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# The timing of voluntary delisting ☆

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ABSTRACT

For many firms, voluntarily delisting from a stock exchange can be optimal. We model an entrepreneur's incentives to voluntarily delist the firm as a trade-off between consumption of private benefits when listed and expected improvements in the firm's performance after delisting. Our model allows for heterogeneity across firms and countries, and various micro and macro shocks affect the delisting decision. Such a model makes novel predictions regarding the delisting patterns around the world. We empirically confirm these predictions using manually collected delisting data from 26 countries. Increasing policy and regulatory uncertainties can partially explain the greater popularity of voluntary delistings.

## 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 still exist if the new listings had stayed as high as a few decades ago. This observation indicates that voluntary exchange delistings have become a prominent feature of modern financial markets. Perhaps a good testimonial for this is the op-ed peace by Michael Dell in November of 2014 where he states that: "At Dell, we faced a confluence of factors in making the decision to end a 25-year run as a publicly traded company. These factors included the big opportunities ahead, the required pace of innovation and investment, and an affliction of short term thinking that drove a wedge between our customer and investor priorities."[1] This statement raises some important questions about the voluntary delistings: Is delisting a firm from an exchange beneficial to the shareholders or are there other considerations by the owner-entrepreneur? What sudden changes in the firm's business conditions could influence this decision? In this paper, we develop a theoretical model that addresses these important questions and empirically tests its novel predictions regarding the micro and macro determinants of the decision to voluntarily delist.

Compared to the period from 1980 to 1999, the voluntary delistings from the US and other major exchanges worldwide have noticeably increased in the last two decades (Doidge et al., 2017). This is part of a global trend to move away from public equity financing (Jensen, 1986; Stulz, 2020; Schlingemann and Stulz, 2022). Since voluntary delisting is a choice, this trend indicates that many firms have recently found

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[1] See the op-ed article by Michael Dell named "Going Private Is Paying Off for Dell" in the Opinion section of Wall Street Journal on November 24, 2014.

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delisting from the stock exchanges to be a rational action to take. Understanding why is the goal of this paper. A theoretical model on delisting is not yet available; this is surprising given that the cost-benefit rationale and agency considerations are at the centre of the decision to be a publicly listed firm (Pagano et al., 1998; Shleifer and Wolfenzon, 2002; Stulz, 2005). There are advantages to being a public firm. It widens the sources of external financing, it improves the access to cheaper capital, it provides firms with the opportunity of using stock options to attract talented managers, and it increases the prestige and market visibility of firms (for a survey on this literature see Ritter and Welch (2002) and 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 (Shleifer and Vishny, 1986; Celikyurt et al., 2010; Arikan and Stulz, 2016). However, being listed also has some disadvantages. Many studies emphasize the importance of agency costs related to the extraction of private benefits by the owner-entrepreneur (briefly, "the entrepreneur") at the expense of minority shareholders.[2] Other costs involve regulatory compliance. For instance, in the US the direct costs of being listed on an exchange include the expenses related to compliance with the Sarbanes-Oxley Act (SOX) of 2002 and the new governance rules and information disclosure requirements (Benninga et al., 2005; Marosi and Massoud, 2007), the potential losses related to disclosing business secrets to a firm's rivals (Maksimovic and Pichler, 2001), the management's "short-termism" associated with quarterly earnings reporting, and the absence of ownership control (Pástor et al., 2008; Zingales, 1995). Hence, if the total net benefit from being publicly listed is sufficiently low, delisting from a stock exchange might become optimal for the entrepreneur.

We develop a theoretical model on the delisting decision of the firms that face agency problems (appropriation of private benefits by the entrepreneur), certain disclosure costs (regulatory requirements), and various internal and external shocks to their business conditions. Our model builds on the theoretical arguments developed by Shleifer and Wolfenzon (2002), Stulz (2005), and Stulz (2009), who describe the trade-offs and incentives faced by the private firms that want to get listed on a public exchange in a given country. In our modelling framework, the delisting decision works in reverse to listing, and it can be applied as a switching model between listed and delisted states over a multiperiod timeline. We assume that the firm is already listed on an exchange and there exists a controlling shareholder(s), who is considering whether delisting is optimal.[3] The decision to delist depends on the trade-offs and the dynamics between two key drivers of the entrepreneur's wealth: the consumption of private benefits in listed and delisted states (the agency motives for delisting) and the expected improvements in the firm's business performance in the delisted state (the economic motives for delisting). Our model succinctly demonstrates that when the economic motives for delisting outweigh the agency benefits from staying listed, the entrepreneur will voluntarily delist at the end of which they will own the entire firm and its future revenue stream. Our model further shows that the agency motives for delisting are, in turn, affected by several key economic variables, such as the entrepreneur's ownership rate, the degree of protection provided to minority shareholders in the country where the exchange is located, the dividend paid to the shareholders, and the costs of being publicly listed. Under the assumptions of our model, the economic motives for delisting are captured by the firm's growth rate (growth of its revenue stream) and its business risk (volatility of its revenue stream). These performance indicators tend to change over time depending on the evolution of the firm's internal business performance, and they can be shocked by external macroeconomic factors (e.g., policy uncertainty shocks as in Baker et al. (2016) and major increases in regulatory restrictions as in Kalmenovitz (2023)). Such changes in the internal dynamics of the firms and various external shocks to its business can make voluntary delisting an optimal choice.

Our model is applied on a multiperiod basis and thus, the entrepreneur continuously compares the benefits they can extract by keeping the firm public with the benefits they can get if the firm is delisted. In the latter case, in addition to receiving all the dividends, they have the benefit of expropriating funds and not being caught or punished by the regulator. The entrepreneur has an insider view on how the firm will do in the future when they will fully own it. While under the listed state, the firm's business characteristics are easier to determine by the external parties; in the delisted state, they become the entrepreneur's private information and thus unobservable to third parties. Finally, our multiperiod model can also be used to reverse the delisting decision (i.e., list the firm again on an exchange) if the conditions that induced delisting have changed and it is optimal to list anew the firm.

The multiperiod (dynamic) aspect of our model allows for analyzing 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). 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 various policy uncertainties, be it the economic policy uncertainty of Baker et al. (2016) or the regulatory risk as in Dawson and Seater (2013), can change the optimal time to delist. In other words, an exogenous policy shock to either the growth rate or business risk can change the calculus of the delisting decision. Furthermore, this common shock could have heterogeneous effects on different firms depending on their unique business operations. Within this framework, our paper shows that external-to-the-firm conditions can potentially explain the recent rise in voluntary delistings.

