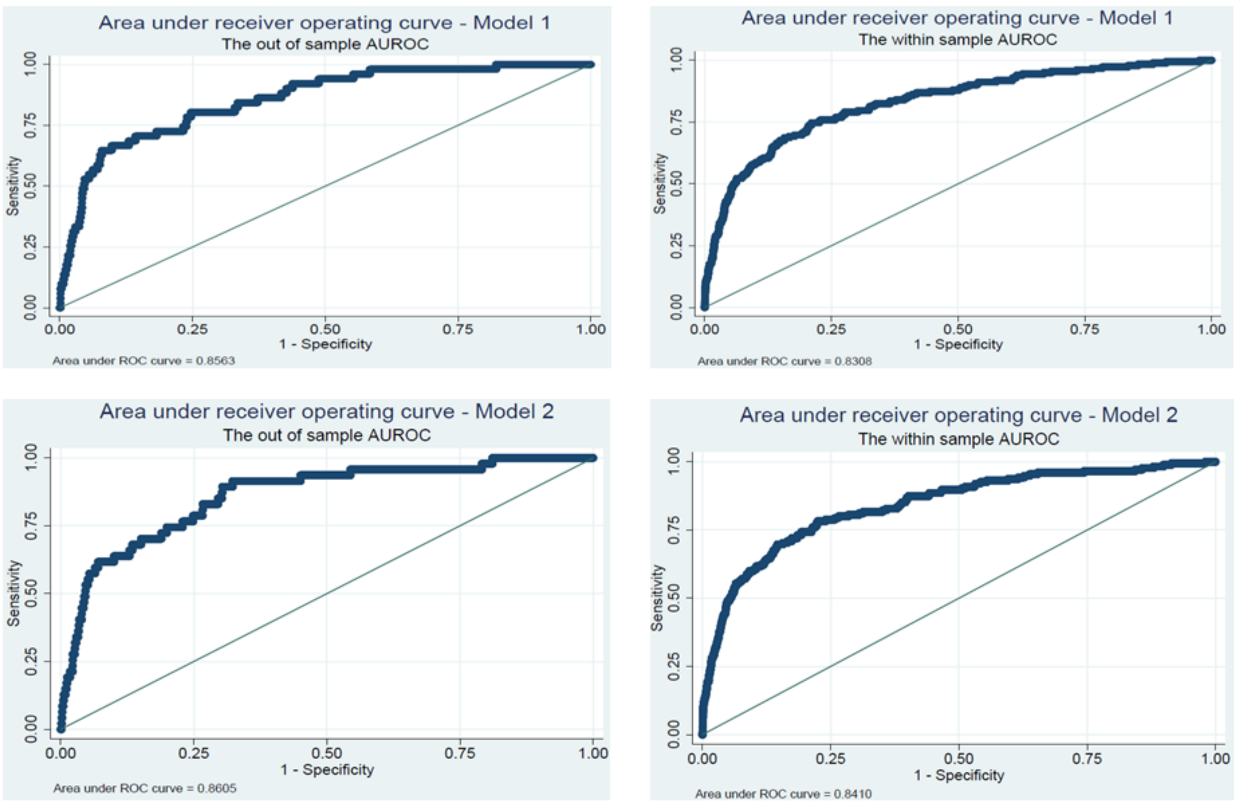


Table 6: Estimation Results: Parametric Model with Unobserved Heterogeneity

The results are based on maximum likelihood estimation of the proportional hazard model using Weibull distribution as the baseline hazard rate as per Equations (15), while taking the effect of unobserved heterogeneity into consideration. Our sample includes 2,577 firms, of which 219 were delisted voluntarily between 1980 and 2016. The dependent variable is the time to delist, which measures the time between the IPO and the delisting event. If the IPO date is not available, we use the first available observations in Compustat. In model (1) we report the parametric model assuming no unobserved heterogeneity ($\upsilon_{i,t} = 0$). In models (2), (3), and (4) we estimate our results under three unobserved heterogeneity assumptions: (i) year and firm random effect ($\upsilon_{i,t}$)(ii) the firm-level frailty ($\upsilon_{i,t} = \upsilon_i$); and the shared frailty effects at the industry level using the two-digit SIC codes ($\upsilon_{i,t} = \upsilon_j$ where j = SIC code (column 6). All estimates are adjusted for right censoring. 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. All the regression covariates are defined in Table 11, in the Appendix B.

