The Timing of Voluntary Delisting*

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Abstract

We model a firm's optimal time to voluntarily delist from an exchange. Three key parameters determine optimal delisting time: firm's growth rate and business risk combined with total costs associated with staying public. Our hazard rate estimations confirm that the aforementioned key variables are significant drivers of delisting time. Rising political and regulatory uncertainty are two channels through which these parameters get shocked, which changes the optimality of delisting. After classifying firms into ones that took an optimal versus those that took a non-optimal decision to delist, we show that stock market reacts differently to each type of delisting announcement.

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1 Introduction

In recent years, the attractiveness of being a public firm has declined, and there is a major listing gap in the US exchanges. According to Doidge et al. (2017), as of 2016 there were more delistings than new listings, and this gap would have still existed if the new listings had stayed as high as a few decades earlier. This observation indicates that exchange delistings have become a prominent feature of modern financial markets. Perhaps a good testimony of the existence of a less effusive sentiment regarding the status of public firms is the tweet by Elon Musk in August of 2018: "Am considering taking Tesla private. Funding secured".[2] Musk reversed this decision, but it raised some important questions about the positive sentiment toward voluntary delistings: Would delisting Tesla from the exchange have benefited the shareholders? Would a delay in the delisting decision of Tesla make it a more (or less) valuable company? Is there an optimal time to delist? This paper addresses these important questions by explaining why in recent years, voluntary delistings have become a valuable option for many public firms.

Compared to the period from 1980 to 1999, the voluntary delistings from the major US exchanges have noticeably increased in the last two decades. Since voluntary delistings are a choice, this trend indicates that many firms have recently found delisting from the main stock exchanges to be an optimal choice. Understanding why is the goal of this paper. A theoretical model on the timing of delisting is not yet available; this is surprising given that the cost-benefit rationale is at the center of the decision to delist. There are advantages to being a public firm. It widens the sources of external financing, improves the access to cheaper capital, provides firms with the opportunity of using stocks or stock options to attract talented managers, and it increases prestige and market visibility of firms (for a survey on this literature see Ritter and Welch, 2002; Lowry et al., 2017). It also facilitates the rebalancing of the accounts after a period of high growth and investment (Pagano et al., 1998; Pour and Lasfer, 2013) or the sale of the firm, either gradually, through a reduction in the ownership, or immediately, through an acquisition (Zingales, 1995).

However, being listed also has some disadvantages. For instance, the direct costs associated with the listing expenses include the costs related to the compliance with the Sarbanes-Oxley Act (SOX) of 2002 and the new governance rules and information disclosure requirements (Benninga

[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.

et al., 2005; Marosi and Massoud, 2007), the potential losses related to disclosing business secrets to firms rivals, the managements “short-termism” associated with quarterly earnings reporting, and the absence of ownership control (Pástor et al., 2008). Hence, if the net benefits from being a publicly listed firm are sufficiently low, delisting from a stock exchange might become optimal.

We develop a theoretical model on the timing of delisting that is based on the real options theory (McDonald and Siegel, 1986; Dixit and Pindyck, 1994). We assume that listed firms have the option to delist, which has value when there is uncertainty about the benefits from the delisting. Our model provides advice on the optimal time to delist, identifies whether the delisting decision is profitable, and shows how far away the delisting threshold is, if indeed the firm has not yet reached it. The option to delist is modeled as a “European spread option” on the accumulated revenue differences between the listed and the delisted states. A firm’s “optimal time to delist” is expressed as a function of three key parameters: a firm’s growth rate, its business risk, and its listing expenses.[3] These three parameters change over time depending on the evolution of the firm’s business, and they can be shocked by external macroeconomic trends like increasing macroeconomic policy uncertainties (see Baker et al., 2016) and rising regulatory burden on firm’s activities (Doidge et al., 2017). Such external shocks combined with firm’s own business risks can make voluntary delisting an optimal choice.

Our model highlights the role of uncertainty in managerial decisions (Bernanke, 1983; Dixit and Pindyck, 1994) and in particular the entry and exit decisions under uncertainty (Dixit, 1989). Building on this framework, it shows that recent external-to-the-firm conditions (e.g., rising economic policy uncertainty (Baker et al., 2016) can potentially explain the recent rise in voluntary delistings. In our model, the delisting decision is a real option with two important characteristics, a timing option and a state switching option. The latter is related to a decision process that the manager of a listed firm could follow to decide *whether* it is beneficial for the firm to go private or to delist. The former refers to finding the *optimal time* when to switch states of the firm from listed to delisted. This distinction is important since delisting may be valuable immediately, but

[3]A firm’s growth rate is the average revenue growth over the past five years and its business risk is defined as the volatility of the revenue stream over the same period. The listing expenses cover the average listing fees that had to be paid over the last five years to the exchange; the administrative costs of preparing accounting reports and other such filings required of listed companies (approximated by firm’s annual audit fees); and the costs of required disclosures and compliances (approximated by Sarbanes-Oaxley compliance fees). For further details, please see the variable definitions in Table A1 in the Appendix.

it may be even more valuable for the shareholders sometime later. Policy uncertainty becomes a more acute problem in stochastic dynamic environments (Dixit and Pindyck, 1994), and it can change the optimal timing of managerial actions. We empirically show that the policy uncertainties, be it economic policy uncertainty as in Baker et al. (2016) or regulatory risk as in Dawson and Seater (2013), can change the optimal time to delist. Put differently, an exogenous shock to the three firm-specific parameters (growth rate, business risk, and listing expenses) from policy uncertainty can change the optimal timing of the delisting. Furthermore, this common shock could have heterogeneous effects on different firms depending on eachs unique business operations.

This model yields certain predictions. First, it can identify which firms should voluntarily delist from the exchanges and approximately when. To validate this aspect of our model, we use a data sample that comprises information on 1,819 US listed firms from 1980 to 2019 during which 165 voluntarily delisted.[4] We classify these firms as listed that should stay listed and delisted that should delist (optimal decision), and listed that should delist and delisted that should stay listed (non-optimal decision). Then, we examine whether there are statistically significant differences between these subsamples regarding the underlying variables of our theoretical model. We also report that the firms that made optimal ongoing listing or delisting decisions have different cumulative abnormal returns (CARs) for various windows around the event date (i.e., the earlier of the delisting announcements or the official delisting filings for the sample of delisting firms and the last month in year 2017 for the sample of listed firms). We find that firms in the subsample of optimally delisted firms experience higher losses in their average CAR than the subsample of non-optimal delisting firms. This finding attests to the economic rationale and the assumptions underlying our model setting.

Second, we use the Cox hazard rate model to test the model's predictions on whether a firm's growth rate and the unpredictability of its future growth (business uncertainty), together with its listing costs, are significant determinants of the voluntary delisting decision. Our findings show that, on average, the delisted firms have less revenue, lower revenue growth, and higher business risk than the listed firms. These results support the use of two independent stochastic processes that describe the evolution of the firm's revenue under the listed and the delisted states and the

[4] To be included in the sample a publicly listed firm has to satisfy certain criteria (see our sample construction described in Section 6), which reduces the sample of listed firms substantially.

use of the growth rate, business uncertainty, and listing costs as the key drivers of the decision to delist. While logical, the literature has not explicitly identified these variables as important drivers of this decision; therefore, by explicitly analyzing them we add to the understanding of the causes of voluntary delistings.

Furthermore, as a third testable hypothesis, we predict that exogenous macroeconomic factors such as policy uncertainty and the number of new regulations imposed on the firm's products and activities can change the value of the delisting option by affecting the aforementioned three parameters of our model. In particular, the mediation analyses (conducted as in Baron and Kenny (1986)) show that policy uncertainty affects the delisting option primarily through the firm's business uncertainty, and the changes in the regulatory burden of a business affects the delisting decision through all three parameters. These are the key insights that help explain the recent trends that made the delisting option an attractive one for many firms (Gao et al., 2013; Doidge et al., 2017).

The delisting literature shows that firms are larger (in total revenues) when they delist than when they go public (Bharath and Dittmar, 2010) and indicates that there is an optimal time to become public (Benninga et al., 2005; Bustamante, 2011). Our findings show that being a larger firm when delisting is not enough to keep the listing status. We show that firms with higher revenue growths after being listed and with a revenue level beyond a given threshold are less likely to delist, while small firms with low or relatively moderate revenue growths after being listed stay in a critical revenue region for longer periods of time and, therefore, are more likely to delist. Firms with high revenue growths also delist but only when they are caught by extremely severe business and regulatory conditions.

The empirical delisting literature is relatively extensive (Sanger and Peterson, 1990; Shumway, 1997; Clyde et al., 1997; Pagano et al., 1998; You et al., 2012; Pour and Lasfer, 2013), although scarce on voluntary delisting decisions with the exception of Clyde et al. (1997) and Leuz et al. (2008). In general, the delisting decision is associated with a substantial decline in stock prices, large jumps in stock volatility, and a widening of the bid-ask spreads (Sanger and Peterson, 1990; Macey et al., 2008). Further, a large group of investors tend to get hurt by the delisting announcements (Sanger and Peterson, 1990; Bharath and Dittmar, 2010; Pour and Lasfer, 2013). Firms often delist because of limited analyst coverage, a decreased interest from institutional investors (Mehran and Peristiani, 2010), or because they want to rebalance their leverage (Pagano et al., 1998; Pour and

Lasfer, 2013).

This paper contributes to this delisting literature in several ways. First, it highlights delisting as a real option and emphasizes the idea that there is an optimal time to do it. Second, it develops a theoretical model on the timing of delisting with novel testable predictions. Third, it provides empirical evidence that stresses the importance of three key drivers of the timing of the delisting decision: firm's revenue growth, its business uncertainty, and its listing expenses. We are the first in this literature to test for these variables' role in delisting decisions and in introducing an empirical proxy of firm's ongoing listing expenses. Fourth, our paper models and tests the proposition that external macroeconomic shocks, like a sudden jump in economic policy uncertainty or an increase in regulatory restrictions, could make it optimal for firms to delist. This channel could explain why voluntary delistings have been frequent during the last two decades (Doidge et al., 2017) in which the political and regulatory uncertainty has rapidly climbed (Baker et al., 2016).

The rest of the paper is organized as follows: Section 2 presents our model and the related modeling assumptions and findings. Section 3 presents our sample selection process and shows the numerical simulation analysis that relies on ex-post (hand-collected) data on the delisted firms. Section 4 develops empirical hypotheses in support of our delisting timing model's assumptions. Section 5 tests the robustness of the "optimal" and "non-optimal" firm's decision classification given by the model. Section 6 presents our research methodology. Section 7 shows our empirical results and related robustness tests. Section 8 provides further empirical evidence on the driving factors of the delisting decision. In Section 9, we conclude and discuss some of the paper's practical implications.

2 The Model

2.1 Modeling Choices

Unlike financial options (e.g., stock options), where the main value driver (stock price) is known, identifying the underlying variable that determines the value of a real option (e.g., delisting option) is more difficult because there could be more than one "underlying" value driver. We argue that a firm's growth rate and the business risk it faces at any given point in time are the most important drivers of its voluntary delisting decision. Having a growing business is amongst the most common determinants of the listing decision and its timing (Maksimovic and Pichler, 2001; Pástor and Veronesi, 2005), and the realization that it is no longer possible to achieve such a growth strategy can become one of the most common reasons for the delisting decision. Amongst the advantages of being listed are the financial visibility (Mehran and Peristiani, 2010) and the access to capital (Bharath and Dittmar, 2010) that lead to a lower cost of capital and higher flexibility to deal with, for instance, mergers and acquisitions and the recruitment of talented employees. Therefore, if firms do not grow at a sufficiently high pace in the years immediately after being listed, the above benefits do not fully materialize, and the voluntary delisting can become a viable option.

Our voluntary delisting model, thus, relies on three key economic concepts (parameters). Two of these parameters describe the evolution of the firm's ongoing business by using indicators such as a firm's growth rate and business risk. The expected growth rate is the change in its sales (revenue) over a given time period, and the business risk is approximated by the uncertainty (volatility) of its growth rate. Both of these performance indicators are affected by the same underlying variable, sales, that changes from year to year following a stochastic process. The third parameter relates to the ongoing listing expenses (K), which the firm saves if it delists. Our ultimate goal is to model the probability of delisting at any future time t given a stochastic evolution of a firm's future revenue stream ($\{S_t\}_{t\geq 0}$).[5]

Our theorized relation between revenue and the probability of delisting is illustrated by Figure 1: at a given revenue threshold ($S^*_{Listing}$) firms become listed the first time. While their revenue is between this threshold and the "critical" revenue level ($S^*_{Critical}$), it is more likely that a small negative event, such as a drop in the profit margins or in revenue, will trigger a delisting. Firms with higher revenue growths in the period immediately after being listed reach $S^*_{Critical}$ sooner and operate henceforth in a revenue region where the delisting is less likely. These firms also stay listed for longer periods of time and when they are delisted it is more likely that the decision is non-optimal. Firms that do not grow fast in the periods immediately after being listed stay, therefore, in a critical revenue region for longer periods of time, so they are more likely to be caught by a negative economic or business event that triggers the delisting. Notice that the delisting of firms

[5] We run a panel logit regression for different groups of firms that we classify according to their revenue percentile. We find that there is a 16% drop in the probability of delisting when firms change from the first revenue percentile (revenue mean of \$5.7 million) to the second revenue percentile (revenue mean of \$28 million). Further, we find a 88.5% drop in the probability of delisting when firms change from the first revenue percentile to the third revenue percentile (revenue mean of \$68.3 million).

whose revenue is beyond this critical revenue region is also possible, but it requires the occurrence of a much more drastic negative event.

[Figure 1 here]

2.2 The Option to Delist

Our model takes the perspective of a firm manager who is evaluating whether to delist the firm and if so in which future period $t \geq 0$. Let τ denote the time of the voluntary delisting decision. We are searching for the optimal time for delisting (i.e., exercising the option) defined by the end of the period $\tau^* \in \{t_1, t_2, \ldots, t_n, \ldots\}$. Our ultimate goal is to model the probability of delisting at any future time t, $P(t \leq \tau < t + dt)$, which for small dt can be approximated by $f(t)dt$ where f is the probability density function of τ.

Next, consider an economy described by a continuous time model over the time period $[0, T^*]$ in which there is a filtered probability space $\{(\Omega, \mathcal{G}, P), (\mathcal{G}_t : t \in [0, T^*])\}$ that satisfies the usual mathematical set-up conditions, where P is the real-world probability measure. The information $(\mathcal{G}_t : t \in [0, T^*])$ observed by the manager contains the filtration information generated by the firm's revenues $\mathcal{F}_t = \sigma(S_u : u \leq t)$ for any time t. Let the firm's revenue process $(\{S_t\}_{t \geq 0})$ follow a geometric Brownian motion (GBM) given by:

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

where $\{W_t\}_{t \geq 0}$ is a standard Brownian motion, α is the expected rate of revenue growth, and σ is the volatility of those revenues per unit of time. Given that the solution to Equation (1) is $S_t = S_0 \exp[\sigma W_t + \nu t]$, with $\nu = \alpha - \frac{\sigma^2}{2}$, we can rewrite this solution using the properties of the Brownian motion:

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

where $\widetilde{W}_t = \frac{\sigma}{2} W_{\frac{4t}{\sigma^2}}$ in the sense that the two processes have the same probability distribution for any given t. A very important variable in this framework that facilitates the computation of the sum of the firm's revenue is captured by the following integral:

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

Since $\widetilde{W_t}$ is a Brownian motion, we can express the future accumulated revenue payoffs as:

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

$$\overset{law}{=} \frac{4}{\sigma^2} S_0 A^{\mu}_{\frac{\sigma^2 T}{4}} \tag{5}$$

where $\mu = \frac{2\nu}{\sigma}$. Knowing the probability distribution law of A_t^{ν} enables us to compute one of the important quantities that determines the value of delisting for a firm in period t which is $\int_0^T S_t dt$. In other words, knowing the probability distribution of A_t^{ν} will facilitate calculation of the probability distribution of $\int_0^T S_t dt$. The following proposition describes the probability density of A_t^{ν}.[6]

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

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

and

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

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

Proposition 2.2 *The expectation 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 $c^a = \frac{2}{2a+1}$.

Next, we describe the trade-off (and the related payoffs) between staying listed and deciding to

[6] Jeanblanc et al. (2009) provides the mathematical proofs for this theoretical part. In particular, the corollary 6.6.2.4 in their monograph provides a closed-form solution for the probability density of A_t^{ν}.

delist. Our model can be simplified by assuming that there are two (possibly) independent states of the world: the listed state and the delisted state. Both revenue growth and business uncertainty may change when firms switch from one state to another which widens the model's applications.[7] Consider that K represents the ongoing listing expenses. The firm saves these expenses if it delists. Let S_t^j be the revenue 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:

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

with the correlation between the two GBMs equal to $E(dW_t^1 dW_t^2) = \rho dt$.

Further, the revenue processes of the listed and delisted states are considered by the firm's manager, so the information filtration stays the same and hence $\rho = 1$. This is a realistic assumption for the delisting process given that the firm is assumed to have the same information about its product sales regardless of the firm being listed or delisted.

Figure 2 shows a timeline that illustrates the two stages of our model. The reference point of decision-making is fixed at time $t = 0$, that is today, and the current values of the revenue streams are shown by S_0^j, with $j = 1, 2$. Thus, these stages can be done recursively as an ongoing decision process that reflects the arrival of new information at the end of each year.

[Figure 2 here]

We are analyzing the optimal delisting time in a multi-period set-up whereby the delisting decision (action) can be taken at the end of each period $\{t_1, t_2, \ldots, t_n, \ldots\}$.[8] The delisting time can be conceptualized as a random stopping time when a specific condition, usually crossing a pre-specified barrier, occurs. Our theoretical model is based on the reasoning that the payoffs acquired by the firm in the post-delisting period, plus the cost savings made from not being listed, should exceed the current revenue stream. The next proposition formalizes this idea, and it focuses our modeling on the delisting time.

[7]Notice that we are not advocating that the listing decision, *per se*, enhances revenue or revenue growth, or that the delisting decision destroys revenue or reduces revenue growth. The evolutions of these variables also depend on the constantly changing market conditions, such as the industry and GDP growth, competition, and the quality of the business strategy and of the management team.

[8]The delisting effective in the time interval $(t_{i-1}, t_i]$ is equivalent to the firm being delisted from time t_i onwards.

Proposition 2.3 *The firm's manager has an incentive to delist at time t_i if $\eta_{t_i} = \int_0^{t_i} S_t^2 dt - \int_0^{t_i} S_t^1 dt$ is greater than the listing costs K. Therefore, the stopping time τ associated with the voluntary delisting decision τ can be expressed as:*

$$\tau = \inf\{t > 0 : \eta_t + K \geq 0\} \tag{10}$$

Moreover, the negative quantity K represents the total costs savings (exchange fees, auditing costs, etc.) that materialize only if the firm is delisted from the stock exchange.[9] The delisting time for the manager is predictable since they have inside information about the firm's instantaneous sales, so they can estimate the delisting time from the revenues pathway evolution. Given the above considerations, our continuous-time model is structural in the sense that Jarrow and Protter (2004) discussed.