This model yields some novel empirical predictions. To test these predictions in a multi-country setting in which the stringency of the expropriation laws can vary substantially across countries (see La Porta et al., 1998) and the policy and regulatory uncertainty shocks can arrive at different times, we manually collect delisting information from 26 countries by reading the relevant news around the delisting event to determine the reasons for it.[4] We classify the delistings as voluntary, involuntary (liquidation or bankruptcy), or mergers and acquisitions (M&A). Our cross-country sample covers the period from 1990 to 2020; and it comprises 26,090 firms of which 6,708 delisted due to M&As, 1,035 involuntarily delisted, and 832 voluntarily delisted. Since our theoretical framework is suitable primarily for voluntary delistings in which the entrepreneur has a choice, the predictions from our model should not be relevant for the involuntary and M&A delistings. There-

[2] Some examples of papers that theoretically model this extraction of private benefits are: Burkart et al. (1997), Shleifer and Vishny (1997), Pagano and Röell (1998), Bebchuk and Roe (1999), La Porta et al. (2002), Shleifer and Wolfenzon (2002), Doidge et al. (2004), Stulz (2005, 2009). La Porta et al. (1999) and Faccio and Lang (2002) show empirically that most firms outside the US are controlled by large shareholders who can extract private benefits from the corporations they control.

[3] Throughout the paper, we shall refer to this controlling shareholder (or a syndicate of large shareholders with aligned interests) as "the entrepreneur." Many public firms around the world are managed by large shareholders who typically are the founders (La Porta et al., 1999). Anecdotal examples of such large and influential shareholders/entrepreneurs who can use their large ownership (and substantial influence capabilities on other shareholders) to delist their firm include Michael Dell of Dell Inc and Elon Musk of Tesla Inc. Another set of anecdotal examples involve influential CEOs who organize many small shareholders to take their firm private with the help of external financing (e.g., leveraged buyouts). Morck et al. (2005) discuss the ways insiders control votes in excess of their fractional ownership of cash flows.

[4] As explained later on in the paper, the list of these countries is determined by the availability of the economic policy uncertainty index of Baker et al. (2016) for that country.

fore, we use a competing risk analysis (as in Fine and Gray (1999) and Mehran and Peristiani (2010)) to empirically test our model's predictions. Competing risk is a special type of survival analysis that aims to estimate the marginal probability of an event (voluntary delisting) in the presence of competing events (liquidation and M&A). This empirical setup enhances the power of our tests as it allows for rejecting the null of voluntary delisting by contrasting it with the firms that delist due to bankruptcy or acquisition. It is particularly helpful when some of the covariates are possibly endogenous regarding the delisting decision (Fine and Gray, 1999; Wheelock and Wilson, 2000; Mehran and Peristiani, 2010). Using the above multi-country sample and the competing risk econometric model, we estimate the determinants of voluntary delisting decisions of the firms around the world.

We obtain some valuable insights from this analysis. First, a novel prediction of our theoretical model is to highlight the relative importance of agency motives behind the voluntary delisting decisions of firms around the globe. Indeed, our competing risk estimation shows that some key variables that determine the optimal amount of cash flows to be expropriated by the entrepreneur, such as the expropriation penalty parameter of a country and the entrepreneur's ownership stake, are economically very relevant for the decision to voluntarily delist. Both are positively related to it. A firm's listing expenses (e.g., auditing fees) also relate positively to this type of delisting, and the dividend ratio of the firm relates negatively to it. Another novel aspect of our theoretical model is to assess the relative importance of economic motives for making the delisting decision. The variables capturing the economic motives (growth rate and business risk) are also statistically significant determinants of delisting but economically they appear to be of lesser importance to the entrepreneur than some of the agency variables. Their estimated marginal effect ranks behind the insider ownership stake but above the expropriation penalty parameter of a country, the listing expenses, and dividends. Furthermore, as a third testable hypothesis derived from our model, we predict that exogenous macroeconomic factors such as policy uncertainty and the number of new regulations imposed on the firm's production activities can increase the delisting probability by affecting the aforementioned economic parameters of our model. In particular, the mediation analyses (Baron and Kenny, 1986) show that policy and regulatory uncertainties accelerate the delisting decision through two economic channels: the reduced growth rate and the increased business risk channels. These are the key insights that help explain the recent trends that made the delisting decision an optimal one for many firms (Gao et al., 2013; Doidge et al., 2017).

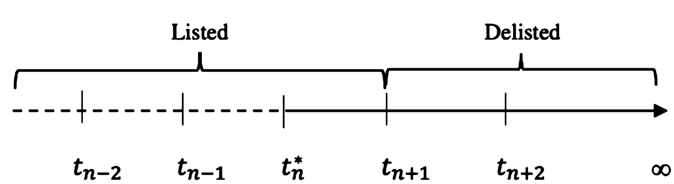
This paper contributes to the delisting literature in several ways. First, to the best of our knowledge, it is the first to theoretically model the controlling shareholder's incentives to voluntarily exit the public equity markets at an optimal time. This delisting model yields novel testable predictions regarding the relative importance of agency issues and economic performance in inducing voluntary delisting. Second, the paper provides empirical evidence that stresses the importance of several key determinants of the voluntary delisting decision: expropriation penalty costs in a country, degree of insider ownership, firm's growth rate, and its business risk. The dividend payout and listing expenses are also relevant. We are the first in this literature to test the role of these variables in the voluntary delisting decision and to introduce an empirical proxy for the firm's ongoing listing expenses.[5] Third, we model and test 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 immediately rather than waiting. 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 been rapidly rising (Baker et al., 2016; Kalmenovitz, 2023). Other proposed explanations for such a rise in the number of delistings within the US are the pressure of competition and scale economies (Gao et al., 2013) and the role of financial globalisation (Doidge et al., 2013). We provide explanations for the increase in voluntary delistings in an international setting.

## 2. The model

Our voluntary delisting model is based on the assumption that the firm's initial decision to list on the exchange (the initial public offering (IPO) event that took place in the past) was based on the theory developed by Shleifer and Wolfenzon (2002), Stulz (2005), and Stulz (2009). These authors describe the incentives of the entrepreneur (or group of insiders with perfectly aligned motives and interests) with regards to shareholder expropriation and the related agency problems it creates. Our next assumption is that the firm is already listed on a country's stock exchange and that the same agency-related incentives (shareholder expropriation) that guided the IPO decision are still in effect as long as the firm stays listed. We also assume that in the current period the firm has already made the initial investment and the production is ongoing. At the end of each yearly period the manager, who is the entrepreneur or somebody closely aligned with them, considers whether to delist from the exchange or keep the firm listed. The entrepreneur (insiders) act in their own best interests and optimize their own private benefits when making the delisting decision, but the appropriation of private benefits has a deadweight cost that is paid by the insiders (e.g., legal penalties). We model this cost explicitly by following Stulz (2009), who provides a concrete expression of a generic deadweight cost function that was originally proposed by Shleifer and Wolfenzon (2002).

### *2.1. Entrepreneur's benefits when firm stays listed*

Fig. 1 shows a timeline that illustrates the two stages of our model: listed and delisted. The decision to delist can be made at any point in time (..., $t_{n-2}$, $t_{n-1}$, $t_n$, $t_{n+1}$...) from the moment the firm is listed. In each period, the entrepreneur monitors whether the firm should stay listed in the exchange or should delist, up until the moment ($t_n^*$) when it becomes optimal to delist the firm from the exchange. The delisting decision materializes at $t_{n+1}$ and from that moment onwards the firm is privately owned by the entrepreneur.