Variable	Baseline (1)	$\upsilon_{i,t}$ (2)	$\upsilon_{i,t} = \upsilon_i$ (3)	$\upsilon_{i,t} = \upsilon_j$ (4)
TurnoverGr	-0.556**	-0.567***	-0.592***	-0.549**
	(0.229)	(0.218)	(0.220)	(0.217)
TurnoverVol	0.631***	0.631***	0.629***	0.624***
	(0.215)	(0.237)	(0.230)	(0.233)
Turnover	-0.252***	-0.232***	-0.261***	-0.255***
	(0.043)	(0.041)	(0.039)	(0.038)
Intangible	-0.912	-0.908*	-0.967*	-0.827
	(0.562)	(0.546)	(0.541)	(0.543)
Age	-1.225***	-1.276***	-1.235***	-1.201***
	(0.171)	(0.219)	(0.179)	(0.103)
Leverage	1.009***	0.976***	1.074***	0.950***
	(0.260)	(0.288)	(0.277)	(0.284)
MB	-0.287***	-0.263***	-0.295***	-0.270***
	(0.102)	(0.068)	(0.068)	(0.067)
CAPEX	-2.238	-2.178	-2.054	-2.356*
	(1.487)	(1.334)	(1.315)	(1.354)
Dividend	-0.748***	-0.733***	-0.711***	-0.797***
	(0.172)	(0.180)	(0.177)	(0.179)
NEI	-1.856**	-1.879**	-1.956**	-1.741**
	(0.729)	(0.771)	(0.770)	(0.757)
FCF	-0.727***	-0.611**	-0.721***	-0.795***
	(0.230)	(0.247)	(0.229)	(0.233)
STR	-0.537	-0.452	-0.477	-0.617
	(0.766)	(0.695)	(0.678)	(0.689)
Return	-0.263***	-0.397	-0.255***	-0.267***
	(0.057)	(0.260)	(0.090)	(0.085)
ReturnVol	0.087***	0.143***	0.085***	0.089***
	(0.014)	(0.038)	(0.018)	(0.017)
Constant	-5.928***	-6.381***	-5.818***	-5.874***
	(0.379)	(0.473)	(0.390)	(0.431)
Wald chi2	945.89***	238.24***	744.32***	307.13***
Likelihood ratio test	-1376.916	-682.77655	-808.391	-683.09338
AIC	2847.831	1399.553	1373.2	1400.187
BIC	3265.262	1550.539	1523.329	1551.172
ρ		2.772	2.683	2.654
		(0.227)	(0.185)	(0.099)
θ		0.223	0.313	0.043
Likelihood ratio test		2.610	2.210	1.970
$H_0 : \theta$=0				
Firm-year observations	53,183	53,183	53,183	53,183
Number of groups			2,577	9

Table 7: Theoretical Model and Empirical Implications

This table reports the number of firms which are delisted and, according to our real option model, it was a good decision, and the number of firms which are delisted and, according to our real option model, it was a bad decision. Our data sample comprises information on 2358 listed firms and 219 voluntary delisted firms.

Status	**Good Decision**	**Bad Decision**
Delisted	62 delisted firms which should be delisted	Total 157 firms of which 88 delisted firms which should be listed 69 delisted firms which should have waited longer
Listed	Total 1676 firms of which 1091 listed firms which should be listed 585 delisting is profitable but not yet optimal	682 listed firms which should be delisted now

Table 8: Mean Difference Test: Good Decision *vs.* Bad Decision

This table reports the mean values of the regression variables which we have concluded were statistically significant determinants of the delisting decision. Panels A and B show the mean values of the delisted and listed firms, respectively, using the "Quotation" sample. The quotation sample considers the average of all observations for a specific sample for 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). Columns 1 and 2 report the mean values for the Delisted firms which made a good and a bad decision, respectively, and columns 3 and 4 show the mean values for the listed firms which made a good and a bad decision, respectively. For both cases we show the t-test.