The result in Proposition (2.1) could be expanded to compute the probability of delisting at time t, $P(t \leq \tau < t + dt)$, which for small dt can be approximated by $f(t)dt$ where f is the probability density function of τ. Thus, if $F(t) = P(\tau \leq t)$, $f(t) = F'(t)$. Furthermore,

$$P(t < \tau \leq t + dt | \tau > t) = \frac{F(t + dt) - F(t)}{1 - F(t)} \approx \frac{f(t)dt}{1 - F(t)} \tag{11}$$

Denoting $h(t) = \frac{f(t)}{1-F(t)}$, which can be recognized as the hazard function, and solving the differential equation $-\frac{(1-F(t))'}{(1-F(t))} = h(t)$, it leads to the following well-known relation:

$$F(t) = 1 - \exp\left(-\int_0^t h(s)ds\right) \tag{12}$$

For practical purposes one can assume that the hazard rate is piecewise constant such that $h(t) = h_i$ for all $t_i \leq t < t_{i+1}$. Therefore,

$$f(t) = h_i e^{-h_i t} 1_{[t_i, t_{i+1})}(t) \tag{13}$$

and, consequently, between t_i and t_{i+1}, the time to delist would have an exponential distribution.

An analyst[10] who observes the firm's revenue only at some discrete points in time, say annually,

[9] In our model and in our empirical tests, K is assumed to be a constant fraction of a firm's current sales. However, from a modeling perspective, this quantity can be taken more generally as a separate deterministic or stochastic process.

[10] The analyst in this context could be investors outside the firm such as hedge funds, speculators, private equity

can extend the analysis by also utilizing the information filtration set generated by the delisting time τ and possibly a vector of state variables X_t. In that case, the model becomes a reduced form model and, conceptually, the delisting time can be understood as a stopping time generated by a Cox process $\{N_t\}_{t\geq 0}$ that is defined by $N_t = 1_{\tau\leq t}$ which is determined by an intensity process $\lambda_t(X_t)$. Hence, if the calculation of the delisting time is done from a more general reference point of view, the information filtration changes to $\mathcal{F}_t = \sigma(\tau, X_u : u \leq t)$ which is a subset of the initial information filtration $\mathcal{G}_t$. If the delisting process is seen as the first arrival time that is associated with the Cox arrival process, then:

$$P(\tau \leq t) = E\left(E(N_t = 1|\sigma(X_u : u \leq T^*))\right) = E(\exp\left(-\int_0^t \lambda_u(X_u)du\right)) \tag{14}$$

In an applied world, a good starting point would be to consider the arrival rate process λ_u a given constant. In Section 6 of this paper, we will merge the ideas of piecewise hazard rates in Equation (13) with the intensity rate λ_t that is dependent on state vectors X_t. This merge will allow us to apply the Cox proportional hazard rate model to ascertain whether our theoretical model empirically matches the findings from our data.

One way to identify an optimal period for delisting is to consider the difference between the *expected* value of the total revenue generated up to the potential delisting time t_i if the firm is listed and the total revenue the firm would generate, plus the savings costs, if the firm delists. Therefore, we are searching for the year when the quantity:

$$\Delta_{t_i} = E\left(\int_0^{t_i} S_t^2 dt - \int_0^{t_i} S_t^1 dt + K\right) \tag{15}$$

is at a maximum level. This "on average" approach not only makes greater computational simplifications possible, but it also permits projecting the delisting savings values on a yearly basis up to any future horizon such that an optimal timing of delisting can be identified. We estimate the parameter K based on our data sample and conclude that it is about 6.14% of the annual revenue smoothed over a five-year period. Section 4 provides the details on the estimation of this parameter. Based on Equation (15), and expressing K as a percentage of the annual revenue, we

funds, or even regulators.

obtain:

$$\Delta_{t_i} = E\left(\int_0^{t_i} S_t^2 dt\right) - 0.9386E\left(\int_0^{t_i} S_t^1 dt\right) \tag{16}$$

Denoting the first and the second expectation in Equation (16) by m_2^i and m_1^i, respectively; using this result in Proposition 2.2, we obtain:

$$m_j^i = \frac{S_0^j}{\sigma_j^2}\left[1 + \frac{2\sigma_j}{2\alpha_j - \sigma_j^2 + 2\sigma_j}\exp\left(\frac{\sigma_j t_i}{2}(2\alpha_j - \sigma_j^2 + \sigma_j)\right)\right] \tag{17}$$

for any given i and $j = 1, 2$. Therefore, we have an analytical solution for each $\Delta_{t_i} = m_2^i - 0.9386m_1^i$ that can be calculated for $i = 1, 2, \ldots$ which enables us to determine where the maximum over a given decision horizon is. Furthermore, if the sequence $\{\Delta_{t_i}\}_{i=1,2,\ldots}$ is increasing, it means that it is never optimal to delist, therefore, the firm should stay listed.

With the ebbs and flows of new information on the market, the parameters of the GBM process of the revenue values may change. If so, the decision has to be revalued using the new parameter values. This methodology can be extended to consider recursive listing and delisting events or to compute the value of the option to delist.

3 Sample Selection and Simulation Analyses

Our model relies on two sets of parameters: the GBM process for revenue growth rate for each state (α_1 if the firm is listed and α_2 if the firm is delisted) and the revenue uncertainty (i.e., business risk) (σ_1 if the firm is listed and σ_2 if the firm is delisted); and the ongoing listing expenses (K), which is a savings cost if the firm is delisted.

3.1 Sample Selection

Our sample focuses on voluntarily delisted firms from the main US exchanges: the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ. Delisted firms are identified using the shares delisting code (DLSTCD) from the research in security prices (CRSP). Firms are organized into three delisting categories: mergers and acquisitions (DLSTCD codes 200-399 excluding 332), involuntary delistings due to bankruptcy or liquidation (DLSTCD codes >=400 excluding 570 and 573), and voluntary delistings (DLSTCD codes 332, 570 and 573).[11] Our initial sample covers the time period between 1980 and 2019.

We initially start with a sample of firms extracted from the merged Compustat and CRSP datasets. In this sample, we follow studies such as (Bharath and Dittmar, 2010; Pour and Lasfer, 2013) and exclude financial, insurance, and utility firms. Further, we remove firms listed on exchanges other than the NYSE, AMEX, and NASDAQ. Our real option model in Section 2 relies on switching between listed and delisted as two possible states of the world. Therefore, firms who end up delisting due to any other reasons such as M&A, liquidation, and bankruptcy (i.e., delisting codes other than 332, 570, or 572) are excluded from the sample. Based on this filtration, we end up with a sample of 3,425 firms, of which 368 have voluntarily delisted.[12]

For the reliability of the estimation of our model parameters, we require that firms have been listed for at least three consecutive years and then either continue to remain listed or voluntarily delist. Therefore, we obtain financial information for certain firms starting from year 1977. Firm-year observations with missing values are dropped from our sample. Finally, we manually check the list of voluntarily delisted firms and verify that the delisting is indeed voluntary (i.e., the firm did not go into a M&A or a bankruptcy after voluntarily delisting decision). Based on this step, we identify and drop 17 voluntarily delisted firms which went into a M&A or a bankruptcy within one year after filing to voluntarily delist from an exchange. These exclusions leave us with information on 1,984 firms of which 1,819 were still listed on the NYSE, AMEX, or NASDAQ, and the remaining 165 voluntarily delisted from one of these exchanges.

We use the CRSP database to extract daily trading information. We use Compustat and IBES to obtain corporate financial and auditing information. In order to measure the stock market reaction to the firm's delisting decision, we search for the dates of delisting announcements based on press releases, SEC filings, and firm's websites. Further, we search for delisted firms, from our voluntarily delisted subsample, which continue to trade on the Over the Counter Bulletin Board (OTCBB) or PinkSheet. We identify 31 delisted firms. To run our numerical simulation, we hand-collect quarterly revenues values for these 31 delisted firms up to two years (8 quarters) after their

[11]After delisting, a firm can still be traded on the OTCBB. Some of the voluntarily delisted firms, which are included in our sample, are also deregistered from the SEC. After delisting, we do not make a further distinction between voluntarily delisted and deregistered firms. For more details on the deregistration process, please see Marosi and Massoud (2007).

[12] Refer to Table 1 for further details.

delisting date. Revenues values of these firms are available after delisting as they continue to trade on PinkSheet or the OTCBB.

Table 1 has the details on the breakdown from these data sources and the exclusion criteria. Our final sample of 165 voluntarily delisted firms is relatively comparable to the sample of 434 delisted firms (of any kind) provided by Doidge et al. (2017). In their paper, Doidge et al. (2017) include all the voluntarily delisted firms from the AMEX, NASDAQ, and the NYSE that are available from CRSP database for the period from 1975 to 2012. Unlike us, Doidge et al. (2017) do not impose any filtration on their sample, hence, they end up with a relatively higher number of delisted firms.

[Table 1 here]

Figure 3 shows the number of voluntarily delisted firms over our data sample time period. It indicates that the number of delisted firms changes significantly over time, particularly near well-known economic, financial, or regulatory-related events. For instance, it increases after the SOX Act of 2002 and during the 2008-2009 financial crisis.

[Figure 3 here]

3.2 Numerical Simulation

In order to proceed with the simulation analysis, we hand collect data on the revenue of the delisted firms (i.e., post-delist). As this information is not publicly available for all the firms in the delisted sample, we use a subsample of 31 delisted firms and quarterly revenues for up to eight quarters.[13]

Panel A of Table 2 presents the descriptive statistics of the key parameters that underlie our theoretical model for the subsample of 31 delisted firms. On average, delisted firms have sales values of approximately $4,183 million before voluntarily delisting that then increase to $4,274 million in the two years that follow the delisting. A similar observation occurs for the firms' growth rate which rises from 1.9% per annum before delisting to 2.88% per annum within two years after the delisting. Simultaneously, firms business risk increases from 5.3% before delisting up to 8.36% for the period after the delisting. These results are in line with our theoretical prediction where, on average, delisted firms are able to improve their sales and growth rate prospects within a period of

[13] Of the 165 delisted firms in our sample, we find post-delisting financial information on 31 firms only. Those are the firms that are trading on PinkSheet or OTCBB. For further discussion on this and other aspects of our data, see Section 3.1.

two years after the delisting event as compared to pre-delisting. Furthermore, these firms are faced with higher uncertainty that is reflected by higher business risk after delisting from the exchange.

Panel B of Table 2 provides a more nuanced numerical analysis of the individual firms included in this subsample. The column MaxProfit represents the maximum delisting value achievable for each firm, while TimeMax shows the year when the MaxProfit occurs during the 25-year horizon. The BreakEven represents the time when the value of the delisting option is at-the-money, that is, there is no profit or loss made if the firm is delisted. However, we have denoted that the respective time is 25 years or longer. Therefore, if BreakEven is reported as 25 and TimeMax as 1, it means that the delisting value curve is downward sloping to eventually reach the cross-even line. This slope would be the case for when delisting is optimal for a firm. If BreakEven is reported as one and TimeMax as 25, the initial value of delisting is positive and close to zero, that is, the firm can delist at any time later, but it would not be optimal doing so because the delisting value curve is increasing and continues to rise beyond the 25 years. Finally, if BreakEven is one and TimeMax is zero then the value of delisting is always in the non-positive territory and the firm should not delist.

We observe in Table 2 that several firms should not have delisted because they had a TimeMax equal to zero. Further, there were five firms that delisted optimally as indicated by their TimeMax of one. The majority of firms that delisted optimally had a higher growth rate post-delisting ($\alpha_2 > \alpha_1$). Moreover, for many of the firms which should not have delisted, we observe the opposite ($\alpha_2 < \alpha_1$ or $\alpha_2 < 0$) and, in general, they were medium to large firms. For these firms, the maximum delisting profit achievable indicates that the delisting option was deep out-of-the-money. The majority of firms which should have delisted and for which the delisting option value was maximal at the end of time horizon were those that experienced an increase in the revenue growth rate and also in business uncertainty. Hence, the revenue growth rate appears to play a key role in the delisting decision, followed by the business uncertainty.

[Table 2 here]

Figure 4 shows our simulation results for six different delisting scenarios. The baseline scenario is represented by the graph in the top left-hand side in which we assume that the business risk and the revenue growth rate of the listed and the delisted states are the same: $\sigma_1 = \sigma_2 = 0.32$ and

$\alpha_1 = \alpha_2 = 0.24$. For this baseline case, the delisting is profitable and a delay would make it even more profitable as the profit is increasing with time. The remaining graphs represent scenarios where we change either the business risk or the revenue growth rate of the listed or the delisted states, *ceteris paribus*. For instance, the graph in the top right-hand side represents a scenario in which the revenue growth rate of the delisted state stays the same, but the business risk drops from 0.40 to 0.32. Comparing our findings for this scenario with those of the baseline scenario, when the business risk is higher in the period prior to delisting, there is some small positive value to delisting which decays and becomes negative after a few years. This graph also shows that the revenue growth rate is the main driver of the delisting option, with business risk playing an important but secondary role.

The second graph in the top left-hand side represents a scenario in which we change the business risk prior to delisting from 0.32 to 0.10. For the first few years the delisting option is in the negative territory, breaks even after 10 years, and increases afterwards. The delisting of the firm is profitable in the long horizon so a delay in the delisting makes it more profitable. Hence, an increase in the revenue growth coupled with a rise in business risk increases the chances that the delisting will be more profitable in the future. Over time, the revenue growth compensates for the increase in business risk. The second graph in the right column displays the situation when the revenue growth rate increases from 0.10 to 0.24 while the business risk decreases from 0.4 to 0.32. The delisting option is always positive and increases in a nonlinear manner with the horizon. In this scenario both drivers are at work, revenue increases while business risk decreases post delisting.

The third graph in the top left-hand side represents a scenario where we contemplate a reduction in revenue growth from 0.30 to 0.24 and an increase in business risk from 0.20 to 0.32. The small loss of revenue is compensated by larger business risk. In this scenario the delisting value increases with the horizon but at a lower rate, and a delay in the delisting makes it advisable. The third graph in the right column shows the situation when revenue growth stays the same, but business risk drops from 0.32 to 0.10. Initially, the delisting option has a small positive value. When the revenue growth rate is substantial and positive, as in this case, the greater business risk will generate extreme profits and losses. This effect will dampen the value of delisting which decays with the horizon. Thus, delisting now is optimal to waiting.

Overall, our simulations show that both business risk and the revenue growth rate of the delisted state significantly affect the timing and profitability of the delisting. However, the value of delisting is more sensitive to the revenue growth rate than to business risk.

[Figure 4 Here]

In the Online Appendix, we show a more detailed sensitivity analysis that complements that showed in Figure 4 - see Figure OA.1. We also provide a sensitivity analysis, relying on hand-collected empirical data from six firms that voluntarily delisted, to study the optimal time for them to delist. In Figure OA.2, we show our results where each of these cases represents a typical case for the delisting. There are different values for the firm's revenue (S) just prior to the time of delisting, for the revenue growth rate (α) before and after the delisting, and for the business uncertainty (σ) again before and after the delisting.

4 Model Testing and Hypothesis Development

In this section, we develop three empirical hypotheses which aim to test for the validity of our theoretical delisting model that indicates the firm's revenue growth rate and business uncertainty play key roles in the delisting decision. If this assertion is true, then the revenue growth rate (α) and the business uncertainty (σ) of the listed and the delisted states are key determinants of the delisting decision. We test these research hypotheses as well as that which affirms that the listing expenses (K) also affect the delisting decision.

An economic rationale which supports the above pronouncements is that firms are relatively small when they are listed the first time and become listed mainly because of their ambitions for high revenue growth. However, becoming a listed firm also brings additional costs which are not negligeable for small firms. Consequently, recently listed firms try to grow as rapidly as possible not only because that means that they are achieving their business goals which enhances financial visibility, but also because of the weighting of the listing expenses on their operating costs which decreases as the revenue increases. Therefore, if a few years after being listed revenue growth is below expectations or clearly will not materialize, the probability of delisting increases significantly.

We also note that the delisting decision involves switching (option) from the listed state to the delisted state, so the revenue growth and the revenue uncertainty that are conjectured for the (ex post) delisted state should also play a role in the delisting decision.

4.1 Revenue Growth Rate

Our model assumes that revenue growth is a key determinant of the delisting decision, particularly for small firms and during the period immediately after being listed. Firms are usually small and are ambitious for high revenue growth when they are at first listed. Thus, if revenue growth in the years immediately after being listed is low or, a few years after the listing decision, it becomes clear that the initial ambitions on revenue growth will never materialize, the probability of delisting increases significantly. The urgency for revenue growth in the years immediately after the delisting is supported by Bharath and Dittmar (2010) to some extent, who show that firms are larger when they delist than when they went public, and also by Mehran and Peristiani (2010) who conclude that a significant number of the firms that elected to delist in the US between 1990-2007 decided, on average, about five years after becoming listed. Thus, we hypothesize that the probability of delisting is negatively related to revenue growth:

H1: *The probability of delisting decreases with firm's revenue growth.*

4.2 Revenue Uncertainty

It well known that uncertainty reduces the pace of investment. The so-called real option theory (Dixit and Pindyck, 1994) advocates that, when the option to invest is proprietary to one firm only, the investment cost is irreversible, and the future benefits from the investment are uncertain, then there is an option value to invest which increases with the uncertainty, and that the optimal timing to exercise that option does not coincide with the timing that is indicated by the net present value (NPV) technique. It is argued that at the moment the firm exercises the option to invest, it exchanges the value of the option with the present value of the expected benefits from the investment. Thus, investment decisions should be made when the NPV is higher than the value of the option to invest and not when the NPV is positive. Therefore, higher uncertainty delays investments because it increases the value of the option to invest, which is often also called the "option to wait". Brennan and Schwartz (1985) develop one of the first theoretical models that follow the above economic rationale, and McDonald and Siegel (1986) show that the value of the option to invest can be significantly higher than the investment cost. Dixit (1989) studies entry and exit timing decisions under output price uncertainty following the same framework.

The revenue uncertainty is usually assumed to be correlated with the macroeconomic uncertainty, but there are other types of uncertainties that can also create unfavorable market sentiments towards investments. For instance, policy uncertainty that affects stock prices, which is studied by Pástor and Veronesi (2012), and that can be split into the uncertainty related to the unpredictability of government policy changes and, for instance, the effects of the policy change on profits.