This figure shows a timeline of the delisting decision for our model framework. From the moment the firm is listed (..., $t_{n-2}$, $t_{n-1}$,...), the entrepreneur decides in each time period whether to delist or not. If in the period starting at ($t_n^*$) it becomes optimal to delist, the delisting action is materialized at $t_{n+1}$ and from this moment onward, the firm is delisted.

**Fig. 1.** Delisting timeline.

[5] 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 this literature is scarce on voluntary delisting decisions with the exception of Clyde et al. (1997), Leuz et al. (2008), and Cohn et al. (2014). In general, the forced (involuntary) delistings are 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 announcements of involuntary delisting events (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).

Let $K_n$ denote the total capital invested in the firm at the beginning of period $n$. The period $n$ refers to the timeframe $[n, n+1)$. The wealth of the entrepreneur is $W_n$ and we assume that $W_n < K_n$, since the entrepreneur needs external shareholders to make the initial investment. The entrepreneur's ownership stake in the firm at the beginning of period $n$ is $\alpha_n$. The firm's total cash flows are determined by a random variable $R_{n+1}$, for the gross investment return that becomes known at time $n+1$.

The cash flows, $R_{n+1}K_n$, produced by the firm are used for several purposes. A fraction $v_n$ of these cash flows is expropriated by the entrepreneur for private consumption. The direct costs of being publicly listed include auditing fees, risk management, exchange fees, and other legal costs; therefore, they are modelled as a proportional fraction $l_n$ of the firm's cash flows. The shareholders are paid a dividend equal to a proportion $d_n$ from the residual cash flows after paying for the private consumption of the entrepreneur and the costs associated with being listed. The risk free rate for period $n$ is $r_n$. Like in Stulz (2009), the total penalty for expropriation of shareholder funds is expressed by $0.5 b_n R_{n+1} K_n v_n^2$, and it will be paid by the entrepreneur from their personal funds. The choice of the penalty function as $f(v) = 0.5 b v^2 RK$ satisfies the assumptions stated in Shleifer and Wolfenzon (2002) for such a function, that is $f(0) = 0, f'(0) = 0, f''(v) = vRK > 0$ and that $\frac{\partial(f'/f'')}{\partial v} = 1 > 0$. The parameter $b_n$ is country-specific, and it reflects the costs of shareholder expropriation. This parameter is expected to be very high for countries that have strict minority shareholders protection laws (La Porta et al., 1998).

Since the firm is already in production, the entrepreneur's wealth at the end of period $n$ is:

$$W_{n+1} = \alpha_n d_n (1 - v_n)(1 - l_n) R_{n+1} K_n + v_n R_{n+1} K_n - \frac{1}{2} b_n v_n^2 R_{n+1} K_n \tag{1}$$

Further, the entrepreneur pays the penalty from their own account; and in countries with very high penalties, the entrepreneur has less of an incentive to consume private funds. From the total return $R_{n+1}K_n$, the entrepreneur first consumes private money at the rate $v_n$ and then receives dividends in proportion to their ownership stake after paying the listing expenses.

The optimal rate of consumption of private funds $v_n$ is determined by the entrepreneur under the assumption that the firm stays listed throughout the period $n$. This is determined by maximizing $E_n(W_{n+1})$ subject to a rational constraint imposed by the minority shareholders in order to keep them invested in the firm (Shleifer and Wolfenzon, 2002; Stulz, 2009). This constraint is expressed as:

$$d_n(1 - \alpha_n)(1 - l_n)(1 - v_n) E_n(R_{n+1}) K_n \geq (K_n - W_n) r_n \tag{2}$$

The rational entrepreneur can and will always change $W_n$ by taking more money out (e.g., private trips, executive gifts, etc.) and make the constraint binding. Hence, the solution for $K_n$ is:

$$K_n = \frac{W_n r_n}{r_n - d_n(1 - \alpha_n)(1 - l_n)(1 - v_n) E_n(R_{n+1})} \tag{3}$$

Then, the optimisation problem that is solved by the entrepreneur is

$$\max_{v_n} \Big[\alpha_n d_n (1 - v_n)(1 - l_n) E_n(R_{n+1}) K_n + E_n(R_{n+1}) K_n v_n - \frac{1}{2} b_n E_n(R_{n+1}) K_n v_n^2\Big] \tag{4}$$

The first order condition gives

$$v_n^* = \frac{1 - \alpha_n d_n (1 - l_n)}{b_n} \tag{5}$$

The numerator in (5) is always a number between zero and one given that $\alpha_n, d_n$ and $l_n \in (0, 1)$. In order to ensure that $v_n^* \in (0, 1)$, we have with necessity that $b_n \geq 1$, for any $n$.

However, $v_n^*$ is a solution known only to the entrepreneur.[6] For notational simplicity we, henceforth, drop the $^*$. Thus, when the ownership stake of the entrepreneur increases, the optimal rate of consumption of private funds decreases.[7] The same is true for a dividend payout. However, if the costs of being public increase, then the entrepreneur can get away with a higher optimal rate of consumption of private funds. A higher $b_n$ means better regulated and more transparent economies that results in a lower rate of consumption of private funds by the entrepreneur.

After replacing $v_n$ from (5) and taking $K_n$ from to (3) into (1), we get:

$$W_{n+1} = (1 - b_n v_n)(1 - v_n) R_{n+1} K_n + v_n R_{n+1} K_n - \frac{1}{2} b_n R_{n+1} K_n v_n^2 \tag{6}$$

After applying the expectation at the beginning of period $n$, we obtain:

$$E_n(W_{n+1}) = E_n(R_{n+1}) K_n - b_n v_n E_n(R_{n+1}) K_n + \frac{1}{2} b_n E_n(R_{n+1}) K_n v_n^2 \tag{7}$$

or

$$E_n(W_{n+1}) = K_n E_n(R_{n+1})(1 - b_n v_n + \frac{1}{2} b_n v_n^2) \tag{8}$$

The factor $(1 - b_n v_n + \frac{1}{2} b_n v_n^2)$ represents the *entrepreneur's ability to extract wealth from the company*. To simplify, we denote this factor as $\Psi(b_n, v_n)$, and we rewrite the last equation as:

$$E_n(W_{n+1}) = K_n E_n(R_{n+1}) \Psi(b_n, v_n) \tag{9}$$

Therefore, in each period $n$ the entrepreneur is considering their own benefit from being involved with the firm, and their expected wealth is determined by three factors. The first is the capital used in the production, $K_n$, which is multiplied by the second factor that reflects the expected returns from the production $E_n(R_{n+1})$. However, $E_n(R_{n+1})$ depends directly on the firm's gross investment return that can be represented by the firm's annual revenues. The last factor, $\Psi(b_n, v_n)$, reflects the entrepreneur's ability to extract private benefits from the firm given the regulatory efficiency in the country, $b_n$, where the firm is listed during the period $n$. Hence, when the firm is listed, the entrepreneur's expected wealth depends on how they distribute the cash flows, the capital available for investment, and the production of goods that the firm can sell.