Variable	Panel A - Delisted Firms			Panel B- Listed Firms		
	Good Decision (1)	Bad decision (2)	t-test	Good Decision (3)	Bad decision (4)	t-test
Asymmetric information						
Turnover	3.240	5.043	17.664***	6.397	5.360	-45.93***
Intangible	0.094	0.062	-6.329***	0.133	0.122	-6.422***
Age	2.304	2.445	4.345***	2.812	2.484	-38.13***
Access to Capital						
Leverage	0.260	0.238	-2.667***	0.214	0.211	-1.736**
MB	2.134	1.582	-7.447***	2.036	2.329	16.331***
CAPEX	0.047	0.056	3.6***	0.060	0.065	7.668***
Dividend	0.172	0.459	15.375***	0.559	0.266	-59.641***
NEI	0.079	0.034	-6.916***	0.019	0.074	36.354***
Financial Visibility						
Return	0.093	0.072	-1.636***	0.078	0.0855	2.856***
ReturnVol	0.049	0.035	-15.451***	0.028	0.037	54.4***
Agency Costs						
FCFR	-0.086	0.026	10.922***	0.066	-0.026	-40.592***

Table 9: Estimation Results: Good Decision *vs.* Bad Decision

This table reports the estimated results for the full sample and the samples of the firms which have made a good decision and bad decision according to our theoretical delisting model. The results are based on maximum likelihood estimation of the proportional hazard model using Cox (1972) partial likelihood function as per Equation (13). The full sample includes 2577 firms of which 219 have voluntarily delisted for the period from 1980 to 2016. Following our theoretical model, there are 839 firms took bad decision either to delist (157 firms) or to remain listed (682) and 1,738 firms that took good decision to delist (62 firms) or to remain listed (1,676). 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 (1) is the base model and includes all the firms in our sample. Models (2) and (3) includes the firms which are classified according to our theoretical delisting model into bad decisions and good decisions, respectively. Coefficients and hazard ratios are reported for all models. The hazard ratio gives an estimate of how much the hazard of delisting increases for a unit change in the covariate. All estimates are adjusted for right censoring. The models include time fixed effects using year dummy controls. Coefficients are listed on the first row in each cell, with standard errors reported below in parentheses. The standard errors 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. All the regression covariates are defined in Table 11, in the Appendix B.

Variable	Baseline model (1)		Bad decision (2)		Good decision (3)	
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
TurnoverGr	-0.522**	0.593	-0.528**	0.590	-0.663*	0.515
	(0.211)		(0.210)		(0.340)	
TurnoverVol	0.469**	1.598	-0.147	0.863	1.308***	3.698
	(0.217)		(0.335)		(0.291)	
Turnover	-0.292***	0.747	-0.150***	0.861	-0.622***	0.537
	(0.050)		(0.055)		(0.083)	
Intangible	-1.499***	0.223	-1.247**	0.287	-1.217	0.296
	(0.567)		(0.615)		(0.877)	
Age	-0.313	0.731	0.088	1.092	0.276	1.318
	(0.341)		(0.293)		(0.418)	
Leverage	1.257***	3.513	0.885***	2.422	1.843***	6.318
	(0.266)		(0.327)		(0.530)	
MB	-0.293***	0.746	-0.264**	0.768	-0.346**	0.707
	(0.107)		(0.132)		(0.146)	
CAPEX	-1.556	0.211	-1.952	0.142	0.537	1.710
	(1.317)		(1.378)		(2.546)	
Dividend	-0.240	0.787	0.018	1.018	-0.279	0.757
	(0.171)		(0.192)		(0.349)	
NEI	-1.858**	0.156	-2.452*	0.086	-1.674*	0.188
	(0.742)		(1.303)		(1.017)	
FCF	-0.314	0.731	-0.132	0.877	-0.093	0.911
	(0.256)		(0.361)		(0.454)	
STR	0.053	1.054	0.460	1.583	-1.777	0.169
	(0.759)		(0.719)		(1.369)	
Return	-0.194	0.823	-0.295	0.745	-0.151	0.860
	(0.130)		(0.296)		(0.195)	
ReturnVol	0.122***	1.129	0.069	1.071	0.211***	1.235
	(0.030)		(0.061)		(0.044)	
Wald chi2	945.89***		744.32***		94374.5***	
Likelihood ratio test	-1376.916		-808.391		-312.727	
AIC	2847.831		1706.781		723.455	
BIC	3265.262		2050.618		1141.707	
Firm-year observations	53,184		15,380		37,638	