Building on the above arguments, we hypothesize that the probability of delisting is positively related to the business uncertainty:

H2: *The probability of delisting increases with firm's revenue uncertainty.*

4.3 Listing Expenses

According to our model, the listing expenses are one of the key determinants of the delisting decision. However, the information on listing expenses is not publicly available. Nevertheless, Ritter (1987) estimates that firms pay about 7% of the IPO gross proceeds to cover the variable costs related to auditing, certifying, and disseminating accounting information and the listing fee. Moreover, Benninga et al. (2005) show that there is an average increase of $62 million in the SGA costs between the pre-IPO and the post-IPO years which means that the costs associated with the IPO are about 10% of the annual profit. Therefore, we hypothesize that the cost savings which are associated with delisting is an important determinant of that voluntary choice:

H3: *The probability of delisting increases with the firm's listing expenses.*

There are numerous examples of relatively small firms that delisted to save the direct and indirect costs that are associated with the listing.[14] The types of costs that could be saved through this delisting decision include exchange fees, SOX compliance fees, and auditing fees. The exchange fees for each firm come from the exchange on which the firm is listed. The average annual SOX compliance costs are estimated based on the information released in 2017 by the Protiviti consulting and professional services according to which these costs include the internal compliance fees and

[14]hhttps:www.prnewswire.com/news/news-releases/education-management-announces-intention-to-voluntarily-delist-shares-from-nasdaq-255232737.html, and https://www.businesswire.com/news/home/20160311005966/en/Steel-Excel-Announces-Voluntary-NASDAQ-Delisting-SEC, for instance.

vary with the firms size, which is measured by the total revenue.[15] Finally, we get the total auditing fees for each firm-year observation from the AuditAnalytics database. Since this information starts in year 2000, to avoid losing sample observations, we extrapolate the audit fees from year 1980 to 1999 by using the average firm's auditing fees between 2000 and 2016. We then multiply this average by the firm's selling, general, and expenses (SG&A) for each firm-year observation from 1980 to 1999 and adjust it by 1980 dollar value. In order to obtain a ratio of these listing expenses, we scale each of them by the revenue for each firm-year observation and add the three expenses to obtain the total ratio of listing fees ($TotalFeeRatio$).

4.4 The Role of Macroeconomic Shocks

Financial decisions at the firm level are severely affected by uncertainty (McDonald and Siegel, 1986; Dixit and Pindyck, 1994). Uncertainty affects firms by changing the value of real options, in particular the option to delay irreversible investments (Bernanke, 1983). Many empirical studies have examined the effect of political risk on firms' investments (Leahy and Whited, 1996; Bloom, 2009; Julio and Yook, 2012; Gulen and Ion, 2016) and large asset purchases (Bonaime et al., 2018; Nguyen and Phan, 2017). Their findings are in line with the real options argument in that firms should exercise their option to delay the investment when facing higher uncertainty (Leahy and Whited, 1996; Jens, 2017).

A different branch of the literature argues that policy uncertainty lowers the value of a firms assets in general (Pástor and Veronesi, 2012, 2013) which increases the equity premium (Brogaard and Detzel, 2015) and makes it unattractive for the firms to issue seasoned equity (Gungoraydinoglu et al., 2017) or an initial public offering (Çolak et al., 2017). Elevated policy uncertainty is also associated with uncertainty over macroeconomic indicators, taxes, and labor policies, among others. These uncertainties can manifest into the unpredictability of the firms' operations and profits (Sialm, 2006; Ulrich, 2013). Specifically, this effect can have a material effect on the firms' growth rate and business risk which are the two key parameters in our real options model: the option to delist. These findings indicate that periods of elevated policy uncertainty can create optimal conditions for a firm to voluntarily delist; the firm's equity and assets are undervalued, the growth rate is lower, and the benefits of being public are lower (external financing is constrained).

[15] For further details, see: https://www.protiviti.com/US-en/insights/sox-compliance-survey.

Furthermore, the introduction of new rules and regulations also create their own uncertainties. The accumulated effects of these regulations can have numerous potential consequences to the affected firms. Several studies have identified the macro- and micro-level negative effects of regulation accumulation or regulatory burden. For example, Dawson and Seater (2013) find that over their study period, the accumulation of federal regulations slowed US economic growth by an average of 2% per year. McLaughlin (2016) tests the effect of regulation on a firm's investment choices. He finds that regulations negatively affect the firm's investment choices that lead to innovation, which in turn leads to a reduction of the annual growth rate of the US GDP.

In general, our theoretical model shows that a significant shock to political or regulatory uncertainty could lead to a lower growth rate and higher business risk that, in turn, increase the probability of voluntary delisting. The role of such economic channels are theoretically shown in Appendix A, whereby we derive the sensitivity of the delisting payoff to the three underlying drivers of this payoff (growth rate, business risk, and listing expenses). Put differently, any exogenous shock to the three firm-specific parameters can change the optimal timing of the delisting for a given firm. Furthermore, this common shock could have a heterogeneous effect on the firms depending on their parameter values (i.e., depending on firm's unique business operations).

Building on the above discussion, we conjecture that policy uncertainty and higher regulatory burden could be important economic channels that affect the firm's probability of delisting by decreasing the growth rate and increasing the business risk and listing expenses. Our model predicts that such uncertainties should increase the value of the real option to delist.

H4A: *The probability of delisting increases when policy uncertainty is elevated.*

H4B: *The probability of delisting increases when regulatory burden is high.*

5 Model Validation Tests

If our theoretical model is effective in classifying firms' behavior, as optimal and non-optimal in what regards firms' decisions to stay listed or to delist, so the group of firms which the model classifies as having a non-optimal behavior should have different characteristics from the group of firms which the model classifies as having an optimal behavior.

Thus, the classification provided in Panel A of Table 3 is driven by our theoretical model and it shows that of the 165 firms that were delisted, 68 made an optimal decision and 97 made a non-optimal decision. Moreover, of the 1,819 ongoing listed firms, 1,587 firms made an optimal decision in staying listed and 232 firms made a non-optimal decision, that is they should have been delisted.

Panel B of the table provides a mean comparison test among the main theoretical underlying variables, considering whether or not current (listed or delisted) status of the firm is an optimal or non-optimal decision. Our results indicate that there are significant mean differences between optimal and non-optimal sub-samples within each of the delisted and listed samples of firms. The sample of delisted firms that according to our theoretical model took the optimal decision to delist, on average, has a significantly higher business risk (16.32%) and listing expenses (60.48%) compared to those that took the non-optimal decision to delist with (9.68%) and (10.11%), respectively. The mean difference of growth rate between both samples is not statistically significant.

As per the sample of listed firms, we find that the sub-sample of listed firms which took the optimal decision to remain listed have significantly lower growth rate (28.25%), business risk (8.36%) and listing expenses (11.41%) compared to their counterpart firms which took the non-optimal decision to delist with mean values of (47.70%), (21.70%), and (48.57%) for growth rate, business risk and listing expenses, respectively. These findings further reinforce the reliability of our modelling assumptions.

Finally, in order to empirically test the robustness of the above theoretical classification, we examine how stockholders perceive the firm's decision to delist or to remain listed conditional on being classified in either the optimal or non-optimal sub-samples.

For the sample of (de)listed firms only, we split the sample into two sub-samples; the sub-sample of (de)listed firms that made an optimal decision to (delist) remain listed and the sub-sample of firms that made a non-optimal decision to (delist from) remain listed in the exchange. Then, we analyze the stock price reaction to the (de)listing event. To do this, we conduct an event study. For the sample of delisted firms, it is easier to identify the event date, which, in our case, is defined as the earlier of the delisting announcement or the official delisting filing. Regarding the sample of listed firms, we identify the event date as the last month in year 2017 which allows us to create an out of sample period for our event study of up to 2 years from end of 2017 to end of 2019.

In panel C of Table 3, we report the cumulative abnormal returns for various windows around the event date. For delisted firms sample, we compute the cumulative abnormal returns using daily stock price observations. The date (0) refers to the day of the delisting event. The first window, (0, +1) captures the immediate investors' reaction to the delisting event. The second and third windows, i.e., (0, +2) and (0, +5), allow for the slower dissemination of information for these less visible and infrequently traded stocks. For the listed sample, as there is no clear (announced) event similar to that of the delisted firms, we expect investors' reaction, reflected through the short-term CAR, to be less reliable and instead the long-term returns should be used. Therefore, we measure the cumulative abnormal returns using monthly stock price observations and create three long-term event windows namely: (0, +12), (0, +18), and (0, +24), where the event window is based on months rather than days. Following Leuz et al. (2008), we calculate the cumulative abnormal returns using a simple daily/monthly market adjusted return based on the daily/monthly value weighted CRSP market index.

Starting with the full sample of delisted firms, we find the event window returns to be negative and significant. During the event windows (0,+1), (0, +2), and (0,5), the voluntary delisted firms generate excess return of -5.26%, -4.97%, and -7.12%, which is in line with the negative excess return reported by Leuz et al. (2008), Marosi and Massoud (2007), and Pour and Lasfer (2013). Additionally, these results also indicate that stockholders experience significant wealth losses from firms' decision to delist.

Given that our aim is to test the the robustness of the theoretical model in distinguishing the firms that made an optimal decision from the firms that made a non-optimal decision, we test the stockholders' reaction to both sub-samples of firms. Overall, we find the cumulative average abnormal return to be negative and significant for both sub-samples of firms and for all the event windows. Interestingly, we find that the sub-sample of optimally delisted firms to experience higher losses in their cumulative average abnormal return compared to the sub-sample of firms with non-optimal delisting decision.[16] These findings show that investors are able to identify the firms that made the optimal decision in being delisted from those that made a non-optimal decision.

As per the event analyses for the full sample of listed firms, we find that the economic impact of the cumulative abnormal returns to be significantly positive for the different event windows. This

[16]In an untabulated results, we find qualitatively similar results when computing the cumulative abnormal returns based on the equally weighted CRSP market index and also when bootstrapping the standard errors.

is an expected finding given that those firms do not suffer from any major restructuring event. What is interesting in the sample of listed firms is that, on average, investors reward the firms which optimally decided to stay listed. Specifically, for the sub-sample of optimally ongoing listed firms, we find positive and significant coefficient values for the (0, +12), (0, +18) and (0, +24) event windows, whereas we do not find any statistically significant coefficients for the sub-sample of non-optimally ongoing listed firms.

[Table 3 here]

6 Empirical Testing Methodology

In this section, we describe our hazard model and the research methodology used. The state vector X_t impacting the intensity arrival rate of the Cox process in (14) is:

$$X_t = (T_g, T_b, T_e, C_{controls}) \tag{18}$$

where T_g is the growth rate, T_b is the business risk, T_e is the listing expenses ratio and $C_{controls}$ is the vector of control variables. We employ a widely used technique in bankruptcy estimations (Campbell et al., 2008; Mehran and Peristiani, 2010) that can handle any variation of the covariates under investigation over time, and allowing us to explicitly model the voluntarily decision to delist as a function of the explanatory variables.

The hazard function $h(t)$, which is the limiting probability that the firm will delist in a given time interval in the future, conditional on it not yet being delisted at the beginning of the interval, as the length of the interval decreases to zero, can be parametrized as $h_i(t) = m(t, \beta X_{i,t})$. One important aspect in this estimation is that we need to identify a functional form for the relation between the hazard time and $X_{i,t}$ covariates. One regression specification is that which allows a hazard function $h(t|0)$ to be multiplied by $e^{\beta X_{i,t}}$. $h(t|0)$ is also known as the baseline hazard. In our case, it captures how the probability of delisting changes over time assuming that all the covariates are equal to zero. This formulation is called the proportional hazards (PH) model. As we are using the Cox semi-parametric PH model, the functional form of the basline hazard $h(t|0)$

is left unspecified.[17] [18]

Considering the above discussion, we define our semi-parametric PH cox model on a panel data structure as follows:

$$h(t|X_{i,t}) = h(t|0)e^{\beta X_{i,t}} \tag{19}$$

Equation (19) represents the hazard rate of firm i conditional on the firm not delisting 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 for firm i at time t (i.e., Size, FirmAge, Leverage, KZ, ROA, CAPEX, Dividend, R&D, NEI, Turnover, DRET, and SDDRET),[19] and 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. Furthermore, we include time and industry fixed-effects using year dummies and industry dummies at the 2-digit SIC codes as controls.

The control variables used are derived from a set of hypotheses that are found to affect the firm's decision to delist. First, the asymmetric information hypothesis: 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 delisted again. Furthermore, Pour and Lasfer (2013) advocates that smaller firms with a high intangible assets value have higher adverse selection costs, which increases the probability of delisting. We use the five years moving average of the logarithm of firm's total assets (Size) and age (FirmAge) as proxies for the adverse selection cost.

Second, the access to capital hypothesis: it is well-documented that public firms have access to a wider range of financing sources. We use the five years moving average of the firm's dividends payment (Dividend) to measure the financial constraints, following Bharath and Dittmar (2010). There is also evidence that firms often go public to rebalance their leverage (Pagano et al., 1998); hence, as proxies for access to capital, we use the five years moving averages of leverage (Leverage), KZ ratio (KZ), capital expenditure intensity (CAPEX), research and development expenses (R&D), and net equity issuance (NEI).

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

[18]Section 7.3 re-estimates the hazard function assuming that the baseline hazard follows a Weibull distribution (it is a fully parametric model) while also addressing heterogeneity concerns.

[19]The variable definitions of the control variables are provided in Appendix A1.

Third, the financial visibility hypothesis: financial visibility increases with the public-firm status which facilitates access to cheaper capital. Therefore, financial visibility might be a reason for listing (Bharath and Dittmar, 2010; Pagano et al., 1998). When the visibility that is expected with the public-firm status does not materialize, the stock return becomes low and the likelihood of delisting becomes high (Mehran and Peristiani, 2010). We consider the five years moving average stock return (DRET) and stock return volatility (SDDRET) as proxies for financial visibility, following Pour and Lasfer (2013)

Fourth, the agency costs hypothesis: These are higher for public 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 delist again. We use the five years moving average of return on asset ratio(ROA) as a proxy for the agency costs, following Pour and Lasfer (2013).

Fifth, stock liquidity hypothesis: This improves significantly with the public-firm status. Bharath and Dittmar (2010) show that firms with less liquid stocks are more likely to be delisted. We use the five years moving average of stock turnover (Turnover) as a proxy for the liquidity, following Amihud and Mendelson (1988).

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 time to delist. Alternatively, we can interpret 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 reveals how much the hazard of the delisting event increases with 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). To correct for this right censoring problem, 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 (listed) - see Kiefer (1988).[20]

[20] Section 7.3 provides further robustness tests. Furthermore, we also take into account the left-censoring problem.

7 Prediction Testing and Robustness Tests

7.1 Univariate Analysis

In Table 4, we provide a univariate analysis for the variables used in our main model. Specifically, we report the mean and standard deviation of the listed and voluntary delisted sub-samples and the full sample. Further, we report the t-test results for the differences in means between listed and voluntary delisted sub-samples.

For an average firm in our sample, we find that the five years moving average growth rate, business risk, and listing expenses are 12.69%, 5.31%, and 6.14%, respectively. The t-test of these variables shows that the mean differences between the listed and voluntary delisted firms are statistically significant at the 1% level. On average, the sub-sample of listed firms enjoys a revenue growth rate of 12.81% which is significantly higher than that of the voluntary delisted sub-sample with 10.64%. Also, the sub-sample of listed firms has significantly lower ratios of business risk (5.17%) and listing expenses (5.7%) compared to that of the voluntary delisted sub-sample with business risk and listing expenses of 7.68% and 13.56%, respectively.

Further, the *t*-test results show statistically significant differences in means of control variables between the listed and voluntary delisted sub-samples of firms. For the asymmetric information proxy variables, we find that listed firms, on average, have larger size (6.0285 compared to 4.8843) and are younger (2.8063 compared to 2.4217) than their voluntary delisted counterparts. These findings are in line with those of Marosi and Massoud (2007) and Pour and Lasfer (2013).

For the access to capital proxy variables, we find that the leverage ratio mean of the listed firms is lower than that of the voluntary delisted firms (18.58% compared to 22.16%), which supports the view that firms which voluntarily delisted follow more aggressive, and not always successful, revenue growth strategies and, therefore, rely more on debt. The means of KZ, NEI, and Dividend ratios of the listed firms are significantly lower than those of the delisted firms with mean values of 0.0492 compared to 0.2161, 0.0559 compared to 0.0738, and 0.0130 compared to 0.0155, for listed and delisted sub-samples, respectively.

For the financial visibility proxy variables, we conclude that the mean of the stock return of the listed firms is lower than that of the delisted firms (0.2295 compared to 0.4879). The mean of stock return volatility of the listed firms is lower than that of the delisted firms (1.2557 compared to 2.7738). For the agency costs proxy variable, we find that the listed firms have a higher ROA than the delisted firms (0.0274 compared to -0.0691).

Finally, we report the means of the total listing costs per annum and their individual components. We find that, on average, the total listing costs per annum for the full sample is 4.66% of the annual revenue. As per the individual components, the highest ratio is that of the firm's auditing fees (36%), followed by the annual exchange listing fees (1.18%), then the SOX compliance fees (0.82%).

Regarding the mean differences analysis, our t-test shows that the mean of the annual total listing costs, as a percentage of the annual revenue, differs significantly between the listed sample and the delisted sample. This difference remains statistically significant for auditing fees and SOX compliance fees ratios. Our estimation above is not far from the 10% of gross profits of Benninga et al. (2005), who use a dataset that covers the time period between 1982 and 2000. The difference between the two estimations might also be due to the fact that Benninga et al. (2005) used information on the listed firms only.

[Table 4 here]

7.2 Multivariate Analysis

Model (1) of Table 5 provides the results while estimating our hazard model for the set of control variables only. Further, in Model (3), we add to this base model the growth rate and business risk (Model 2), while, in Model (5), we add the total listing expenses ratio. This is because we want to examine whether these variables, used in our real options model, affect the voluntary delisting decision.

The results in Models (3) and (5) provide supporting evidence for our three main hypotheses. Overall, we find that the coefficient values of growth rate, business risk and listing expenses to be statistically significant. Also, the hazard rate of voluntary delisting decrease with the growth rate and increase with business risk and listing expenses. As per Model (5), the negative coefficient of growth rate indicates that firms with lower revenue growth are more likely to delist - the hazard ratio is 0.2884, which means that the hazard rate of delisting changes by -71.16% (=0.2884 - 1) for each unit increase in growth rate. This supports our H1. Moreover, the higher the business risk, the more likely is the delisting - the hazard ratio suggests that a unit increase in business risk changes the probability of delisting by 226.76% (=3.2676 -1) which is in line with our H2. Finally, the hazard ratio of listing expenses indicates that a one unit increase of the listing expenses leads to a change of the probability of voluntary delisting by 132.61%. This is also in line with our H3.

The control variables in all of the three models provide qualitatively similar results to each other and all are in line with the findings in the previous literature. Specifically, the hazard rate decreases with Size, firm age, KZ, and stock turnover and increases with leverage and stock return volatility. These results support the asymmetric information, access to capital, financial visibility, and stock liquidity hypotheses.

[Table 5 here]

7.3 Robustness Tests

In this subsection, we run several tests to check the validity of our main results. First, our data sample could suffer from the problem of left censored observations. The reason being that the cases where the IPO date is not available, we use the first record date in Compustat as the duration starting date. We cannot ignore this problem because it can bias our parameters estimations (Ongena and Smith, 2001). Thus, we follow Heckman and Singer (1984) and remove from our sample all the left censored observations. Then, we re-estimate Equation (19) in order to compare the results with those obtained in Model (3) in Table 5. The results are provided in Model (1), Panel A of Table 6.

Ongena and Smith (2001) also advocate that if the results are sensitive to left censored observations, a change in the first observed year creates instability among the parameter estimates. Therefore, we change the starting date of our sample time period to 1985 and run our baseline hazard model again. We repeat this procedure considering the requirement of a minimum of three observations per firm for a firm to be considered in our sample. After eliminating the left censored observations, if the number of firm-year observations is below three years, we remove the entire observations for this firm. Model (2) of Table 6, provides the results. Overall, the results in reported in both Models (1) and (2) lead to similar qualitative results as those of our baseline model.