### 2.2. Entrepreneur's benefits when firm is delisted

The entrepreneur would consider delisting the firm if and when it becomes more profitable for them to do so. The entrepreneur would decide at time $n$ whether it is beneficial for them to delist the firm by the

[6] When the entrepreneur is the only shareholder, they will not expropriate funds because those funds will come out of their pocket. Similarly, when there is only a small group of shareholders, these shareholders can monitor the entrepreneur and act as a deterrent, so the entrepreneur has only limited ability to expropriate funds. However, when the firm is public, as it is the case with the initial status of the firm in our model, the ownership being dispersed implies that individual shareholders find it cost prohibitive to monitor the entrepreneur because of limited access to information. Minority shareholders also cannot change actions taken by the entrepreneur easily and in this case the entrepreneur can expropriate funds much easier. Recall also that the entrepreneur can decide on the size of the project $K_n$ and the degree of their ownership $\alpha_n$. The consumption of private benefits directly implies a decrease in the wealth of the entrepreneur because of the payoff decrease from the shares they own, hence the entrepreneur's perks is inversely related to their ownership stake $\alpha_n$. These important points were discussed at length in Stulz (2009) and Stulz (2020).

[7] Within any given period with a given fixed level of ownership $\alpha \in (0, 1)$ for the entrepreneur and the firm's total dividend payout $d \in (0, 1)$ and the total listing fees $l \in (0, 1)$, it is true that: $\frac{\partial v}{\partial \alpha} = -d(1 - l)/b < 0$; $\frac{\partial v}{\partial d} = -\alpha(1 - l)/b < 0$; $\frac{\partial v}{\partial l} = \alpha d/b > 0$; and $\frac{\partial v}{\partial b} = -\frac{1 - \alpha d(1 - l)}{b^2} < 0$.

end of the period. At the time of the decision, the entrepreneur would not yet know the value of $R_{n+1}$. The total value of the firm at the time of delisting is expressed by $R_{n+1}K_n$ and the entrepreneur owns $\alpha_n$ percent of that. Thus, when the firm delists, the wealth of the entrepreneur becomes $W_{n+1} = \alpha_n R_{n+1} K_n$.

The decision to delist during the period $[n, n+1)$ is essentially based on comparing the expected wealth of the entrepreneur when the firm is listed, as given in (9), with the expected wealth of the entrepreneur when the firm is delisted, that is calculated as:

$$E_n(W_{n+1}) = E_n(\alpha_n R_{n+1} K_n) = \alpha_n K_n E_n(R_{n+1}). \tag{10}$$

The entrepreneur may have inside information about possible changes in the firm's business conditions that may occur after the delisting of the firm. For example, upon delisting, the entrepreneur may change the direction of production and marketing such that the firm's growth rate is expected to increase. To reflect more correctly the decision-making process, we denote as $\widetilde{E}_n$ the expectation under the delisting information filtration of the entrepreneur, which is not available in full to external shareholders. The entrepreneur would decide at time $n$ whether to voluntary delist by considering whether

$$K_n E_n(R_{n+1})\Psi(b_n, \upsilon_n) < \alpha_n K_n \widetilde{E}_n(R_{n+1}) \tag{11}$$

If the condition is verified, then the firm may be delisted; if it is not, the firm should stay listed. Therefore, one of the main results of this paper is contained in the following proposition.

**Proposition 1.** *A firm is listed on an exchange and it is owned by an entrepreneur who sold shares to outside shareholders. For the entrepreneur, it is optimal to delist at the end of each time period n if:*

$$\frac{\Psi(b_n, \upsilon_n)}{\alpha_n} < \frac{\widetilde{E}_n(R_{n+1})}{E_n(R_{n+1})} \tag{12}$$

The proof is derived above between (1) and (11).

As condition (12) highlights, our theoretical model is based on the intuitive idea that the delisting occurs when the ratio of the economic payoffs $\widetilde{E}(R_{n+1})$ to $E(R_{n+1})$ is larger than what the entrepreneur can maximally expropriate under the listed state relative to their share of the firm $(\Psi(b_n, \upsilon_n)/\alpha_n)$. The left-hand side of (12) represents mainly the ability and willingness of the entrepreneur to expropriate firm resources. The right-hand side is the ratio of the income production revenues of the firm in the delisted state over the listed state. It reflects the internal and external factors that affect the economic performance of the firm besides the entrepreneur's selfish motives. The condition in (12) succinctly summarizes two main drivers of the voluntary delisting decision: managerial agency problems (left-hand side) and firm's economic performance (right-hand side). The entrepreneur can make the voluntary delisting decision due to the desire to improve the cash flows of the firm or to increase (optimize) their expropriation benefits.

The left-hand side of (12) is clearly defined with the existing model's parameters (see also (5)), however the right-hand side is more difficult to express analytically given that the numerator ($\widetilde{E}$) is determined by the entrepreneur's private information (or estimation) about how the firm would perform after delisting. Thus, in the next subsection, we will make some additional modelling assumptions about the distributions of $R_{n+1}$ under the delisting and listed states of the world.

Now, we theorize how various important parameters affect the left-hand side of (12) (i.e., how they affect the delisting decision through a change in the entrepreneur's expropriation motives). Endogenously determined variables for the entrepreneur are the ownership ratio, $\alpha$, and the dividend payout, $d$. Exogenously imposed variables for the entrepreneur are $b$ and $l$. The optimal rate of consumption of private funds, $\upsilon$, depends both on the endogenously chosen and exogenously imposed parameters (see (5)). Facing a shock to the exogenous variables, $b$ and $l$, the entrepreneur would adjust the endogenous variables $\alpha$ and $d$ to optimize $\upsilon$. When further adjustments are not possible, the entrepreneur would delist the firm.

When making the decision to delist, the entrepreneur must consider simultaneously four inputs. For the first two, the entrepreneur ownership stake $\alpha$ and dividend payout $d$, the entrepreneur has a degree of control that depends on other considerations. The other two, the exchange related costs $l$ and the country penalty parameter $b$, are externally determined. In the next proposition, we formalize the marginal relationship between each of these four parameters and the likelihood of the firm being delisted.[8]

**Proposition 2.** *An entrepreneur's expropriation motives (agency problems) are key determinants of the delisting decision. These expropriation motives are determined by four parameters: the country's expropriation penalty parameter b, the entrepreneur's ownership stake α, the dividend payout d, and the exchange listing costs l. The marginal impact of each of these parameters can be derived analytically. Ceteris paribus,*

*(i) the marginal impact of b on the likelihood of voluntarily delisting is positive.*

*(ii) the marginal impact of α on the likelihood of voluntarily delisting is positive.*

*(iii) the marginal impact of d on the likelihood of voluntarily delisting is negative.*

*(iv) the marginal impact of l on the likelihood of voluntarily delisting is positive.*

See the proof in the Appendix A.