A A more General Case

A more general view on our modeling setting would be that in which listed firms consider delisting at the period when Δ_τ is positive and maximum. Hence, for a fixed maturity (T), the option to delist at T can be conceptualized as follows:

$$C_{Delist}(S_0^1, S_0^2, K, T) = E\left[\max\left(\int_0^T S_t^2 dt - \int_0^T S_t^1 dt - K, 0\right)\right] \tag{16}$$

The option payoff represented by Equation (16) is the same as the payoff of a "European Spread Option" on the cumulated turnover differences between the listed and delisted states. Given the lack of analytical solutions in this case, one can use Monte Carlo simulation calculus, making use of the identity expressed by Equation (5). From a computational point of view, a sample of values for $\{A_t^\nu\}_{t\geq 0}$ can be generated making use of the fact that A_t^ν has the same law as Y_t^ν defined by the following stochastic differential equation (SDE):

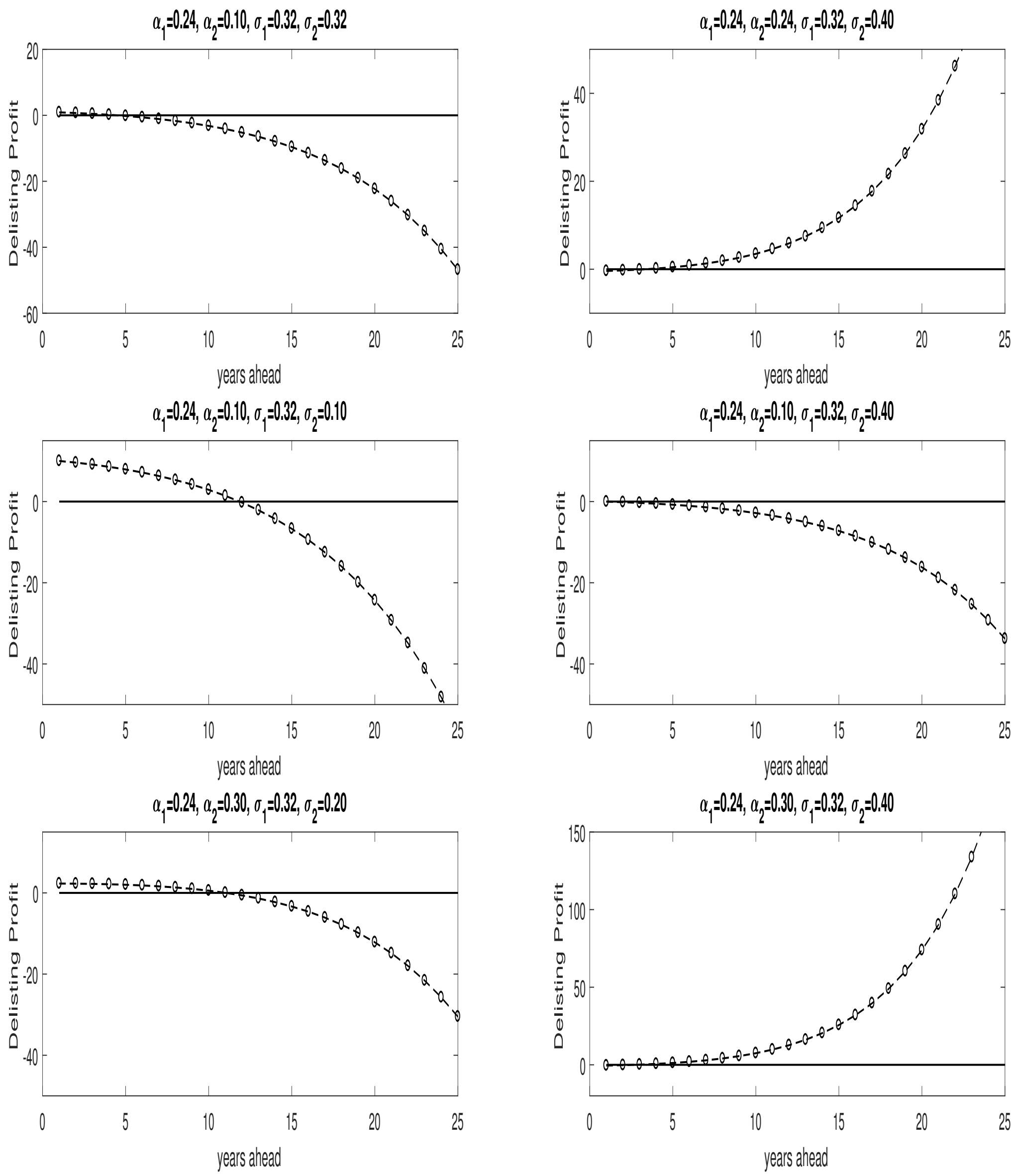
$$dY_t^\nu = [2(\nu+1)Y_t^\nu + 1]dt + 2Y_t^\nu dW_t \tag{17}$$