Second, previous literature on firms' delisting decisions has highlighted the differences in incentives between US and foreign firms listing and delisting/deregistration decisions from the US market (for further details, see Leuz et al. (2008) and Marosi and Massoud (2008)). Given the existence of different motives of delisting from US exchanges between US and foreign firms, we re-run our main model after excluding voluntary delisted foreign firms from our sample. The reported results in Model (3) are qualitatively similar to our main model.

Our third robustness test addresses the unobserved heterogeneity issue at the industry level. For this, we use a parametric model to estimate the hazard rates, assuming that the time to delist follows a Weibull distribution. In survival analysis studies, it is assumed that the population is homogeneous. If this assumption is applied to our research, it means that firms have the same risk of experiencing a delisting event, conditional on a set of covariates, and that the delisting times are independent. However, the latter assumption may not hold because firms can have different risks and hazards. Indeed, an association between the event times of some sub-samples can exist if these share a common characteristic that cannot be observed. If we do not control for unobserved heterogeneity, our results could be biased by the nature of duration dependence and the estimates of the covariates (Heckman and Singer, 1984). To overcome this problem, we control for an unobserved random factor ($\upsilon_{i,t}$), known as "frailty", to account for the unobserved heterogeneity due to unobserved covariates. This factor modifies multiplicatively the hazard function of the firms, or cluster or group of firms, according to Equation (20):

$$h(t|X_{i,t}) = h(t|0)(\omega_{i,t})e^{\beta X'_{i,t}} \tag{20}$$

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

In order to test the validity of our results, while controlling for the unobserved heterogeneity, it is computationally easier to specify the heterogeneity using a parametric model (Weibull) than using a semi-parametric model (Mehran and Peristiani, 2010). In order to test our parametric model with heterogeneity, we use Equation (21):

$$h(t|\beta X_{i,t};\gamma,\theta) = \gamma e^{\beta X'_{i,t}+\upsilon_{i,t}}(te^{\beta X'_{i,t}+\upsilon_{i,t}})^{\gamma-1} \tag{21}$$

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

The results are reported in Panel C of Table 6. Model (4), shows our results for the parametric models, considering the existence of a shared frailty at the industry level $\upsilon_{i,t} = \upsilon_j$ (j = 2-digit SIC). Overall, the results reported are qualitatively similar to those reported in our main model, thus, providing additional support for the effect of growth rate, business risk, and listing expenses on the probability of voluntary delisting.

Finally, the sub-sample of listed firms may be fundamentally different from that of the voluntary delisted firms. Table 4 gives credence to this argument. Although we include various control variables in our main regression estimation, our results could still be biased and could pick up non-linear effects of the control variables on the voluntary delisting decision. To address this concern, we run two tests namely: Entropy Balancing and Propensity Score Matching (PSM). First, following Hainmueller (2012), Chapman et al. (2019), and Jacob et al. (2019), we employ the entropy balancing test to control for observable differences among listed and voluntary delisted firms. The results obtained from Model (5), further reinforces our main model's results.

Second, to conduct the PSM test, we follow Drucker and Puri (2005), by creating two sub-samples of firms that are comparable across all the control variables but differ only in terms of whether the firm is listed or delisted. Then, we match the firm-year observations of the 165 delisted firms (treatment group) with firm-year observations of listed firms (control group) with similar characteristics based on the nearest-neighbor method, combined with one-on-one matching without replacement. Based on this matching procedure, we obtain 3,194 pairs of matched firm-year observations. Model (6) reports the estimates of the logistic regression regression for the post-match sample. All regression coefficients for the post-match sample are statistically insignificant. Thus, there are no significant differences in the observable characteristics between the treatment group and the control group. These results indicate that by using the PSM technique, we successfully remove any differences in the observable characteristics other than the difference in the main variables of interest (i.e., growth rate, business risk, and listing expenses).[21]

[21] In untabulated results, we verify the validity of the conditional independence assumption by comparing the mean differences for each observable firm characteristic between the treated and control groups. All the mean differences between firm-year observations of listed and delisted firms are statistically insignificant.

[Table 6 here]

8 Macroeconomic Factors and the Delisting Option

Our theoretical predictions and empirical findings in Table 5 show a negative (positive) association between the firm's growth rate (business risk) and its probability of voluntarily delisting. Also, we find that the listing expenses positively and significantly affect the probability of delisting. In this section, we test Hypothesis 4 which relates to the macroeconomic shocks that can disproportionately affect certain firms and make it optimal for them to voluntarily delist. In a sense, these are economic channels through which some firms' growth rate and business risk as well as listing expenses get shocked that ultimately leads to changes in the probability of delisting.

Therefore, we test whether political uncertainty and regulatory burden affect the firm's growth rate, business risk, and listing expenses that in turn trigger the voluntary delisting decision. In other words, growth rate, business risk, and listing expenses may play a mediating role and through them macro conditions could create optimal conditions under which many firms voluntarily delist from major stock exchanges. To test and establish such a mediating relation, we follow studies such as that of Baron and Kenny (1986) and perform a series of mediation analyses. These studies have used this method to establish direct evidence on the underlying channels in other settings (see Tsang et al., 2019; Francis et al., 2021, for instance).

Figure 5 illustrates the mediation relation. Path A indicates the association between the causal variable (macroeconomic shock) and the mediating variable (i.e., growth rate, business risk, or listing expenses). Path B shows the link between the mediating variable and the outcome variable (the probability of voluntarily delisting).

[Figure 5 here]

For a mediation effect to exist, three conditions have to be met. First, the causal variable has to be significantly related to the mediating variables, which is indicated as Path A. Second, in line with Path B, the mediating variable has to significantly affect the outcome variable. To test this relation, we estimate the baseline hazard regression with a Cox semi-parametric PH model on a panel data structure. In this model, we regress the time to delist which simultaneously measures the time between the IPO date and the delisting date on the causal variable and the mediating variable. In the Path B analysis, if the causal variable is insignificant while the mediating variable is significant in explaining the outcome variable, the mediation effect can be viewed as complete. Otherwise, if both the causal and mediating variables are both significant in explaining the outcome variable, the mediation effect would be partial (Francis et al., 2021).

Finally, the mediating effect has to be statistically significant. To test this, we compute Sobel (1982) test to examine whether the mediation effect of the underlying variables of our theoretical model are statistically significant. Specifically, the Sobel test is computed as per the following:

$$SobelTest = (a_a.a_b)/\sqrt{(a_b^2.\delta_a^2) + (a_a^2.\delta_b^2)} \tag{22}$$

where a_a and δ_a are the estimated coefficient and standard error for macroeconomic shocks in Path A analysis; a_b and δ_b are the estimated coefficient and standard error for any of the mediating variables (i.e., growth rate, business risk, or listing expenses) in Path B analysis.

Panel A of Table 7 presents the estimation results for Path A analysis for each of the three mediating variables (growth rate, business risk, or listing expenses). The reported results show that political uncertainty is positively and significantly associated with business risk. In line with our prediction, this indicates that higher political uncertain leads to higher firm's business risk. We do not find significant results for the association between political risk and both growth rate and listing expenses. In addition, we find regulatory burden to be significantly associated with growth rate, business risk, and listing expenses. We find that higher levels of regulatory burden leads to lower growth rate and highr business risk and listing expenses.

Panel B reports the main results for Path B analysis where we run a semi-parametric proportional hazard Cox model on a panel data structure while including the macroeconomic shock and each of the three mediating variables. For the political uncertainty model, i.e., (Models (1), (2), and (3)), we find the coefficients for political uncertainty to be insignificant determinants of the probability of voluntary delisting while the coefficients of the mediating variables (i.e., growth rate, business risk, or listing expenses) are significant in explaining the probability of voluntary delisting in each of the three models. For the regulatory burden models, we find that the regulatory burden measure is significant for two out of the three models presented. Also, the coefficients of the mediating variables (i.e., growth rate, business risk, or listing expenses) significantly explains the probability of delisting. Overall, the results reported in Panel B supports the mediating effect of growth rate, business risk, and listing expenses.

Finally, Panel C reports the results of the Sobel tests for the two macroeconomic variables across the three mediating variables. For the political uncertainty measure, the results show that Sobel test is only significant for business risk variable, where as for the regulatory burden, Sobel test is significant across all the three mediating variables. These results indicate that political uncertainty plays a role in altering the firm's business risk and regulatory burden affects the firm's growth rate, business risk, and listing expenses which ultimately lead to changes in the probability of voluntary delisting. These findings support H4A and H4B.

[Table 7 here]

To offer further evidence of the mediating role of firm's growth rate and business risk, we formulate an alternative instrumental-variable approach. In the first stage, we instrument the firm's growth rate and business risk variables with macroeconomic shocks in the first stage, and exploit the local variable in growth rate and business risk driven by macroeconomic shock to explain the firm's probability of delisting in the second stage. In other words, out tests gauge whether changes in macroeconomic shocks affect the firm's probabilities of voluntary delisting from the exchange. In an untabulated results, we find supporting results to our claim.

9 Conclusion

We model a firm's *option to delist* whose value is determined by the uncertainties regarding both the benefits from being listed and the expected gains from delisting. For each firm, the "optimal time to delist" can be expressed as a function of three key parameters: the firm's revenue growth in recent years, volatility in the firm's revenue growth, and the exchange's listing costs. Furthermore, we also demonstrate that external macroeconomic trends like increasing macroeconomic policy uncertainties and rising regulatory burden can provide shocks to these three parameters. Such external shocks combined with firm's own business risks can make voluntarily delisting an optimal outcome for the firm.

Our model yields several novel and interesting testable predictions. As a first test, we conduct a validation analysis. Using our model, we classify the ongoing listing and the delisting decision as optimal or non-optimal, and we show that stock price reactions to firms' delisting decisions (daily CARs around announcement event) are different for the optimal delistings compared to the non-optimal ones. Also, the firms that make an optimal ongoing listing or delisting decision have characteristics that are statistically different from those of the firms that make a non-optimal decision. Second, we test whether the three key drivers of our stochastic model - growth rate, business risk, and exchange fees of the firm - indeed affect the probability of voluntarily delisting. Using the Cox hazard rate model and a data sample which covers the time period between 1980 and 2019, we verify that all three of these parameters are important determinants of the voluntary delisting decision. These are novel results for the voluntary delisting literature as it has not been able to approximate listing expenses.

Further, our mediation analyses showed that economic policy uncertainty affected delisting odds primarily through increased sales volatility (increasing business risk). Similar analyses for regulatory constraints indicated that increasing regulatory requirements for the listed firms increased the value of the delisting option by affecting all three drivers of our model: growth rate, business risk, and total listing expenses. These findings can explain the rising trend towards voluntary delisting. The uncertainty in US economic policy has been rising in recent decades (Baker et al., 2016). Similarly, according to Doidge et al. (2017), many additional business regulations and reporting guidelines have been imposed on listed firms since early 2000s.

Overall, our model provides insights into the key determinants of the delisting option value and the external factors that affect the timing of delisting. One advantage to this model is that it enables listed firms to know whether they should continue to be listed or to delist and to acknowledge how distant in the future the optimal profitability threshold of delisting is if indeed that firm has not yet reached it. It is easy to implement and computationally not time-consuming. Firms could use it while relying on their best estimates for the model parameters. The model can also be used by investors and financial analysts that are covering listed firms that are more likely to voluntarily delist. We consider different delisting scenarios and identify cases where it is marginally profitable to delist now but a delay makes the delisting even more profitable; and cases where it is profitable to delist now or at any point in time in the near future (up to 25 years) but, as time unfolds, the delisting becomes less profitable.

This paper raises new testable empirical research hypotheses, such as regarding the effect of non-optimal delisting on the value and financial performance of the (now delisted) firms, and the effect of changes in the listing fee or the regulation rules on the optimal time to delist. Our delisting model can be extended in several ways. For instance, it assumes that the ongoing listing costs disappear with the delisting decision. However, there is a lag time between the date of the delisting decision and the date at which the firm is released from the obligations of being a public firm and, if this time lag is relatively long, it affects the timing of the delisting and should be accounted for. The study of whether this time lag factor speeds up or delays a voluntary delisting would be of particular interest for the exchanges and the financial market authorities. Also interesting would be the existence of a theoretical model for the optimization of the threshold rules for involuntary delisting used by the exchange. This study could also include a welfare analysis so as to confront, in terms of the optimal thresholds for delisting, the perspective of the exchange with that of a central planner (i.e., market regulator).

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Figure 1: Revenue-Probability of Delisting Relationship

This figure illustrates the relationship between the revenue level and the probability of delisting, where $S^*_{Listing}$ is the revenue level that triggers "listing" and $S^*_{Delisting}$ is the revenue threshold beyond which firms are in a "safer" ongoing listing (revenue) region in which the probability of delisting is less sensitive to changes in revenue. These two revenue thresholds define a critical revenue region in which delisting is more likely.

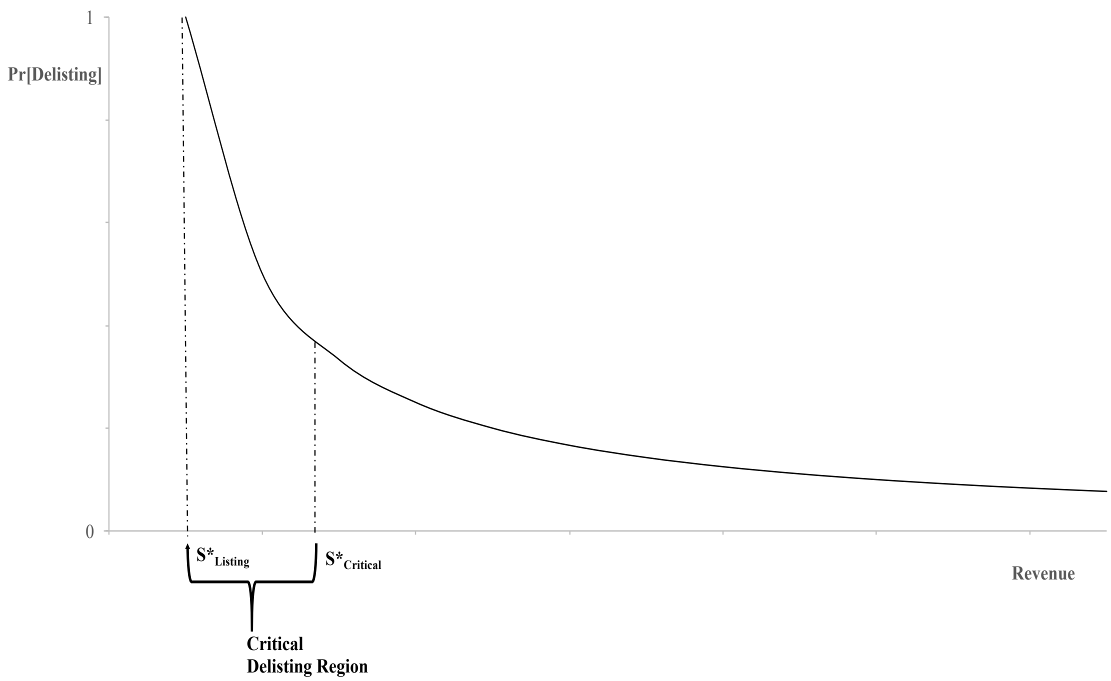


Figure 2: Delisting Timeline

This figure shows a timeline of the delisting decision for our modelling framework: the timing optimization of the exercise of the delisting option starts at $t = 0$, when the firm is listed; at $t = \tau^*$ it is optimal to delist; from $t = \tau^*$ onwards, the firm is delisted and does not have the option to be listed again.

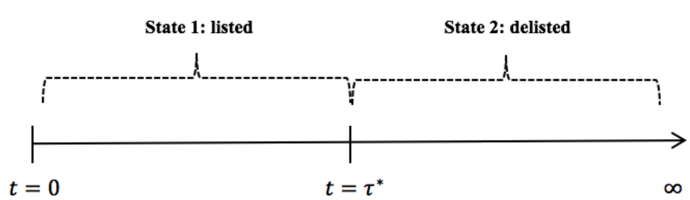


Figure 3: Delistings Over Time

This figure shows the number of firms that voluntary delisted from the exchange over our data sample time (1980 and 2019). This is based on our final sample of 165 voluntary delisted firms from three major exchanges in the U.S. namely the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ during the period between 1980 and 2019. Voluntary delisted firms are identified using the Research in Security Prices (CRSP) shares delisting codes - DLSTCD codes corresponding to 332, 570 and 573. The sub-sample of voluntary delisted firms includes both firms which also deregistered from the SEC and the ones which moved from one of the major exchanges to PinkSheet or OTC.

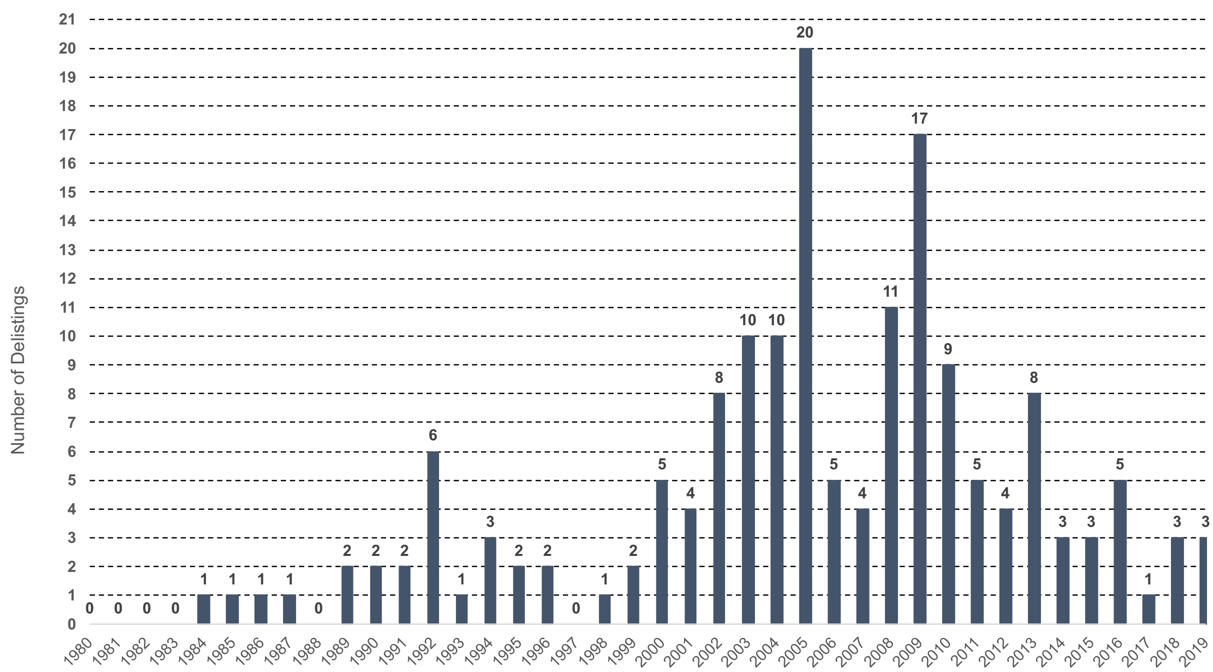


Figure 4: A Sensitivity Analysis on the delisting Profitability

This figure shows the effect of changes in the business risk (revenue uncertainty) and the revenue growth rate on the profitability of the delisting decision. The solid horizontal line represents the zero going delisted profit threshold, and the convex or the concave curves represent the profit if the firm is delisted, as a function of time that is given in years. We report our projected annual calculations up to 25 years into the future from the presumed decision time. S denotes the firm's sales values and it is taken equal to 1 for all companies for par comparison purposes. α_1 (α_2) represents the hypothetical before (after) delisting growth rate which is defined as the five years moving average of the annual change in firm's revenues. σ_1 (σ_2) represents the hypothetical before (after) delisting business risk which is defined as the standard deviation of the firm's growth rate.