### *2.3. Further modelling assumptions and new theoretical insights*

In this subsection, we focus on the right-hand side of condition (12) and make further assumptions about the dynamics of the firm production return $R$. In our model, the firm's economic performance is defined by the expected value of $R$ in either the listed or delisted state depending on which state the firm is in. We assume that the production output (revenue) of the firm at time $n$ is $S_n$ and that $\{S_n\}_{n\geq 0}$ follows the dynamics of a geometric Brownian motion with drift parameter $\mu$ and volatility parameter $\sigma$. Recall that $R_{n+1}$ is the gross investment return in the period $[n, n+1)$. Under our model assumptions, $R_{n+1}$ depends only on the process $\{S_n\}$, $R_{n+1} = \frac{S_{n+1}}{S_n}$. Hence, we can calculate $E[R_{n+1}]$ from the distributional properties of $\{S_n\}$. For empirical purposes, we work with a typical geometric Brownian motion for which the estimates of parameters $\mu$ and $\sigma$ are updated with additional information learned in period $n$. Therefore, we use estimates of $\mu_{n+1}$ and $\sigma_{n+1}$ that represent the growth rate and the business uncertainty of the firm following period $[n, n+1)$.

Furthermore, the entrepreneur may have a different expectation for the next period based on their inside information on the firm's activities and other latent projects. As mentioned before, "∼" denotes the entrepreneur's inside calculations or knowledge about the expected economic performance of the firm when it delists. Under the assumptions regarding the distribution of investment return $R$, this notation also encompasses the future growth rate $\mu_{n+1}$ and business risk $\sigma_{n+1}$. We can analytically formalize the delisting condition (12) in the following proposition.

**Proposition 3.** *The firm's economic performance (production return R) in listed and delisted states is also an important determinant of the en-*

[8] The entrepreneur is also interested in the optimum level of expropriation funds $\upsilon$. As $\upsilon$ increases, everything else being equal, delisting becomes more likely but the relationship is non-linear. By definition $\Psi(b, \upsilon) = 1 - b\upsilon + \frac{1}{2}b\upsilon^2$. Then $\frac{\partial\Psi}{\partial\upsilon} = -b + b\upsilon = b(\upsilon - 1) < 0$. Therefore, when $\upsilon \uparrow \implies \Psi \downarrow$ and when $\upsilon \downarrow \implies \Psi \uparrow$.

*trepreneur's delisting decision. Under our probability distributional assumptions for investment return $R$, delisting is optimal at the end of each time period $n$ if:*

$$\frac{\Psi(b_n, \upsilon_n)}{\alpha_n} < \frac{1+\widetilde{\mu}_{n+1} - 0.5\widetilde{\sigma}^2_{n+1}}{1+\mu_{n+1} - 0.5\sigma^2_{n+1}} \tag{13}$$

*where $(\mu_{n+1}, \sigma_{n+1})$ are the firm's growth rate and business risk in the listed state, and $(\widetilde{\mu}_{n+1}, \widetilde{\sigma}_{n+1})$ are the same variables for the delisted state.*

The proof is in the Appendix A.

The right-hand side of condition (13) is determined by the business performance of the firm and it can be interpreted as follows. Delisting becomes more likely when the current business performance of the firm is low, but by delisting the entrepreneur believes they can improve the situation. When there is more to make by exploiting the natural production environment of the firm, the entrepreneur would delist in order to maximize their wealth. The firm's conditions can improve either by increasing the growth of the firm (a higher $\widetilde{\mu}_{n+1}$ than the $\mu_{n+1}$) or when the current business risk is high and by delisting the entrepreneur believes they can reduce it, that is, when $\sigma_{n+1}$ is high and $\widetilde{\sigma}_{n+1}$ is lower.

An important benefit of our model is that it allows for internal or external shocks to the firm's business conditions to trigger the delisting decision. In response to these shocks, the entrepreneur can choose to move towards a new equilibrium whereby they adjust $\alpha_n$ and the corresponding optimal expropriation $\upsilon_n$. However, if this adjustment is still not sufficient to overturn the inequality in condition (13), they may select the voluntary delisting route.

**Proposition 4.** *Under our model assumptions, the following results hold:*

*(i) If a firm's growth rate $\mu_{n+1}$ is shocked by an additive factor into $\mu_{n+1}+\varepsilon$, then the likelihood of delisting decreases (increases) with positive (negative) shocks to the growth rate.*

*(ii) If a firm's business risk is shocked by an additive factor such that $\sigma^2_{n+1}+\varepsilon$, then the likelihood of delisting decreases (increases) with positive (negative) shocks to the business risk.*[9]

See the proof in the Appendix A.

Further, our model is general and it can be used in a sequential series of listing and delisting decisions. Essentially, the condition (13) could also work in the reverse sense whereby in the future the entrepreneur can decide to enlist the firm again on a public exchange as in Shleifer and Wolfenzon (2002), Stulz (2005), and Stulz (2009). If the firm is delisted in the past but the condition underlying (13) did not materialize, like the entrepreneur hoped for, then they may consider relisting the firm.[10] Thus, our multi-period model offers a general set-up for covering listing and voluntary delisting decisions of the firm. However, this generality comes at a cost whereby to not lose the salience of the model, we are forced to abstract from various institutional settings of public listing and delisting actions that may be inadvertently linked to key economic and/or agency motives. For example, along with the ever increasing size and breadth of the institutional investor community and the related shareholder activism, the agency motives of the intermediaries can become an important determinant of switching costs between listed and delisted states.

[9] Without loss of generality, we use both $\sigma$ and $\sigma^2$ as two closely related measures of firm's business risk.

[10] This was exactly what happened to Dell Inc, a company founded in 1984 by Michael Dell, who took it public (IPO) for the first time in 1988, then took it private in 2013, and made it a public company again in 2018.

## 3. Towards an empirical testing framework

### 3.1. Testable implications and hypothesis development

Next, we briefly outline the testable implications of our model and its propositions. We develop several empirical hypotheses that allow for formal testing of these theoretical propositions.

#### 3.1.1. Relevance of key model parameters

Proposition 1 points to several key parameters that the entrepreneur considers when making the delisting decision. Four of these variables ($b$, $\alpha$, $d$, and $l$) directly affect the left-hand side of the condition (13) that represents the entrepreneur's ability and willingness to expropriate firm resources. Thus, we will refer to them briefly as *managerial agency variables* that affect the delisting decision. Two additional variables ($\mu$ and $\sigma$) affect the right-hand side of the condition (13) that represent firm's return from investments. Thus, we will briefly refer to these variables as *economic performance indicators*.