For further details and a proof see Carmona et al. (1997) and Dufresne (1989). This more advanced and heavier computational approach is however not pursued in this paper.

B Further Sensitivity Analysis

Figure 5: Theoretical Findings

This figure shows the effect of changes in the value of the turnover volatility and growth rate on the profitability of the delisting. The solid horizontal line represents the zero delisting profit threshold, and the convex or the concave curves represent the profit if the firm is delisted as a function of time which is given in years. We assume that the delisting option has a maturity of 25 years.



C Proof of Proposition 3.2

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

$$\Phi \frac{K - \mu(Q)}{\sigma} \tag{18}$$

The first derivative of Equation (18) is:

$$\varphi\left(\frac{K - \mu(Q)}{\sigma}\right)\left(-\frac{1}{\sigma}\right)\mu'(Q) \tag{19}$$

where,

$$\mu(Q) = \frac{1}{\eta}\left(-Q - \frac{1}{2}(\sigma_1^2 - \sigma_2^2)\right) \tag{20}$$

Therefore,

$$\mu'(Q) = -\frac{1}{\eta} \tag{21}$$

Hence, the first derivative of (18) is:

$$\varphi\left(\frac{K - \mu(Q)}{\sigma}\right)\left(-\frac{1}{\sigma}\right)\left(-\frac{1}{\eta}\right) \tag{22}$$

After rearranging its terms, it yields:

$$\varphi\left(\frac{1}{\sigma\eta}\right)\left(\frac{K - \mu(Q)}{\sigma}\right) > 0 \tag{23}$$

D Variables Definitions

Table 10: 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 theoretical delisting 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 Survey in 2015 and 2017.
AUDITFEES	Direct Auditing Fees	Average cost of annual auditing fees based on the firms annual turnover following PwC reports in 2012 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 turnover
SGA	Selling, General and Administrative	The value of Selling, General, and Administrative Expenses taken from Compustat
SGAratio	The ratio of SGA	The value of SGA as a percentage of turnover

Table 11: 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				
Turnover	Turnover Size	LOG (SALES)	Natural logarithm of total sales in 1980 dollars	(-)
Intangible	Intangible Assets	INTAN/AT	intangible assets/total assets	(+)
Age	Log of Firm Age		The natural logarithm of the firm's age which is defined as 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	(+)
Stock 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 traded) / log(Number of shares outstanding)	(-)
Others				
TurnoverGr	Firms turnover growth	(sale[_n] - sale[_n-1])/sale[_n-1]		(-)
TurnoverVol	turnovers volatility		The standard deviation of quarterly turnover growth each year	(+)