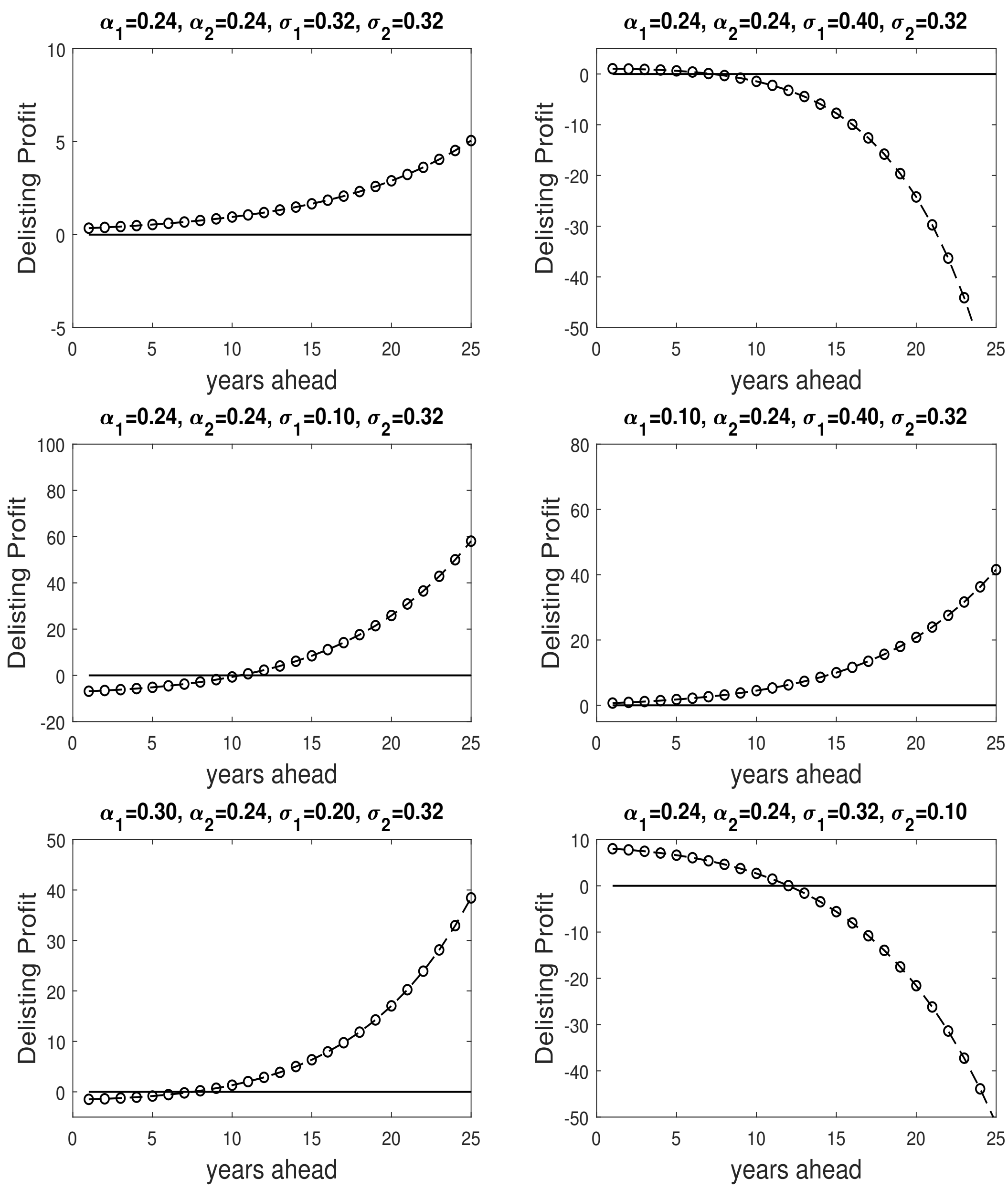


Figure 5: Mediation Relationship

This figure illustrates how the mediation relationship works. The first step relates to Path A. It shows how each of the underlying real options variables, i.e., growth rate, business risk, and listing expenses, is affected by the macroeconomic shock variables, i.e, political uncertainty and regulatory burden. The second step relates to Path B. In this step, we show how the voluntary delisting decision is driven by the growth rate, business risk, and listing expenses. For a detailed explanation of our mediation analyses see section 5.

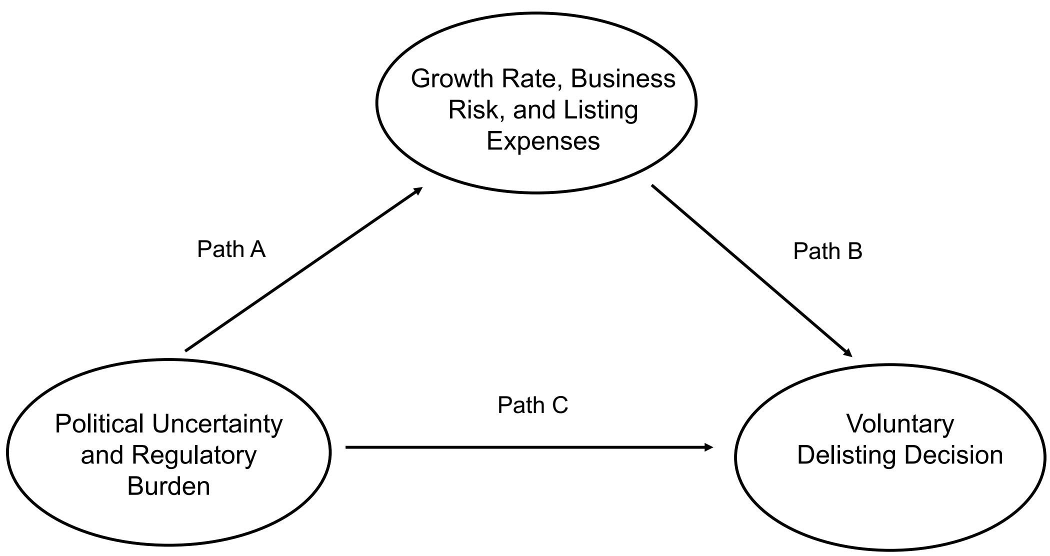


Table 1: Sample Selection Process

This table provides a breakdown of the exclusion criteria followed while constructing the data sample. The table reports the number of listed and voluntary delisted firm during each step. We start with a sample of firms extracted from Compustata and CRSP datasets. The merged dataset, after excluding financial, insurance and utility firms, contains 13,401 firms. The final sample contains 1,984 firms of which 165 voluntary delisted firms over the period from 1980 to 2019. Delisted firms are identified using the Research in Security Prices (CRSP) shares delisting code (DLSTCD). Firms are organized into three delisting categories: mergers and acquisitions (DLSTCD codes 200-399 excluding 332), involuntary delistings due to bankruptcy or liquidation (DLSTCD codes >=400 excluding 570 and 573), and voluntary delistings which account for firms that delist on its own request (DLSTCD codes 332, 570 and 573). After the event of voluntary delisting, we do not make a further distinction between voluntarily delisted and deregistered firms. So, a voluntary delisted firms can either be traded on the OTCBB and PinkSheet or deregister from the SEC.

Explanation	Sample Period	Number of firms (excl. voluntary delisted firms)	Number of voluntary delisted firms	Total Number of firms
Merged Compustat & CRSP firms (without firms with 6 or 49 SIC codes)	1980-2019	12,991	410	13,401
Less: firms listed on other exchanges (i.e., not listed on NYSE, AMEX, and NASDAQ)	1980-2019	-1,734	-42	-1,776
Less: inactive firms due to M&A and Bankruptcy (i.e., delisting codes other than: 332, 570, or 572)	1980-2019	-8,200		-8,200
Less: firm-year observations with missing values and firms with less than 3 years of firms-year observations	1980-2019	-1,238	-186	-1,424
Less: firms that went into M&A and bankruptcy after the voluntary delisting decision (manually checked)	1980-2019		-17	-17
Total Sample		1,819	165	1,984

Table 2: Numerical Simulations Analysis

This table reports the numerical simulations analysis of the key parameters underlying the theoretical model. The numerical simulation analysis uses a sub-sample of 31 delisted firms (out of 165 delisted firms used in the full sample) for which revenues-related information is available for the period before and after the delisting decision is made. The sub-sample of 31 firms represents firms that delisted from one of the main exchanges and are traded on the PinkSheet or OTC. Panel A presents the descriptive statistics (i.e., minimum, mean, and maximum) of the theoretical model's parameters (i.e., sales in millions of U.S. dollars, growth rate, and business risk) for both periods before and after the delisting date. Panel B, lists the names of the firms included in the sub-sample of 31 delisted firms along with the values of the parameters and the simulation results for each firm before and after the delisting decision. α_1 (α_2) represents the before (after) delisting growth rate which is defined as the five years moving average of the annual change in firm's revenues. σ_1 (σ_2) represents the before (after) delisting business risk which is defined as the standard deviation of the firm's growth rate. MaxProfit represents the maximum delisting value achievable for each company whilst TimeMax shows the year, between first year and last of 25 years horizon considered, when MaxProfit will be reached. The BreakEven calculates the time when the value of the delisting option is at-the-money, that is, there is no profit or loss made if the firm is delisted.

Panel A: Descriptive Statistics for the 31 Delisted Firms

	Before Delisting			After Delisting							
	Sales (1)	α_1 (2)	σ_1 (3)	Sales (4)	α_2 (5)	σ_2 (6)	$[\alpha_2 - \alpha_1]$ (7)	$[\sigma_2 - \sigma_1]$ (8)	(9)	(10)	(11)
Minimum	0.4790	-0.2097	0.0073	0.6120	-0.1281	0.0153	-0.1920	-0.1500			
Mean	4182.5791	0.0190	0.0530	4274.3019	0.0288	0.0836	0.0098	0.0306			
Maximum	75126.6360	0.1933	0.2380	75161.6200	0.2375	0.5111	0.1905	0.4920			

Panel B: The Key Parameters Values for the 31 Delisted Firms

Firm Name	Before Delisting			After Delisting							
	Sales	α_1	σ_1	Sales	α_2	σ_2	$[\alpha_2 - \alpha_1]$	$[\sigma_2 - \sigma_1]$	MaxProfit	TimeMax	BreakEven
YOCREAM INTERNATIONAL INC	19.5630	0.0471	0.0776	50.7330	0.2375	0.0783	0.1905	0.0006	25.8897	1	25
ALTANA AG	2030.1540	-0.0013	0.0282	1703.3680	-0.0054	0.1353	-0.0041	0.1071	0	0	1
ULURU INC	0.4850	-0.0988	0.0505	0.7170	0.0669	0.2552	0.1657	0.2048	11.6118	25	1
AMERITYRE CORP	3.6990	0.1557	0.0381	4.7940	0.0695	0.0302	-0.0862	-0.0078	0	0	1
PHOENIX FOOTWEAR GROUP INC	12.4000	-0.2097	0.0147	15.9040	-0.1085	0.0382	0.1012	0.0234	0	0	1
QEP CO INC	40.8900	0.1933	0.0136	60.3300	0.1259	0.0713	-0.0674	0.0577	0	0	1
FEDERAL SCREW WORKS	25.7900	-0.0090	0.1021	19.1700	0.0260	0.0954	0.0350	-0.0067	57.2652	25	1
FLANDERS CORP	51.6800	-0.0864	0.1355	63.3300	-0.1098	0.2041	-0.0234	0.0686	0	0	1
NIDEC CORP	10764.8420	0.0473	0.0401	13702.3370	0.0914	0.0268	0.0440	-0.0132	0	0	1
ROCKFORD CORP	52.9750	-0.1614	0.0443	60.8470	-0.0456	0.0644	0.1158	0.0201	633.6796	25	1
EMRISE CORP	33.5310	-0.0274	0.1785	35.6650	0.0393	0.0490	0.0666	-0.1295	310.9703	25	1
ENVIRONMENTAL TECTONICS CORP	66.2940	0.1045	0.0179	37.3400	0.0021	0.0171	-0.1024	-0.0008	0	0	1
WIRELESS XCESSORIES GRP INC	24.1960	0.0935	0.0235	40.2440	0.1648	0.0428	0.0712	0.0194	0	0	1
FINISHMASTER INC	347.0120	0.1219	0.0073	486.0130	0.0592	0.0190	-0.0627	0.0116	0	0	1
MORGANS FOODS INC	80.9600	0.0931	0.0257	90.5440	0.0166	0.0197	-0.0765	-0.0060	0	0	1
UNITED CAPITAL CORP	90.1450	0.0728	0.0240	119.1080	0.1341	0.0483	0.0613	0.0243	0	0	1
SCHEIB (EARL) INC	10.5200	0.0180	0.2380	10.2000	-0.0850	0.0880	-0.1030	-0.1500	136.5693	1	25
CORRPRO COMPANIES INC	139.7190	-0.0328	0.0164	156.8340	0.0809	0.0495	0.1137	0.0331	3251.4334	25	1
DELTA GALIL INDUSTRIES LTD	622.8340	0.0145	0.0157	974.7190	0.0827	0.0153	0.0682	-0.0004	0	0	1
SAPPI LTD	5925.0000	0.0169	0.0101	5141.0000	-0.0508	0.0745	-0.0677	0.0644	0	0	1
RHODIA	7657.8130	0.0288	0.0191	7442.5820	0.0176	0.5111	-0.0112	0.4920	0	0	1
PHARMAXIS LTD	0.4790	0.0700	0.0853	4.7470	0.0607	0.0518	-0.0093	-0.0335	1.8686	1	25
KUBOTA CORP	14649.3490	0.0452	0.0342	15542.9500	0.0489	0.0207	0.0037	-0.0135	0	0	1
PANASONIC CORP	75126.6360	-0.0298	0.0340	75161.6200	-0.0069	0.0756	0.0230	0.0416	0	0	1
ORBIT INTERNATIONAL CORP	19.1600	-0.0494	0.0124	24.6580	-0.0017	0.0547	0.0477	0.0423	0	0	1
OHIO ART CO	20.6220	-0.1002	0.0838	25.0730	-0.0608	0.2302	0.0394	0.1465	1176.1694	1	25
HEAD NV	453.8010	0.0245	0.1011	494.2070	0.0093	0.1152	-0.0152	0.0141	1844.9167	1	25
TELEKOM AUSTRIA AG	7307.4840	0.1785	0.0203	5817.3850	-0.0135	0.0201	-0.1920	-0.0002	0	0	1
MSI ELECTRONICS INC	1.1040	-0.0354	0.0485	0.6120	-0.1281	0.0167	-0.0926	-0.0318	0	0	1
DASSAULT SYSTEMS SA	1857.8820	0.1430	0.0310	2846.9110	0.1093	0.0540	-0.0338	0.0230	0	0	1
KONAMI HOLDINGS CORP	2222.9320	-0.0377	0.0724	2369.4180	0.0659	0.0186	0.1036	-0.0538	0	0	1

Table 3: Empirical Model Validation: Stock Market's Reaction

This table provides the number of firms which, according to our delisting timing model, made an Optimal or Non-optimal decision in being delisted or continuing to be listed. It also shows the mean differences between the group of firms that made optimal decisions and the group of firms that made non-optimal decisions, regarding the key variables of our delisting timing model: Growth rate, business risk, and listing expenses. In addition, this table provides the results for the market reaction to the delisting announcement. Panel A reports the number of firms that made an optimal (de)listing decision to (delist) remain listed, columns (1) and (4) respectively, and the number of firms that made a non-optimal decision to (delist) remain listed, columns (2) and (5) respectively. Panel B reports the results of the mean differences test between the group of firms that made optimal decisions and the group of firms that made non-optimal decisions. Panel C shows the results of an event study that tests the impact of the voluntary delisting announcement and an arbitrary date for the listed firms on the stock prices. This event study is preformed for the full sample of 165 delisted firms (column 3) and 1819 listed firms (column 6), the group of firms that made an optimal (de)listing decision (column 1 (4)) and the group of firms that made a non-optimal delisting decision (column 2 (5)), using the following model $R_{i,t} = \alpha_i + \beta_i R_{M,t} + \epsilon_{i,t}$, where $R_{i,t}$ is the stock return of the ith company in our sample at time t; $R_{M,t}$ is the return on the value-weighted CRSP market index at time t, and $\epsilon_{i,t}$ is the error term. The data on the stock returns for each of the above samples was obtained from CRSP. The market model was estimated using the Scholes-Williams adjustment for thinly traded firms ending 30 days before the event day (for the sub-samples of delisted firms). For the sample of delisted firms, daily return data are used and the event window is estimated in days. As per the sample of listed firms, monthly return data are used and the event window is estimated using months. The event date (month) for listed firms is specified as December 2017. Robust standard errors are reported in parentheses. ***, **, and * indicates statistical significance at the 1%, 5%, and 10% level, respectively. Our data sample comprises information on 1,984 listed firms of which there are 165 delisted firms.

Panel A: Firms' Distribution (n = number of firms							
	Delisting Decision				Ongoing Listing Decision		
	Optimal (1)	Non-Optimal (2)	Full Sample (3)		Optimal (4)	Non-Optimal (5)	Full Sample (6)
	68	97	165		1,587	232	1,819
Panel B: Univariate Test							
	Optimal	Non-Optimal	t-test		Optimal	Non-Optimal	t-test
GrowthRate	0.3277	0.2247	-1.3963		0.2825	0.4770	5.5745***
BusinessRisk	0.1632	0.0968	-2.7026***		0.0836	0.2170	12.9836***
ListingExpenses	0.6048	0.1011	-3.7693***		0.1141	0.4857	9.6862***
Panel C: Event Study: Market Reaction							
Event Window (Days)	Optimal	Non-Optimal	Full Sample	Event Window (months)	Optimal	Non-Optimal	Full Sample
(0, +1)	-0.0783***	-0.0376***	-0.0526***	(0, +12)	0.0246***	0.0185	0.0238***
	(0.0271)	(0.0121)	(0.0127)		(0.0073)	(0.0336)	(0.0077)
(0, +2)	-0.0601***	-0.0437***	-0.0497***	(0, +18)	0.0175**	0.0370	0.0200***
	(0.0245)	(0.0168)	(0.0139)		(0.0085)	(0.0401)	(0.0090)
(0, +5)	-0.1132**	-0.0469*	-0.0712***	(0, +24)	0.0191*	0.0296	0.0205***
	(0.0513)	(0.0272)	(0.0256)		(0.0109)	(0.0446)	(0.0111)

Table 4: Univariate Analysis

This table displays summary statistics on firm characteristics for the entire sample as well as the sub-samples of firms corresponding to listed and voluntary delisted firms. Covariates are defined in Table A1. The sample consists of 1,984 firms, of which 1,819 listed and 165 voluntary delisted firms, that covers the period from 1980 to 2019. t-tests are conducted to test for differences in means between listed and voluntary delisted sub-sample of firms. All variables included in our main empirical model are winsorized at the 1st and 99th percentiles. The superscripts ***, **, and * mean that the coefficients are significant at the 1%, 5%, and 10% level, respectively.