Two of the managerial agency variables ($b$ and $l$) are exogenously imposed on the entrepreneur by the governing bodies of the country, while the other two agency variables ($d$ and $\alpha$) are part of the decision-making process within the firm. Thus, as per the condition (13), the levels of these variables are expected to be informative of the delisting plans of the entrepreneur. The effects of these four agency variables (left-hand side of condition (13)) on the voluntary delisting decision have not been properly analyzed in the literature.[11] Our model (see Proposition 2) provides theoretical insights about the expected sign of the relationship between each of the key parameters and the delisting decision. Thus, in our first empirical hypothesis, we test whether these four agency variables are indeed relevant to the delisting decision and if so, what is the direction of their effect. We organize the first hypothesis into four empirically testable sub-hypotheses.

From Proposition 2(i) it directly follows that:

**H1A:** *The probability of voluntary delisting increases with country's expropriation penalty parameter $b$.*

From Propositions 2(ii)-2(iv), the levels of $\alpha$, $d$, and $l$ are also expected to be informative about the delisting decision. The expression in (5) and (13) make that clear. According to Proposition 1, when the total value of the $\Psi(b, \upsilon)$ factor rises, the inequality is less likely to be satisfied and the probability of the delisting decreases. Hence, we state our next three sub-hypotheses as:

**H1B:** *The probability of voluntary delisting increases with entrepreneur's insider ownership $\alpha$.*

**H1C:** *The probability of voluntary delisting decreases with the size of the dividend payout $d$.*

**H1D:** *The probability of voluntary delisting increases with listing expenses $l$.*

In our Hypothesis 2, we test whether the entrepreneur takes into consideration the current performance of the firm or do they just focus on the agency variables when making the decision. The two performance parameters are the first two moments in the distribution of $R$. Our model is the first to show the relevance of these variables for the delisting decision (see Section 2). Proposition 3 compares the growth rates in the delisted state ($\widetilde{\mu}$, which is a latent variable that is difficult to measure) to the growth rate $\mu$ in the listed state. This proposition

[11] The role of listing costs ($l$) in any kind of delisting decision has not been analyzed in the existing literature. Doidge et al. (2004) and Marosi and Massoud (2008) have shown the importance of a country's expropriation penalty parameter ($b$) in the cross-listing decision, but its role in the voluntary decision to delist is still an open question. Bharath and Dittmar (2010) treat the dividend payout ratio ($d$) as a control variable, but they do not identify it as a key driver of the voluntary delisting decision. Marosi and Massoud (2007) and Marosi and Massoud (2008) briefly discuss the role of insider ownership ($\alpha$) in making the cross-listing and cross-delisting decision from multiple exchanges, but not for voluntary delisting.

states that, *ceteris paribus*, the probability of delisting decreases with the rise in $\mu$, which is an observable quantity since the firm is currently publicly listed and has to report on its accounting performance. Thus, we hypothesize that the probability of delisting is negatively related to a firm's growth rate:

**H2A:** *The probability of voluntary delisting decreases with firm's growth rate* $\mu$.

Proposition 3 also compares the firm's business risk in the delisted state ($\widetilde{\sigma}$, which again is a latent variable that is difficult to measure) to the business risk $\sigma$ in the listed state. The algebraic expression in the right-hand side of (13) indicates that, *ceteris paribus*, the probability of delisting increases with the rise in business risk $\sigma$ which is a measurable quantity using firm's annual accounting reports. This claim is stated in our next sub-hypothesis:

**H2B:** *The probability of voluntary delisting increases with firm's business risk* $\sigma$.

### 3.1.2. The role of macroeconomic shocks

Hypothesis 2 argues that the firm's performance variables are relevant to the delisting decision. To a certain extent, these variables can be changed by the entrepreneur by making modifications to the operation of the firm (e.g., improving the production technology). However, in certain circumstances, the investment return ($R$) of the firm and its distribution moments ($\mu$ and $\sigma$) can be altered by sudden political and socioeconomic shifts that are completely out of the control of the entrepreneur. Thus, in the next hypothesis, we will emphasize how macroeconomic shocks that are exogenous to the firm can trigger delisting decisions regardless of the entrepreneur's desires for expropriation. The distributional moments of $R$ will act as mediators of the delisting decision. We focus on two kinds of macroeconomic variables: i) the political uncertainty shocks as measured by the Baker et al. (2016) indicators for the 26 countries in our sample, and ii) the changes in the general shifts in a country's governing and regulatory uncertainty as measured by the World Bank's Governance Indicators for that country.[12]

Financial decisions at the firm level are severely affected by uncertainty (McDonald and Siegel, 1986; Dixit and Pindyck, 1994). It 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 that firms should exercise their option to delay the investment when facing higher uncertainty.

A different branch of the literature argues that policy uncertainty lowers the value of a firm's 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 to conduct initial public offerings (Çolak et al., 2017). Elevated policy uncertainty is also associated with uncertainty over macroeconomic indicators, taxes, and labour policies, among others. These uncertainties can manifest as the unpredictability of the firms' operations and profits (Sialm, 2006; Ulrich, 2013). Specifically, this effect can have a substantial impact on the firms' growth rate and business risk which are the two key parameters in the option to delist that is inherent in our model. 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).

Furthermore, the introduction of new rules and regulations also create their own uncertainties. The accumulated effects of these regulations can have numerous potential consequences for the affected firms. Several studies have identified the macro- and micro-level negative effects of more regulations or the 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 in the annual growth rate of the US GDP.

In general, our Proposition 4 claims that a significant external shock, $\epsilon$, that emanates from policy uncertainty or regulatory changes could lead to a lower growth rate and higher business risk that, in turn, increase the probability of voluntary delisting. Put differently, any exogenous shock to the firm's economic performance variables ($\mu$ and $\sigma$) 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 unique business operations.

Building on the above discussion, we conjecture that two key macroeconomic factors, namely policy uncertainty and regulatory conditions within a country, could be important economic channels that affect the firm's probability of delisting by decreasing the growth rate and increasing the business risk. Our model predicts that shocks to these macroeconomic variables would increase the value of delisting for the entrepreneur. Thus, we formulate our third hypothesis as follows:

**H3A:** *The probability of voluntary delisting increases when policy uncertainty in a country rises.*

**H3B:** *The probability of voluntary delisting increases when the overall regulatory uncertainty in a country rises.*

## 3.2. Empirical methods: competing risks hazard rate model

In this subsection, we move from theoretical modelling towards an empirical setup that allows for proper testing of our model's predictions. In the Online Appendix, we show how the delisting time implied by our theoretical condition in (13) can be linked to a hazard rate process. Then, our model predictions can be tested with a hazard model or a logistic regression model. Most of our empirical results are based on the former, and thus we focus on it explicitly.