Variables	Listed firms		Delisted firms			Full Sample	
	Mean	SD	Mean	SD	t-test	Mean	SD
GrowthRate	0.1281	0.2472	0.1064	0.2529	3.6201***	0.1269	0.2476
BusinessRisk	0.0517	0.0993	0.0768	0.1137	-10.3494***	0.0531	0.1003
ListingExpenses	0.0570	0.2874	0.1356	0.5066	-10.6800***	0.0614	0.3046
ExchFeeRatio	0.0157	0.2857	0.0081	0.0630	1.1257	0.0152	0.2780
SOXRatio	0.0082	0.0325	0.0084	0.0346	-0.2453	0.0082	0.0326
AuditFeeRatio	0.0383	0.2546	0.1042	0.4373	-10.1349***	0.0420	0.2687
Size	6.0285	2.2847	4.8843	2.7337	20.4201***	5.9638	2.3275
FirmAge	2.8063	0.8073	2.4217	0.7400	19.7491***	2.7845	0.8085
Leverage	0.1858	0.1602	0.2216	0.1636	-9.2031***	0.1879	0.1606
KZ	0.0492	1.1596	0.2161	1.2349	-5.9176***	0.0586	1.1646
ROA	0.0274	0.7453	-0.0691	0.7131	5.3551***	0.0219	0.7439
CAPEX	0.0538	0.0442	0.0565	0.0492	-2.5326***	0.0539	0.0445
Dividend	0.0130	0.0520	0.0155	0.0800	-1.8650**	0.0132	0.0540
R&D	0.0778	0.1325	0.0687	0.1237	2.8345***	0.0773	0.1320
NEI	0.0559	0.1731	0.0738	0.1604	-4.2837***	0.0569	0.1724
Turnover	6.0029	9.1622	7.4060	19.1916	-5.7897***	6.0822	10.0060
DRET	0.2295	1.2080	0.4879	3.1007	-7.6972***	0.2441	1.3870
SDDRET	1.2557	1.4220	2.7738	3.3177	-39.3873***	1.3415	1.6287

Table 5: Prediction Testing Analysis - Semi-Parametric Hazard Models

This table provides the estimates of the proportional hazard model, based on maximum likelihood estimation, using Cox (1972) partial likelihood function as per Equation (19). Our sample includes 1,984 firms of which 165 were voluntary delisted between 1980 and 2019. The coefficients measure the partial impact of each covariate on the likelihood of delisting conditional on the duration. The dependent variable is the time to delist, which measures the time between the IPO date and the delisting date. When the IPO date is not available, we use the first available observations in Compustat. Model (1) is the base hazard model which includes all the control variables discussed in Section 7. Model (2) considers the growth rate and business risk. Model (3) considers the ratio of total listing expenses variable, in line with our delisting timing model of Section 2. For these models, we report the regression coefficients in Columns (1), (3) and (5) and the hazard ratios in Columns (2), (4) and (6). All models include time and industry fixed effects using year and sic 2-digit industry code dummy controls and the estimates are adjusted for right censoring. The standard errors are reported below the coefficients in between brackets and are corrected for firm-level clustering effects using a robust-variance estimation methodology. The hazard ratio gives an estimate of how much the hazard of delisting increases for a unit change in the covariate. The superscripts ***, **, and * mean that the coefficients are significant at the 1%, 5%, and 10% level, respectively. LLR denotes to Log-likelihood ratio. All the regression covariates are defined in Table A1.

	Control Variables		Control & Main Explanatory Variables			
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
	(1)	(2)	(3)	(4)	(5)	(6)
GrowthRate			-1.3097**	0.2699	-1.2435**	0.2884
			(0.5427)		(0.4890)	
BusinessRisk			1.8795***	6.5505	1.1841*	3.2676
			(0.6438)		(0.6349)	
ListingExpenses					0.8442***	2.3261
					(0.1643)	
Size	-0.3289***	0.7197	-0.3123***	0.7318	-0.2980***	0.7423
	(0.0510)		(0.0508)		(0.0506)	
FirmAge	-0.4375**	0.6456	-0.4363**	0.6464	-0.4961**	0.6089
	(0.1999)		(0.1966)		(0.1984)	
Leverage	2.7329***	15.3771	2.6875***	14.6949	2.6666***	14.3910
	(0.5456)		(0.5443)		(0.5415)	
KZ	-0.1441*	0.8658	-0.1417*	0.8679	-0.1257	0.8819
	(0.0812)		(0.0825)		(0.0834)	
ROA	-0.0341	0.9664	-0.0123	0.9878	-0.0081	0.9919
	(0.0938)		(0.0921)		(0.0899)	
CAPEX	-3.7984*	0.0224	-2.5563	0.0776	-2.4922	0.0827
	(2.1439)		(2.1461)		(2.0860)	
Dividend	0.3255	1.3847	0.1069	1.1129	0.1435	1.1543
	(1.3719)		(1.4195)		(1.3921)	
R&D	-0.2716	0.7621	-0.7965	0.4509	-1.1466	0.3177
	(0.8988)		(0.9641)		(0.9690)	
NEI	-0.6186	0.5387	-0.3913	0.6762	-1.2966	0.2735
	(0.8278)		(0.8306)		(0.9265)	
Turnover	-0.0145***	0.9856	-0.0131***	0.9870	-0.0112***	0.9889
	(0.0041)		(0.0040)		(0.0039)	
DRET	-0.0399	0.9609	-0.0338	0.9667	-0.0359	0.9648
	(0.0416)		(0.0410)		(0.0452)	
SDDRET	0.2091***	1.2326	0.2002***	1.2216	0.2017***	1.2234
	(0.0222)		(0.0224)		(0.0232)	
Industry FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Wald Chi^2	1,855		970.6		1,192	
LLR	-1,007		-1,000		-991.8	
Observations	31,920		31,920		31,920	

Table 6: Prediction Testing Analyses - Robustness Tests

This table provides our robustness tests results. Panel A reports the results after addressing the left censoring problem. Model (1) shows the results based on Heckman and Singers (1984) estimation strategy (i.e., HS 1984), and Model (2) shows our results when we change the first year of the sample from 1980 to 1985. Panel B, Model (3), provides the estimates of the proportional hazard model, based on maximum likelihood estimation, using Cox (1972) partial likelihood function as per Equation (19) after removing all the cross-listed firms from the sample. Panel C reports the results based on maximum likelihood estimation of the proportional hazard model using Weibull distribution as the baseline hazard rate as per Equations (21), while taking the effect of industry unobserved heterogeneity into consideration. Model (4) is estimated under the assumption of shared frailty effects at the industry level using the two-digit SIC codes ($\upsilon_{i,t} = \upsilon_j$ where j = SIC code. Panel D reports the coefficient estimates based on the entropy balancing method similar to that used by Hainmueller (2012), Model (5), and using the propensity score matching technique, Model (6). Models (1), (2), (3), and (5) reports the estimates of the proportional hazard model, based on maximum likelihood estimation, using Cox (1972) partial likelihood function as per Equation (19). Model (4) reports the estimates of the proportional hazard model, based on maximum likelihood estimation, using the parametric model with heterogeneity as per Equation (21). Model (6) reports the estimates of a logistic regression where the dependent variable is a dummy variable equals one if the firm is volunatry delisted and zero otherwise. For Models (1) to (5), the dependent variable is the time to delist, which measures the time between the IPO and the delisting event. 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. Models (1), (2), (3), (5) and (6) include time and industry fixed effects using year and industry dummy controls. The estimates are adjusted for right censoring. The superscript ***, **, * means that the coefficients are significant at the 1%, 5%, and 10% level, respectively. LLR denotes to Log-likelihood ratio. All the regression covariates are defined in Table A1.

	Panel A: Left Censoring		Panel B	Panel C	Panel D: Self selection bias	
	HS 1984	Starting 1985	Without cross-listed firms	Unobserved Heterogeneity	Entropy Balancing	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
GrowthRate	-1.0756**	-1.1945**	-1.1547*	-0.9914**	-0.4898*	-1.2505***
	(0.4798)	(0.4918)	(0.6863)	(0.4428)	(0.2816)	(0.2973)
BusinessRisk	1.2392*	1.1756*	1.3804**	1.2777*	1.9532***	2.0778***
	(0.6762)	(0.6625)	(0.6817)	(0.6616)	(0.4642)	(0.7245)
ListingExpenses	0.7107***	0.7865***	0.7660***	0.6625***	0.1471	0.4561*
	(0.1811)	(0.1779)	(0.2168)	(0.1635)	(0.1465)	(0.2597)
Size	-0.2305***	-0.2788***	-0.7311***	-0.2589***	0.2097***	0.0034
	(0.0607)	(0.0516)	(0.0698)	(0.0434)	(0.0367)	(0.0642)
FirmAge	-0.3144	-0.5647***	0.3989	-1.0699***	2.8510***	0.0633
	(0.2990)	(0.2083)	(0.2906)	(0.1377)	(0.1066)	(0.1317)
Leverage	2.9301***	2.6976***	3.2761***	2.4133***	0.6243	-0.4058
	(0.5869)	(0.5522)	(0.7516)	(0.5559)	(0.6047)	(0.6230)
KZ	-0.1864*	-0.1174	-0.1405	-0.0913	0.0782	0.0403
	(0.1055)	(0.0849)	(0.1039)	(0.0811)	(0.0821)	(0.0853)
ROA	-0.0105	0.0231	0.0229	-0.0729	-0.1891**	0.0619
	(0.0950)	(0.0914)	(0.1288)	(0.0868)	(0.0889)	(0.0806)
CAPEX	-3.6792	-3.4224	-0.7441	-2.3746	3.7692**	1.2139
	(2.4175)	(2.3689)	(2.6617)	(2.0126)	(1.7414)	(1.9340)
Dividend	-4.8497	0.0405	0.0379	0.0106	-1.9682	-0.2645
	(5.4057)	(1.3703)	(2.1398)	(0.7453)	(1.6745)	(0.5526)
R&D	-1.3735	-1.4835	0.0969	-0.9847	0.2401	-0.4658
	(1.0713)	(0.9894)	(1.1339)	(0.8411)	(0.5477)	(1.0853)
NEI	-0.8200	-0.9814	-1.9217	-1.1267	-0.0097	0.0423
	(0.9371)	(0.9021)	(1.2285)	(0.7851)	(0.6494)	(0.7189)
Turnover	-0.0162***	-0.0090**	-0.0082**	-0.0100**	0.0103**	-0.0009
	(0.0062)	(0.0037)	(0.0041)	(0.0044)	(0.0048)	(0.0050)
DRET	-0.0580	-0.0220	-0.0291	-0.0331	0.0020	0.0002
	(0.0514)	(0.0453)	(0.0488)	(0.0343)	(0.0218)	(0.0317)
SDDRET	0.2176***	0.2088***	0.2077***	0.1930***	0.0575**	-0.0082
	(0.0261)	(0.0232)	(0.0296)	(0.0212)	(0.0246)	(0.0448)
Industry FE	Yes	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Wald Chi^2	2,432	3,299	662	232.5	1.062	75.19
LLR	-753.9	-932.0	-521.9	-554.5	-374.5	-2,149
Observations	21,562	30,257	27,024	31,920	31,920	3,194

Table 7: The Impact of Macro Factor: Mediation Analysis

This table reports results of our mediation tests examining whether macroeconomic shock, represented by political uncertainty (*PolRisk*) and regulatory burden (*RegBurden*) measures, affects the key drivers of the delisting option: revenue growth rate (*GrowthRate*), business risk (*BusinessRisk*), and listing expenses (*ListingExpenses*), which, in turn, affects the firm's probability of voluntary delisting. Our mediation test comprises three steps (see section 5 for more details). Panel A, reports the findings of our first step (Path A). In this step, we regress each of the underlying real options variables (mediator) separately, on macroeconomic shock variables. Then, take the coefficient and standard errors for the underlying real option variable ($a_a,$, δ_a). Panel B, reports the results of our second step (Path B). We estimate the baseline hazard regression using a semi-parametric proportional hazard Cox model on a panel data structure. In this model, we regress the time to delist, which measures the time between the IPO date and the delisting date on the causal variable (i.e., macroeconomic shock) and the mediating variable (i.e., underlying variables of the delisting option), simultaneously. In panel C, we report the estimated coefficients and standard errors of interest from the baseline regressions for the two paths for both macroeconomic measures (*PolRisk* and *RegBurden*). Then, we report the computed values of the Sobel test. The real options underlying variables are defined as follows. *GrowthRate* is the five years moving average of the annual change in firm's revenues. *BusinessRisk* is the standard deviation of the firm's growth rate. *ListingExpenses* is the five years moving average of the firm's annual listing costs which are the annual exchange related fees, SOX compliance costs, and auditing fees. The superscript ***, **, * means that the coefficients are significant at the 1%, 5%, and 10% level, respectively. LLR denotes to Log-likelihood ratio. All the regression covariates are defined in Table A1.

Panel A. Path A: The association between macroeconomic shock and the underlying real options variables

	Political Uncertainty Measure (PolRisk)			Regulatory Burden Measure (RegBurden)		
	GrowthRate	BusinessRisk	ListingExpenses	GrowthRate	BusinessRisk	ListingExpenses
	(1)	(2)	(3)	(4)	(5)	(6)
PolRisk	-0.0013	0.0018***	0.0012			
	(0.0017)	(0.0007)	(0.0016)			
RegBurden				-0.0028**	0.0047***	0.0129***
				(0.0013)	(0.0007)	(0.0032)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.1570	0.2156	0.3341	0.1959	0.1942	0.1147
Observations	21,067	21,067	21,067	31,920	31,920	31,920

Panel B. Path B: The association btween both macroeconomic shock and the underlying real options variables and the voluntary delisting probability

	(1)	(2)	(3)	(4)	(5)	(6)
PolRisk	-0.0684	-0.0776	-0.0658			
	(0.0592)	(0.0600)	(0.0581)			
RegBurden				-0.3390	-0.2870***	-0.3091***
				(0.3300)	(0.0941)	(0.1028)
GrowthRate	-1.2742*			-1.8760***		
	(0.7690)			(0.5276)		
BusinessRisk		1.6746**			1.4855**	
		(0.7200)			(0.5803)	
ListingExpenses			0.7750**			0.9710***
			(0.3260)			(0.1717)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	1437	1593.55	1561	270.7	1976.43	83397.44
LLR	-629.2629	-630.1008	-629.9720	-1028.9427	-1034.4891	-1025.5678
Observations	21067	21067	21067	31920	31920	31920

Panel C. Mediation Tests Using Sobel Tests

Outcome 1: Political Unceertainty Measure (PolRisk)						
	GrowthRate		BusinessRisk		ListingExpenses	
	(1)	(2)	(3)	(4)	(5)	(6)
Path	A	B	A	B	A	B
Coefficient	-0.0013	-1.2742	0.0018	1.6746	0.0012	0.7750
Standard error	0.0017	0.7690	0.0007	0.7200	0.0016	0.3260
Sobel Test	0.6943		1.7249*		0.7152	
p-value	[0.4875]		[0.0845]		[0.4745]	
Outcome 2: Regulatory Burden Measure (RegBurden)						
	GrowthRate		BusinessRisk		ListingExpenses	
	(1)	(2)	(3)	(4)	(5)	(6)
Path	A	B	A	B	A	B
Coefficient	-0.0028	-1.8760	0.0047	1.4855	0.0129	0.9710
Standard error	0.0013	0.5276	0.0007	0.5803	0.0032	0.1717
Sobel Test	1.8422**		2.3919***		3.2826***	
p-value	[0.0654]		[0.0168]		[0.0010]	

Appendix

A Sensitivities Analysis

Here we consider the sensitivity of the delisting payoff at time T with respect to the three parameters of the model: revenue growth rate (α), volatility (σ), and expenses saved due to the delisting (K).

A.1 Revenue Growth Rate

It is instructive to consider first the case when the volatility in both periods (i.e., before and after the delisting) are identical.

The case of: $\sigma_1 = \sigma_2 = \sigma$; $\alpha_2 = \alpha_1 + \alpha$.

The delisting payoff is then equal to

$$\Delta_T = \frac{S_0}{\sigma}\Bigg[1 + \frac{2\sigma}{2\alpha_2 - \sigma^2 + 2\sigma}\exp\left(\frac{\sigma T}{2}(2\alpha_2 - \sigma^2 + \sigma)\right) \\ - (1-\kappa_T) - (1-\kappa_T)\frac{2\sigma}{2\alpha_1 - \sigma^2 + 2\sigma}\exp\left(\frac{\sigma T}{2}(2\alpha_1 - \sigma^2 + \sigma)\right)\Bigg] \quad \text{(A.1)}$$

Consider now that $\alpha_2 = \alpha_1 + \alpha$. Then

$$\Delta_T = \frac{S_0}{\sigma}\kappa_T + S_0\Bigg[\frac{\sigma}{\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma}\exp\left(\sigma T(\alpha_1 + \alpha) + \frac{\sigma T}{2}(\sigma - \sigma^2)\right) \\ -(1-\kappa_T)\frac{\sigma}{\alpha_1 - \frac{\sigma^2}{2} + \sigma}\exp\left(\alpha_1 \sigma T + \frac{\sigma T(\sigma - \sigma^2)}{}\right)\Bigg] \quad \text{(A.2)}$$

Then

$$\begin{aligned}\frac{\partial \Delta_T}{\partial \alpha} &= S_0 \sigma e^{(\alpha_1 \sigma T + \frac{\sigma^2}{2}(\sigma - \sigma^2))}\frac{\partial}{\partial \alpha}\left[\frac{e^{\alpha\sigma T}}{\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma}\right] \\ &= S_0 \sigma e^{(\alpha_1 \sigma T + \frac{\sigma^2}{2}(\sigma - \sigma^2))}\frac{\sigma T e^{\alpha\sigma T}(\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma) - e^{\alpha\sigma T}}{(\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma)^2} \\ &= S_0 \sigma \frac{e^{\alpha_1 \sigma T + \frac{\sigma^2}{2}(\sigma - \sigma^2)} e^{\alpha\sigma T}[\sigma T(\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma) - 1]}{(\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma)^2} \end{aligned} \quad \text{(A.3)}$$

Because all the other factors are positive it is evident that

$$\frac{\partial \Delta_T}{\partial \alpha} \gtreqless 0 \Leftrightarrow \sigma T(\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma) - 1 \gtreqless 0 \tag{A.4}$$

Working further on the latter expression we get

$$\begin{aligned}
\sigma T(\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma) - 1 &\gtreqless 0 \\
\sigma T(\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma) &\gtreqless 1 \\
\alpha_1 + \alpha - \frac{\sigma^2}{2} + \sigma &\gtreqless \tfrac{1}{\sigma T} \\
\alpha &\gtreqless \tfrac{1}{\sigma T} + \tfrac{\sigma^2}{2} - \sigma - \alpha_1
\end{aligned}$$

Thus in the region $\alpha > \frac{1}{\sigma T} + \frac{\sigma^2}{2} - \sigma - \alpha_1$ we know that $\frac{\partial \Delta_T}{\partial \alpha} > 0$ so the payoff of delisting is monotonically increasing with the excess growth in turnover after the delisting. This is also the most likely market scenario since α_1 is usually positive, $\frac{1}{\sigma T}$ is negligible for larger horizons T and $\frac{\sigma^2}{2} - \sigma$ is negative for volatility values $\sigma > 0$. In the less likely but still possible scenario that $\alpha < \frac{1}{\sigma T} + \frac{\sigma^2}{2} - \sigma - \alpha_1$ leads to $\frac{\partial \Delta_T}{\partial \alpha} < 0$ so the payoff of delisting is monotonically decreasing with the extra α. Note that the region under this scenario is also described by the negative values of α, which in a sense, for the absolute values of α is still equivalent to increasing monotony in the previous scenario.

This conclusion makes sense intuitively. The more extra growth is likely to occur after delisting ($\alpha > 0$) the larger the delisting payoff and the incentive to delist.

The case of $\sigma_1 \neq \sigma_2 = \sigma$ and $\alpha_2 = \alpha_1 + \alpha$.

Furthermore, the same conclusions occur in the case when $\sigma_1 \neq \sigma_2$. This is true because as you can see in (A.2) the first term related to the pre-delisting period does not carry any terms or factors depending on α and hence upon derivation they vanish. The calculations are identical as above but with σ being replaced with σ_2.

A.2 Revenue Volatility

Now we consider that α_1 and α_2 are fixed and $\sigma_2 = \sigma_1 + \sigma$. As in the previous section the terms including only σ_1 are irrelevant for the sensitivity analysis. Hence, we shall retain only the terms and factors involving σ. Moreover, since

$$\frac{\partial \Delta_T}{\partial \sigma} = \frac{\partial \Delta_T}{\partial \sigma_2}\frac{\partial \sigma_2}{\partial \sigma}$$

and $\frac{\partial \sigma_2}{\partial \sigma} = 1$ we can continue our analysis by looking only at $\frac{\partial \Delta_T}{\partial \sigma_2}$ which is equal to

$$\Delta_T \propto [\sigma_1] + \frac{S_0}{(\sigma_2)^2}\left[1 + \frac{2(\sigma_2)}{2\alpha_2 - \sigma_2^2 + 2\sigma_2} e^{\frac{\sigma_2 T}{2}(2\alpha_2 + \sigma_2 - \sigma_2^2)}\right]$$

Therefore

$$\begin{aligned}\frac{\partial \Delta_T}{\partial \sigma_2} &= -\frac{2S_0}{\sigma_2^3} - \frac{2S_0(2\alpha_2 + 4\sigma_2 - 3\sigma_2^2)}{[2\alpha_2\sigma_2 + 2\sigma_2^2 - \sigma_2^3]^2} e^{\frac{\sigma_2 T}{2}(2\alpha_2 + \sigma_2 - \sigma_2^2)} \\ &\quad + \frac{2S_0}{2\alpha_2\sigma_2 + 2\sigma_2^2 - \sigma_2^3}\left[\frac{T}{2}(2\alpha_2 - \sigma_2^2 + \sigma_2) + \frac{\sigma_2 T}{2}(1 - 2\sigma_2)\right] e^{\frac{\sigma_2 T}{2}(2\alpha_2 + \sigma_2 - \sigma_2^2)}\end{aligned}$$

$$-\frac{2S_0}{\sigma_2^3} - \frac{2S_0 e^{\frac{\sigma_2 T}{2}(2\alpha_2 + \sigma_2 - \sigma_2^2)}}{[2\alpha_2\sigma_2 + 2\sigma_2^2 - \sigma_2^3]^2}\left(2\alpha_2 + 4\sigma_2 - 3\sigma_2^2 - \frac{T}{2}(2\alpha_2\sigma_2 + 2\sigma_2^2 - \sigma_2^3)(2\alpha_2 + 2\sigma_2 - 3\sigma_2^2)\right) \quad \text{(A.5)}$$

Denoting $\xi = \left(2\alpha_2 + 4\sigma_2 - 3\sigma_2^2 - \frac{T}{2}(2\alpha_2\sigma_2 + 2\sigma_2^2 - \sigma_2^3)(2\alpha_2 + 2\sigma_2 - 3\sigma_2^2)\right)$ it follows then that

$$\frac{\partial \Delta_T}{\partial \sigma_2} = -\frac{2S_0}{\sigma_2^3} - \frac{2S_0 e^{\frac{\sigma_2 T}{2}(2\alpha_2 + \sigma_2 - \sigma_2^2)}}{[2\alpha_2\sigma_2 + 2\sigma_2^2 - \sigma_2^3]^2}\xi \quad \text{(A.6)}$$

It is difficult to say whether the right-hand side of this expression is positive or negative. One can remark that of ξ is positive then, since from a practical perspective we can assume that $\sigma_2 \in (0, 1)$, it follows that $\frac{\partial \Delta_T}{\partial \sigma_2} < 0$ which implies that the delisting payoff value is monotonically decreasing with respect to the volatility of the turnovers post delisiting, in other words, when the delisting payoff increases when the volatility post delisting is decreasing.

At the same time ξ can take more negative values at the high end of variable T. The Figures A1 and A2 illustrate $\frac{\partial \Delta_T}{\partial \sigma_2}$ as a function of σ_2 and also across various time horizons between 1 and 20 years. The surfaces in the negative domain confirm that the delisting payoff is negatively (or inversely) related to the post delisting volatility of the firm's revenue.

Figure A1: Surface of $\frac{\partial \Delta_T}{\partial \sigma_2}$ for delisting payoff for Company ULURU Inc

This figure illustrates the partial derivative of the delisting payoff function with respect to the volatility post delisting parameter σ_2 over the range of $\sigma_2 \in (0, 1)$ and for time horizon from 1 to 20.

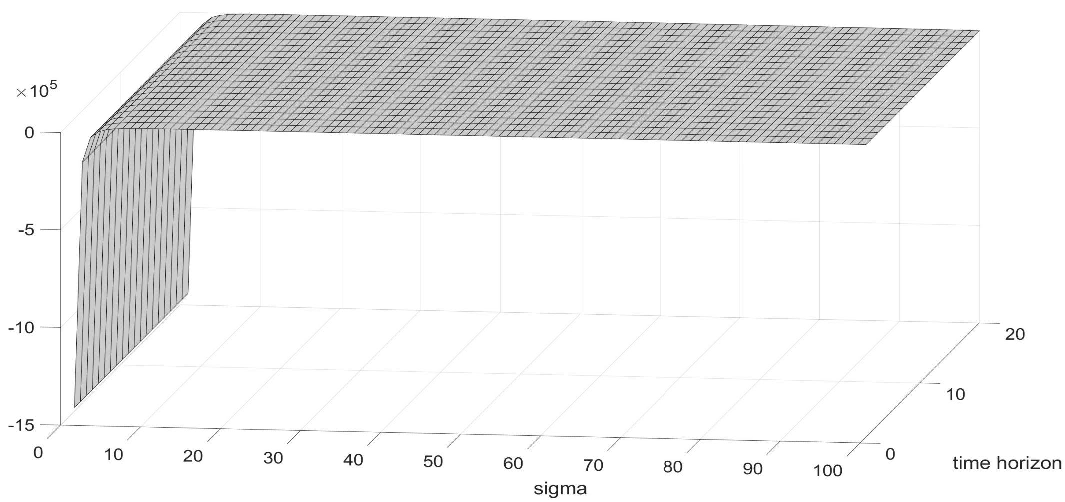
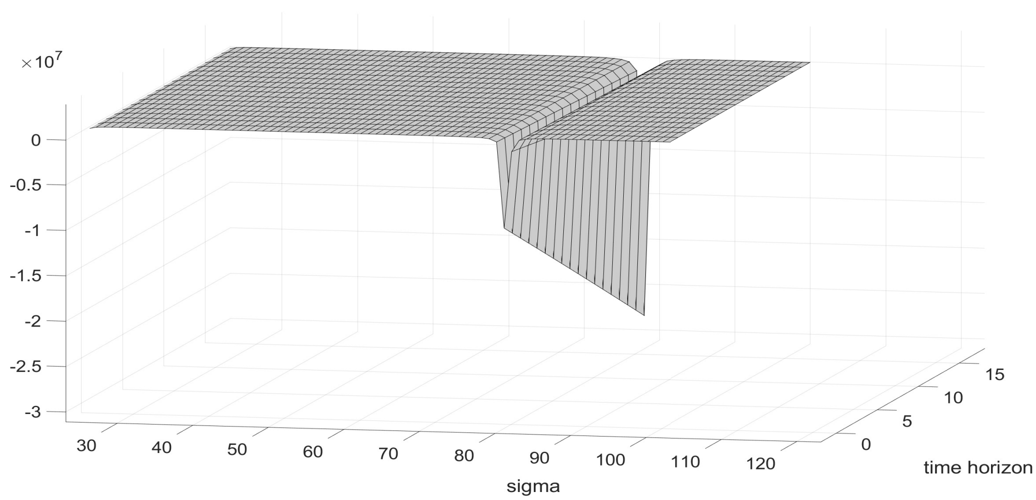


Figure A2: Surface of $\frac{\partial \Delta_T}{\partial \sigma_2}$ for delisting payoff for Company SCHIEB

This figure illustrates the partial derivative of the delisting payoff function with respect to the volatility post delisting parameter σ_2 over the range of $\sigma_2 \in (0, 1)$ and for time horizon from 1 to 20.



A.3 Listing Expenses

The listing expenses K are considered in our model as a proportion κ_T of the cumulative revenue up to time T. In other words, we look at:

$$\Delta_T = E\left(\int_0^T S_t^2 dt\right) - E\left(\int_0^T S_t^1 dt\right) + \kappa_T \left(\int_0^T S_t^1 dt\right) \tag{A.7}$$

and after re-arranging the expression we get:

$$\Delta_T = E\left(\int_0^T S_t^2 dt\right) - (1 - \kappa_T) E\left(\int_0^T S_t^1 dt\right) \tag{A.8}$$

It is clear then that

$$\frac{\partial \Delta_T}{\partial \kappa_T} = E\left(\int_0^T S_t^1 dt > 0\right) \tag{A.9}$$

Thus, when κ_T increases the delisting payoff increases and *vice-versa*, when κ_T decreases the delisting payoff decreases. This is in line with intuition of the delisting process.

Table A1: Variables Definition

This table defines all the variables that are used in the empirical analyses.

Variable Name	Definition	Compustat/CRSP Item Code
Dependent Variable		
Voluntary Delisting	is defined as a dummy variable that equals "1" on a particular year when the firm is delisted and "0" otherwise	DLSTCD codes = 332, 570, or 573
Theoretical Model Underlying Variables		
GrowthRate	The firm's growth rat is defind as the five years moving average (5yrs MA) of the annual change in sales	5 yrs MA((SALE[t] - SALE[t-1])/SALE[t-1])
BusinessRisk	Firm's business risk is defined as the annual standard deviation of the quarterly growth rate (GrowthRateq)	Std. Dev. (GrowthRateq)
ListingExpenses	Listing expenses is defined as the five years moving average of the annual listing expenses ratio.	Authors' calculation
Direct Listing Expenses		
Annual listing expenses ratio	Annual listing expenses ratio is defined as the total listing expenses in millions of U.S. dollars divided by the firm's sales in that particular year.	Authors' calculation
ListingExpenses ($Millions)	Total listing expenses is defined as monetary value of the sum of exchange fees, SOX compliance fees, and Auditing fees	Authors' calculation
ExchangeFees ($Millions)	Fees paid to the exchange at which the firm is listed on in millions of US dollars. Constructed as per the details given in NASDAQ and NYSE websites.	Authors' calculation
ExchangeFeesRatio	Exchange fees ratio is defined as the exchange fees divided by firm's total sales	Authors' calculation
SOXFees	Sarbanes Oxley compliance fees which is computed as the average annual SOX compliance fees based on the firms size following Protiviti Survey. Values are in millions of US dollars	Authors' calculation
SOXRatio	SOX ratio s defined as the Sarbanes Oxley compliance fees divided by firm's total sales	Authors' calculation
AuditFee	Total auditing fees in millions of US dollars. These values are available from AuditAnalytics database from year 2000 to 2019. Audit fees from year 1980 to 1999 are estimated using extrapolation as per the following steps: First, we compute the ratio of audit fees divided by the value of SG&A. (AuditSGA). Second, for each firm, we compute the average ratio of of audit fees scaled by SG&A over the period 2000 to 2019 (AvgAuditSGA). Third, we multiply AvgAuditSGA by SG&A value for firm-year observations from 1980 to 1999 adjusted by 1980 dollar value.	Authors' calculation
AuditFeeRatio	Audit fees ratio is defined as the total auditing fees divided by firm's total sales	Authors' calculation
Control Variables		
Size	The five years moving average of the firm's Size which is defined as the natural logarithm of total assets in 1980 dollars	5 yrs MA(Ln(SALE))
FirmAge	Firm's age is defined as the natural logarithm of the number of years since the firm's IPO date, if not available then we use the number of years since the firm's record first appears in Compustat	Ln(Firm's Age)
Leverage	The five years moving average of the firm's leverage which is defined as the firm's total debt divided by total assets	5 yrs MA((DLTT+DLC)/AT)
KZ	The five years moving average of the firm's KZ ratio 5 yrs MA((3.139 * (DLC + DLTT / AT) + (0.283 * (CSHO * PRCC.F / AT)) - (1.002 * (NI + DP) / LAGAT)) - (39.368 * DV /LAGAT) - (1.315 * CHE/LAGAT))	
ROA	The five years moving average of the firm's ROA ratio which is defined as the firm's return on asset	5 yrs MA(NI/AT)
CAPEX	The five years moving average of the firm's Capital Expenditure which is defined as the firm's capital expenditure divided by total assets	5 yrs MA(CAPX/AT)
Dividend	Dividend is defined as a dummy equals one if a firm paid out dividends during the fiscal year and zero otherwise	
R&D	The five years moving average of the firm's R&D ratio which is defined as the firm's research and development expenditure divided by total assets; missing values of R&D are replaced by zero	
NEI	The five years moving average of the firm's NEI ratio which is defined as net equity issuance to total assets	5 yrs MA((SSTK-PRSTKC)/AT)
Turnover	The five years moving average of the firm's stock turnover which is defined as the firm's natural logarithm of the annual number of shares traded divided by the number of shares outstanding	5 yrs MA(Ln(CSHTR.F/CSHO))
DRET	The five years moving average of the firm's annualized daily stock price return which is computed using the daily stock price return over the past year	5 yrs MA((PRCCD[t] - PRCCD[t-1])/PRCCD[t-1])
SDDRET	The five years moving average of the firm's stock return uncertainty which is defined as the standard deviation of daily stock returns over the past year	Authors' calculation

Online Appendix

This Appendix provides the readers with further sensitivity analyses on the effect of our model's parameters on the optimal delisting time. In Section 1, we provide our results for various theoretical scenarios, whereas in Section 2 we show our findings for six real-life cases for which we hand-collected data.

1. Theoretical Cases

This section provides further sensitivity analyses on the effect of changes in our model's parameters on the optimal delisting time.

The first set of results in Figure OA.1 shows our findings for eight different delisting scenarios. The baseline scenario is represented by the graph at the top on the left-hand side where it is assumed that the revenue uncertainty and the revenue growth rate of the listed and the delisted states are the same: $\sigma_1 = \sigma_2 = 0.32$ and $\alpha_1 = \alpha_2 = 0.24$. We conclude that, although the delisting of the firm now is profitable, a delay would make it even more profitable. The remaining graphs represent scenarios where we change either the revenue uncertainty or the revenue growth rate of the listed or the delisted states, *ceteris paribus*.

For instance, the graph at the top on the right-hand side represents a scenario where the revenue growth rate of the delisted state drops from 0.24 to 0.1. Comparing our findings for this scenario with those of the baseline scenario, we can see that a drop in the revenue growth rate of the delisted state makes delisting (now) slightly less profitable and that a delay in the delisting will make it less profitable. There is no empirical evidence showing that firms will face a lower revenue growth rate after being delisted. However, it is plausible to assume that firm may make conjectures about it and, typically, may not decide to become delisted again in order to grow faster. Therefore, what our findings show is that the more negative are the prospects for revenue growth for the delisted stated, as compared to those of the listed state, the more likely is the delisting. It increases the chances that the delisting now is profitable and optimal. A lower revenue growth rate makes the existence of delisting profitability threshold curves with negative slopes more likely.

The second graph from the top on the left-hand side represents a scenario where we change the revenue uncertainty of the delisted state from 0.32 to 0.4. Comparing this scenario with that of the baseline case, we conclude that the positive sign of the slope of the delisting profitability threshold curve does not change but increases significantly, in particular as the variable time increases. The delisting of the firm (now) is still profitable, although slightly less profitable than for the baseline case, and a delay in the delisting makes it more profitable. Hence, an increase in the revenue uncertainty of the delisted state increases the chances that the delisting will be more profitable in the future. A higher revenue uncertainty in the delisted state makes the existence of delisting profitability threshold curves with higher positive slopes more likely.

The third graph from the top on the left-hand side represents a scenario where we change the revenue uncertainty of the delisted state from 0.32 to 0.1, keeping the revenue growth rate at 0.1. Comparing this graph with that at the top on the right-hand side, we can see the effect of a decrease in the revenue uncertainty of the delisted state. We conclude that it increases the chances that delisting now is profitable and optimal, and a delay in the delisting makes it less profitable. A lower revenue uncertainty in the delisting state makes the existence of delisting profitability threshold curves with (more) negative slopes more likely.

Overall, we show that both revenue uncertainty and the revenue growth rate of the delisted state significantly affect the timing and profitability of the delisting. If these variables decrease, it is more likely that delisting now is profitable and optimal and that a delay in the delisting will make it less profitable.

The three sets of results that follow the one we describe above show further sensitivity analyses.

2. Real-Life Cases

Figure OA.5 shows six real-life case. One typical scenario is represented by YOCREAM INTERNATIONAL INC in the graph in the top left-hand side. The revenue value was at 50.73 million per annum and it increased after delisting, from $\alpha_1 = 0.0471$ (4.71% per annum) to $\alpha_2 = 0.2375$ (23.8% per annum), while business uncertainty stayed almost identical at $\sigma_1 = 0.0776$ and $\sigma_2 = 0.0783$ (about 7.8% per annum). Therefore, our theoretical findings show that this firm delisted too early; the breakeven time, according to our calculations, was one year. The delisting option gets deeper in-the-money after 20 years at which point the delisting was truly beneficial.

The second graph in the top right-hand side shows the FEDERAL SCREW WORKS and displays a firm with a medium turnover $S = 24.05$ million dollars. The delisting changed the turnover growth rate from -0.009 to 0.026 while keeping uncertainty almost the same $\sigma_1 = 0.10; \sigma_2 = 0.0954$. However, the firm should not have delisted for the first 15 years and again the option to delist gets deeper in the money as the horizon increases.