In the context of our paper, delisting can occur for three different reasons: voluntary, involuntary, and M&As. The three different types of delistings can be conceptualized as competing (mutually exclusive) outcomes, thus an appropriate empirical approach would be to use a competing risk hazard rate model.[13] In our case, the primary outcome of interest is the time to voluntary delisting. Delisting for non-voluntary reasons is a competing risk (e.g., firms that delist due to M&A or involuntary reasons). To estimate these risks in the context of our model, we follow Fine and Gray (1999) and use a semi-parametric proportional sub-hazard specification as follows:

$$h(n|X_{i,n}) = h(n|0)e^{\beta X_{i,n}} \tag{14}$$

for all firms $i$ and all yearly periods $n$. The hazard function, $h(n|X_{i,n})$, represents the sub-hazard rate of firm $i$ that is conditional on the firm

[12] These indicators measure the general uncertainty of governance in the country, and they may or may not relate to shareholder expropriation. The six dimensions comprise: (i) voice and accountability, (ii) political stability and absence of violence/terrorism, (iii) government effectiveness, (iv) regulatory uncertainty, (v) rule of law, and (vi) control of corruption.

[13] Such models have been utilized before in financial economics (Fine and Gray, 1999; Wheelock and Wilson, 2000; Doidge et al., 2009; Mehran and Peristiani, 2010) due to certain advantages. Given that the competing risk model is a method of time-to-event analysis, the hazard of an event (i.e., voluntary delisting) happening changes with time. Therefore, the competing risk survival regression allows for explicitly modelling the voluntary decision to delist as a function of the explanatory variables, while recognizing the three types of delisting outcomes (i.e., voluntary, involuntary, and M&A) as competing risks.

not voluntarily delisting until time $n$, while $h(n|0)$ is known as the baseline sub-hazard. In our case, it captures how the probability of voluntary delisting changes over time assuming that all the variables are equal to zero. The $X_{i,n}$ specifies the $X_n$ matrix for firm $i$ that can be expressed as (without loss of generality we drop the subscript $i$):

$$X_n = \left( \underbrace{b_n,\ \alpha_n,\ d_n,\ l_n;}_{\text{Managerial Agency}} \quad \underbrace{\mu_{n+1},\ \sigma^2_{n+1};}_{\text{Economic Performance}} \quad \underbrace{Z_n}_{\text{Controls}} \right) \tag{15}$$

where managerial agency variables $(b_n, \alpha_n, d_n, l_n)$ define the left-hand side value of the delisting condition (13), the firm economic performance variables $(\mu_{n+1}, \sigma_{n+1})$ that contribute to the right-hand side value of the same condition, and $Z_n$ is the vector of control variables. During the empirical estimation of competing risks model, each firm's $\widetilde{\mu}$ and $\widetilde{\sigma}^2$ are known only to the entrepreneur and thus they are reflected in the constant term in $Z_n$.

The coefficients' $\beta$s are estimated using the partial maximum likelihood. The standard errors of the coefficients are corrected for possible firm-level clustering and we apply industry fixed-effects (two-digit SIC codes). The sign of the estimated coefficient $\beta$ for a specific variable from $X_n$ should be interpreted as follows: a positive (negative) $\beta$ estimate represents a shorter (longer) duration to the time to delist. Alternatively, we can interpret $\beta$ as an indication of the partial effect of a given characteristic of the firm on the likelihood of delisting, while holding the duration constant. The sub-hazard ratio is determined by computing the exponentiated model coefficient from the sub-distribution hazard model, $e^{\beta}$, which shows how much the sub-hazard of the voluntary delisting event increases with a unit change in the independent variable, while holding all other independent variables constant. Therefore, we can interpret the sub-hazard ratio as an indication of the relative change in the instantaneous rate of occurrence of the event (i.e., voluntary delisting) in those firms that do not delist or that have experienced an M&A or an involuntary delisting.

As all of the active firms remain listed on the exchange at or after the end of our sample period, 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 pseudo 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). In Section 4.3, we conduct some additional robustness tests, such as considerations for the left-censoring problem.

In the Online Appendix, we show that our theoretical model could also be tested with generic logistic regression models. Thus, as an additional test, following Doidge et al. (2017), we estimate a multinomial logit model in which the firm faces multiple delisting outcomes. Firms that do not delist in a given year constitute the base category and the three delisting outcomes are voluntary delisting, involuntary delisting, and M&A.

### 3.3. Data, sample selection, and variables

#### 3.3.1. Sample construction

Our sample covers 26 countries for which there is an available country-specific measure of the Baker et al. (2016) economic policy uncertainty index. Following Doidge et al. (2017), our sampling period starts in 1990 and ends in 2020.[14] We collect data about listed and delisted firms for the main stock exchanges of each country[15] using several databases such as CRSP, Compustat North America, Compustat Global, and Refinitiv's Datastream. Below, we describe the sample selection procedure of our delisted firms' sample.

For data on US firms, we focus on the CRSP database that covers the listed firms in one of the three main stock exchanges: The New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ. Delisted firms are identified using the share delisting code (DLSTCD) from CRSP. We follow studies such as Bharath and Dittmar (2010) and exclude financial, insurance, and utility firms. The 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).[16] For a reliable estimation of our model parameters (e.g., $\sigma$) in the pre-delisting period, we require that firms stay listed for at least four years, and then either continue to remain listed or delist.[17] Also, we manually check the sample of voluntarily delisted firms and verify that the delisting is indeed voluntary. This sample selection procedure leaves us with 173 voluntary delistings from the US stock exchanges.[18] Panel A of Table 1 provides details on our sample construction procedure for the delisted firms in the USA.

For the remaining 25 countries in our sample, we use Compustat Global and Refinitiv's Datastream databases to create a combined sample of 23,816 firms in total.[19] We again start by excluding financial, insurance, and utility firms. Compustat Global database has a variable named the Reason for Deletion (DLRSN) that allows us to obtain an initial classification of the type of delisting. Similar to the construction of the delisting sample for the US firms, we classify firms into three categories: mergers and acquisitions (DLRSN codes 01 (acquisition or merger) and 04 (reverse acquisition)), involuntary delisting due to bankruptcy or liquidation (DLRSN codes 02 (bankruptcy) and 03 (liq-

[14] Datastream's coverage for many countries is less complete prior to the early 1990s.

[15] The countries and their respective stock exchanges included in our sample are: the Toronto Stock Exchange and TSX Venture (Canada), Australia Stock Exchange (Australia), EuroNext Liffe Brussels (Belgium), Sao Paulo Stock Exchange (Brazil), Santiago Stock Exchange (Chile), Shanghai Stock Exchange and Shenzhen Stock Exchange (China), Bogota Stock Exchange (Columbia), Zagreb Stock Exchange (Croatia), EuroNext Liffe Paris (France), Athens Stock Exchange (Greece), Hong Kong Stock Exchange (Hong Kong), Bombay Stock Exchange and National Stock Exchange of India (India), EuroNext Liffe Dublin (Ireland), Deutsche Boerse AG and Xetra Stock Exchange (Germany), Milan Stock Exchange (Italy), Tokyo Stock Exchange and JASDAQ (Japan), Mexico Stock Exchange (Mexico), EuroNext Liffe Amsterdam (the Netherlands), Pakistan Stock Exchange (Pakistan), Russian Trading System (Russia), Singapore Stock Exchange (Singapore), Korea Stock Exchange and KOSDAQ (South Korea), Madrid Stock Exchange and Mercado Continuo Espangol (Spain), Stockholm Stock Exchange (Sweden), the London Stock Exchange (UK), and the three US exchanges New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ.