The second graph in the top left-hand side represents the case of SCHEIB (EARL) INC. For this firm, the turnover before the event was $S = 10.20$ million dollars that reflected a medium firm. The growth rate decreased from a positive value of $\alpha_1 = 0.018$ to a negative value of $\alpha_2 = -0.085$ while the uncertainty also decreased from $\sigma = 0.24$ to $\sigma = 0.09$. Clearly the delisting was not optimal, and it would not have improved much even after 25 years. The reason is that the negative growth rate *after* delisting, in spite of a substantial reduction in uncertainty, substantially affects the economic value of delisting.

The case depicted in the second graph in the second column of Figure E represents ULURU INC. which is a small firm for which $S = 0.72$ million dollars. In their case the growth rate reduced slightly from $\alpha_1 = -0.10$ to $\alpha_2 = 0.07$ while the (quite high) uncertainty increased from $\sigma_1 = 0.05$ to $\sigma_2 = 0.25$. The option to delist is positive from the start and then increases in a slightly convex manner quite rapidly. In this case the increase in information noise as measured by the parameter of revenue uncertainty is greatly compensated for by the substantial increase in the revenue growth rate.

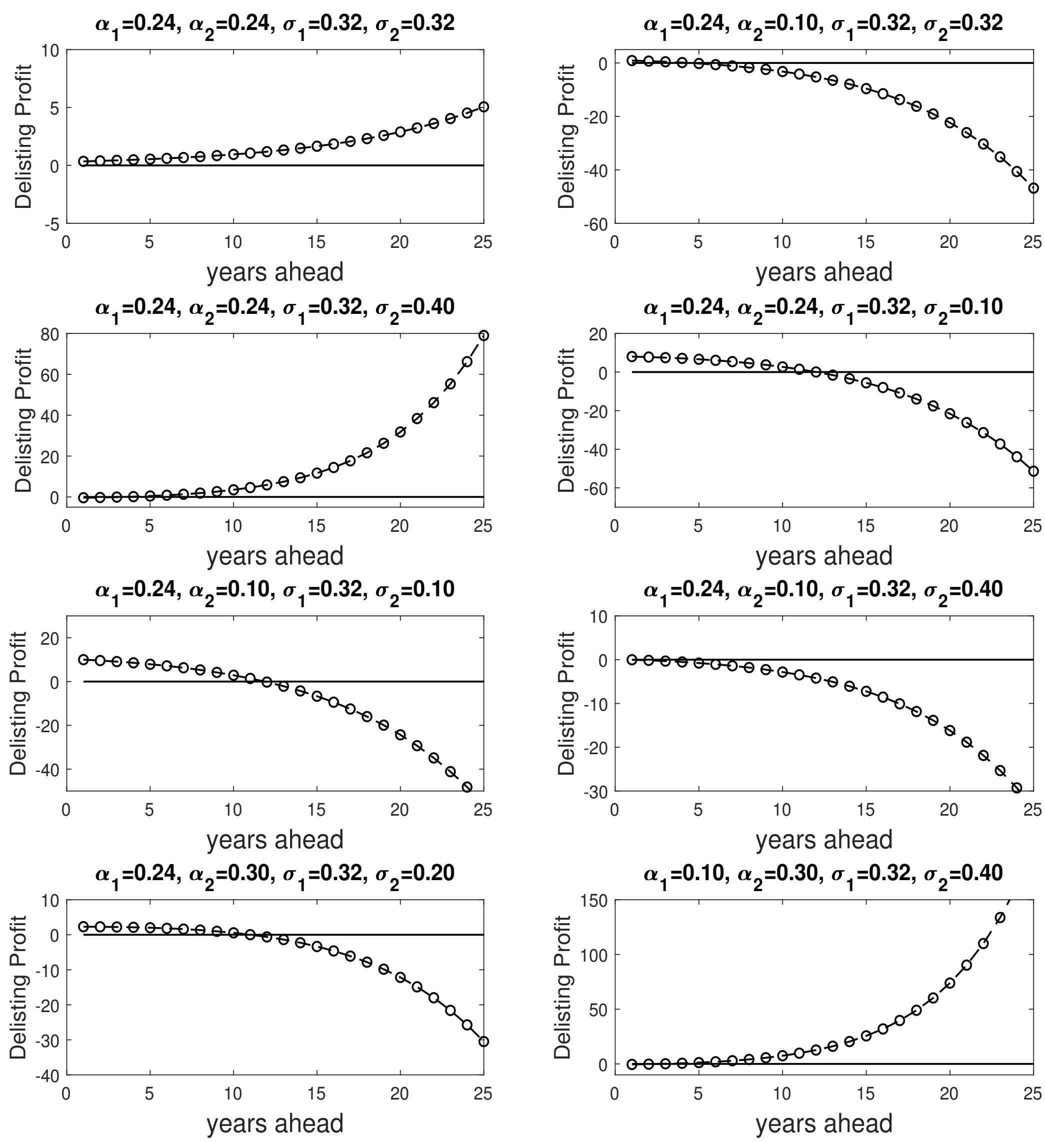
The third graph from the top on the left-hand side is that of PHOENIX FOOTWEAR GROUP INC, a relatively small-to-medium firm as suggested by $S = 15.90$ mil dollars revenue before delisting. In this case there is an increase in revenue growth rate from $\alpha_1 = -0.21$ to $\alpha_2 = -0.11$ coupled with an increase in revenue uncertainty from $\sigma_1 = 0.015$ to $\sigma_2 = 0.038$. This is a textbook case of no incentive for the delisting. Small revenue company manages to improve their revenue growth but since that still stays negative and coupled with an increase in the noise of information, the overall outcome is that they should have not delisted. The delisting real option is out-of-the-money from the beginning and the value of this option increases but very slowly for the projected 25 years. For this firm the option to delist evolves almost similarly to that of SCHEIB (EARL) INC, it is just of a different order of magnitude, justified by the differences in uncertainty parameters.

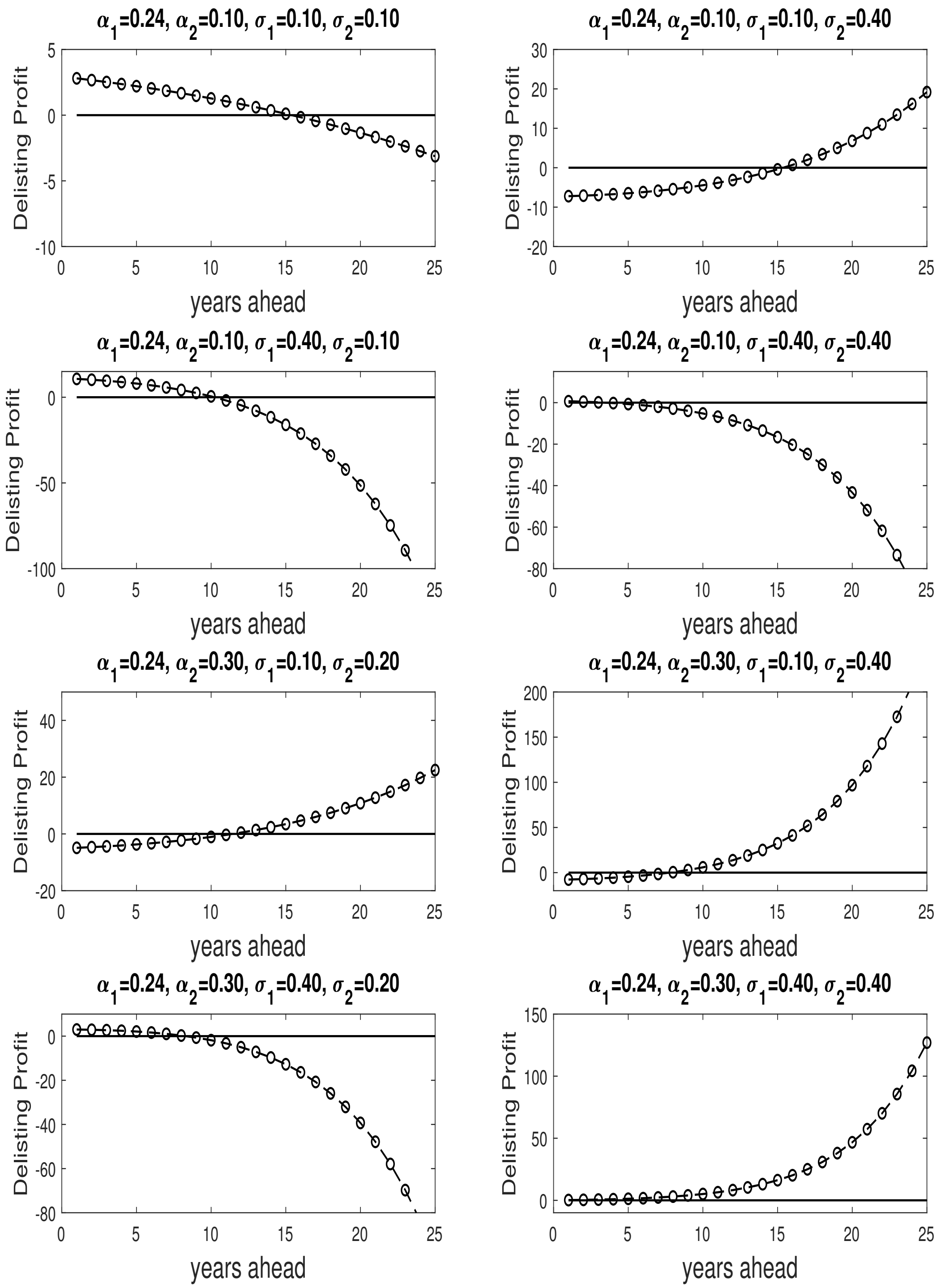
The last graph, third on the second column, describes the delisting exercise for HEAD NV. This is a large company with $S = 494.20$ mil dollars before delisting. The firm experienced a decreased growth rate from $\alpha_1 = 0.025$ to $\alpha_2 = 0.01$ while keeping uncertainty almost the same

$\sigma_1 = 0.10; \sigma_2 = 0.12$. The value of the option to delist is quite high initially mainly due to uncertainty but it declines rapidly such that the cross-even timing point is after 25 years in the future. In this case, it is optimal to delist immediately.

Figure OA.1: A Sensitivity Analysis on the Delisting Profitability

This figure shows the effect of changes in the business risk (revenue uncertainty) and the revenue growth rate on the profitability of the delisting decision. The solid horizontal line represents the zero going delisted profit threshold, and the convex or the concave curves represent the profit if the firm is delisted, as a function of time that is given in years. We report our projected annual calculations up to 25 years into the future from the presumed decision time. S denotes the firm's sales values. α_1 (α_2) represents the hypothetical before (after) delisting growth rate which is defined as the five years moving average of the annual change in firm's revenues. σ_1 (σ_2) represents the hypothetical before (after) delisting business risk which is defined as the standard deviation of the firm's growth rate.

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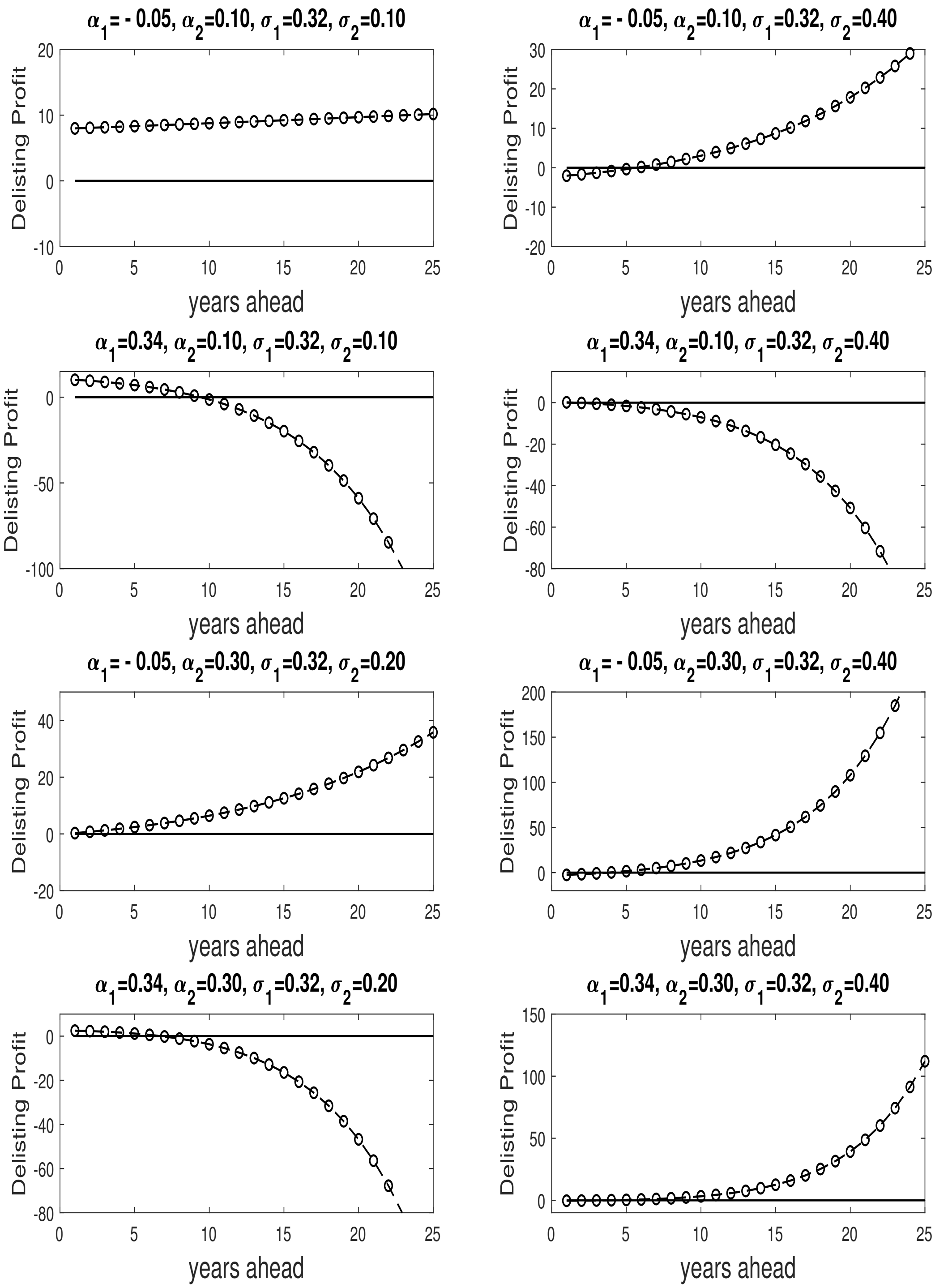
Delisting Profit
years ahead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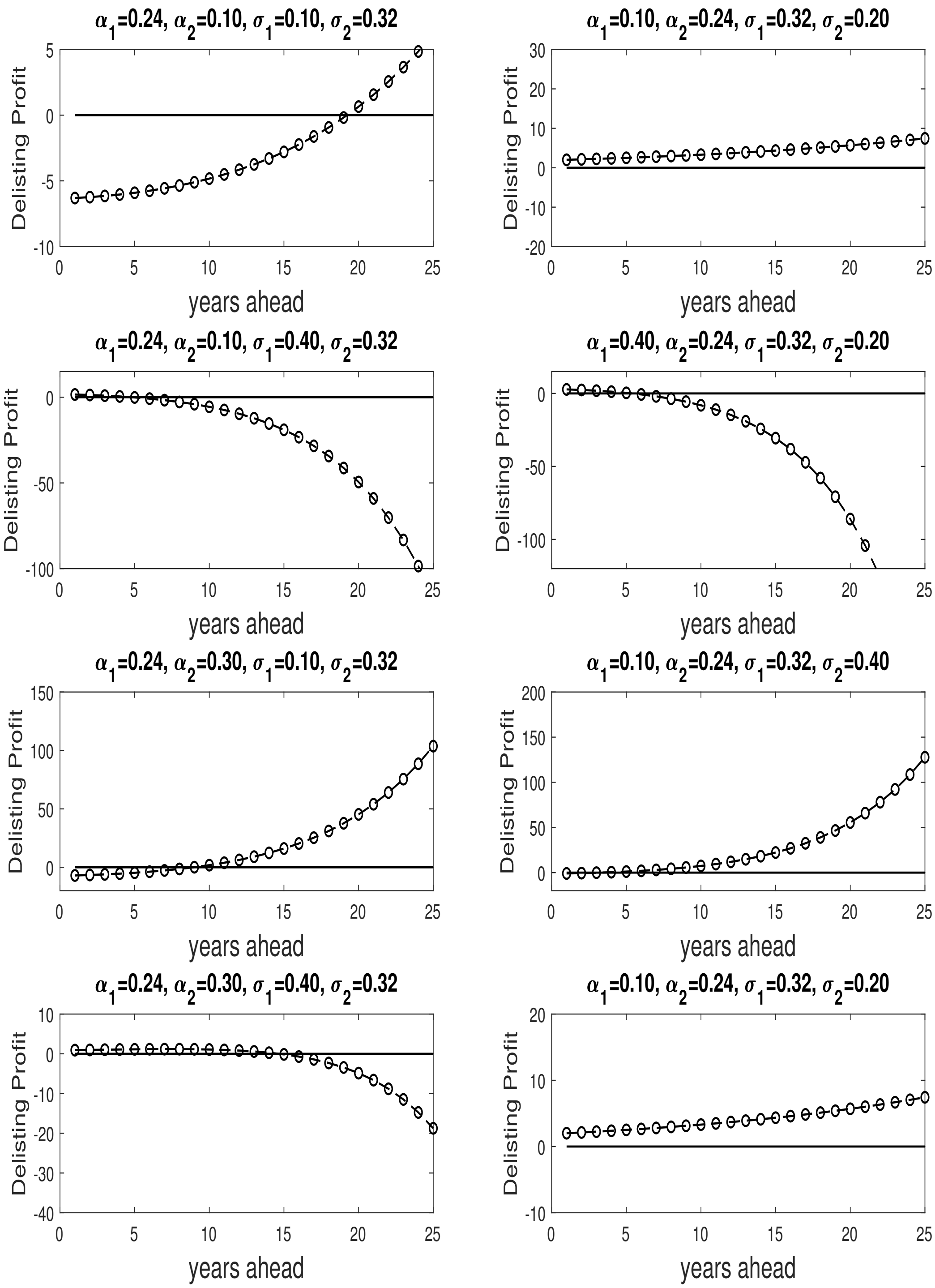
Delisting Profit
years ahead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α1=0.10, α2=0.24, σ1=0.32, σ2=0.20
Delisting Profit
years ahead

Figure OA.2: Some Real Case Examples on the Delisting Profitability

This figure shows the effect of changes in the business risk (revenue uncertainty) and the revenue growth rate on the profitability of the delisting decision. The solid horizontal line represents the zero going delisted profit threshold, and the convex or the concave curves represent the profit if the firm is delisted, as a function of time that is given in years. We report our projected annual calculations up to 25 years into the future from the actual decision time. S denotes the firm's sales values. α_1 (α_2) represents the sample estimate before (after) delisting growth rate which is defined as the five years moving average of the annual change in firm's revenues. σ_1 (σ_2) represents the sample estimate before (after) delisting business risk which is defined as the standard deviation of the firm's growth rate.