[16] 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 any further distinctions between voluntarily delisted and deregistered firms. For more details on the deregistration process, please see Marosi and Massoud (2007).

[17] Effectively, our delisting sample starts in 1994 because our theoretical model relies on business risk ($\sigma$) and for a proper estimation of the standard deviation, we need several years (more than three years) of observations to first calculate firm's growth rate ($\mu$) and then to calculate the standard deviation of the growth rate ($\sigma$).

[18] Our final sample of voluntarily delisted US firms is relatively smaller than the sample of 434 firms reported in Doidge et al. (2017). That paper includes all the voluntary delisted firms from the AMEX, NASDAQ, and the NYSE that are in CRSP database for the period from 1975 to 2012. Unlike Doidge et al. (2017), we have to impose several additional screens (i.e., dropping firm-year observations with missing values of variables used in constructing our model parameters and requiring that firms to stay listed for at least four years).

[19] We obtain 13,908 firms from Compustat Global and 20,924 firms from Refinitiv's Datastream. We, then, merge these data samples into one large sample of 23,816 unique firms from 25 countries spanning three decades between 1990 and 2020. See Table 1 for further details.

**Table 1**
Sample selection procedure.

| Explanation | Total Number Firms | Voluntary | Involuntary | M&A |
|---|---|---|---|---|
| Panel A: USA delisting sample | | | | |
| All firms from the merged Compustat & CRSP database (excluding financial, insurance, and utility firms) | 14,013 | 386 | 3,579 | 5,813 |
| After dropping the firms that are not listed on one of the main exchanges (NYSE, AMEX, and NASDAQ) | 9,448 | 351 | 135 | 5,502 |
| After dropping firms with less than 4 years of data or observations with missing values of regression variables | 6,352 | 244 | 45 | 3,601 |
| After manually checking the actual reason for delisting (reading news articles) | 6,314 | 173 | 61 | 3,618 |
| Panel B: The Other 25 Countries (Excluding USA) - Compustat Global | | | | |
| All Compustat Global firms (excluding financial, insurance, and utility firms) | 23,058 | 3,334 | 201 | 3,693 |
| After dropping the firms that are not listed on one of the main exchanges | 19,753 | 2,706 | 169 | 3,112 |
| After dropping firms with less than 4 years of data or observations with missing values of regression variables | 13,908 | 1,514 | 59 | 1,925 |
| After using SDC database to identify M&A firms | 13,908 | 1,148 | 55 | 2,295 |
| After manually checking the actual reason for delisting (reading news articles) | 13,908 | 597 | 426 | 2,475 |
| Panel C: The Other 25 Countries (Excluding USA) - Refinitive's DataStream | | | | |
| All DataStream firms (excluding financial, insurance, and utility firms) | 44,265 | ...................... 22,213 .................... | | |
| After dropping firms with less than 4 years of data or observations with missing values of regression variables | 20,924 | ........................ 7,499 .................... | | |
| After using the reason for delisting provided, within the name of the firm (for some firms in the sample) | 20,924 | 6,591 | 400 | 508 |
| After using SDC database to identify M&A firms | 20,924 | 4,806 | 400 | 2,293 |
| After manually checking the actual reason for delisting (reading official press releases) | 20,924 | 597 | 1,218 | 5,684 |
| Panel D: Combined Sample of 26 Countries - All Databases | | | | |
| Comprehensive Compustat Global and DataStream combined sample for the 25 countries | 23,816 | 893 | 1,280 | 5,955 |
| Combined sample (USA plus 25 other countries) | 30,130 | 1,066 | 1,341 | 9,573 |
| Final Sample (after dropping the missing observations of $\alpha$) | 26,090 | 832 | 1,035 | 6,708 |

The table provides details on the sample selection criteria we follow while constructing the (de)listing sample for 26 countries. We show the number of delisted firms that remain after each step. For the USA, we use a raw sample extracted from Compustat and CRSP merged dataset, and follow the steps described in Panel A. For the rest of the 25 countries in the sample, to increase our coverage, we use two separate databases: Compustat Global and Refinitiv's DataStream databases. When creating the sample of (de)listed firms from Compustat Global, we follow the steps shown in Panel B. We complement this sample with additional data retrieved from DataStream database as described in Panel C. As DataStream does not provide delisting codes, we are unable to pre-classify the firms into one of the three delisting categories. We only know if a firm is listed or delisted and thus, we manually check the delisting reason for all the delisted firms in that database. In total, we manually check the delisting reason for 244 firms in Panel A, 1,148 firms in Panel B, and 4,806 in Panel C. The final sample contains 26,090 firms, of which 6,708 delisted due to M&A, 1,035 delisted involuntarily, and 832 delisted voluntarily. The remaining 17,515 firms were still listed in a stock exchange as of the end of 2020. Regression variables are the ones used for the analyses in Table 4 (all model variables plus controls; missing values of $\alpha$ are discussed separately in Panel D of this table). Online Appendix provides further details about our sample selection procedure.

uidation)), and voluntary delistings (DLRSN codes 07 (others: no longer files with SEC among other possible reasons but pricing continues), 09 (Now a private company), and 10 (Other: no longer files with SEC among other reasons)). As the codes for voluntary delistings are broad and do not explicitly pinpoint the voluntary delistings as intended by our model, we apply the following additional screening steps. First, we use Thompson Reuters' Securities Data Company's (SDC) Mergers and Acquisitions databases to identify firms that delist because of a merger. Second, using exchange websites and official news releases, we manually check the rest of the voluntary delistings sample (1,148 firms) for the reasons for delisting and re-classify the firm into one of the three categories accordingly. Third, we also verify that the delisting is indeed voluntary. We are left with 597 verified voluntary delistings. Panel B of Table 1 provides further details about our delistings sample obtained from Compustat Global database.

As the Datastream database does not provide delisting codes, we are unable to electronically pre-sort the firms into one of the three delisting categories; we can only discern whether the firm is listed or delisted. Therefore, to identify the exact reason for the delisting of a Datastream firm, we first drop the firms in the financial, insurance, and utility sectors and then repeat the sample selection steps applied for the delisted firms in Compustat Global. We also identify all the overlapping firms with Compustat Global by merging the two samples using ISIN codes. This step yields 4,806 voluntary delistings from Datastream. In the next step, we manually check these delisting cases for the reason for delisting. This check leaves us with 597 voluntary delistings from Datastream, some of which overlap with the voluntary delisting sample from Compustat Global (the sample of 597 voluntary delistings from Panel B). After removing these overlapping cases, we end up with 296 voluntary delistings that are unique to Datastream. This brings the total number of voluntary delistings from Compustat Global and Datastream to 893 (see Panels B, C, and D of Table 1).

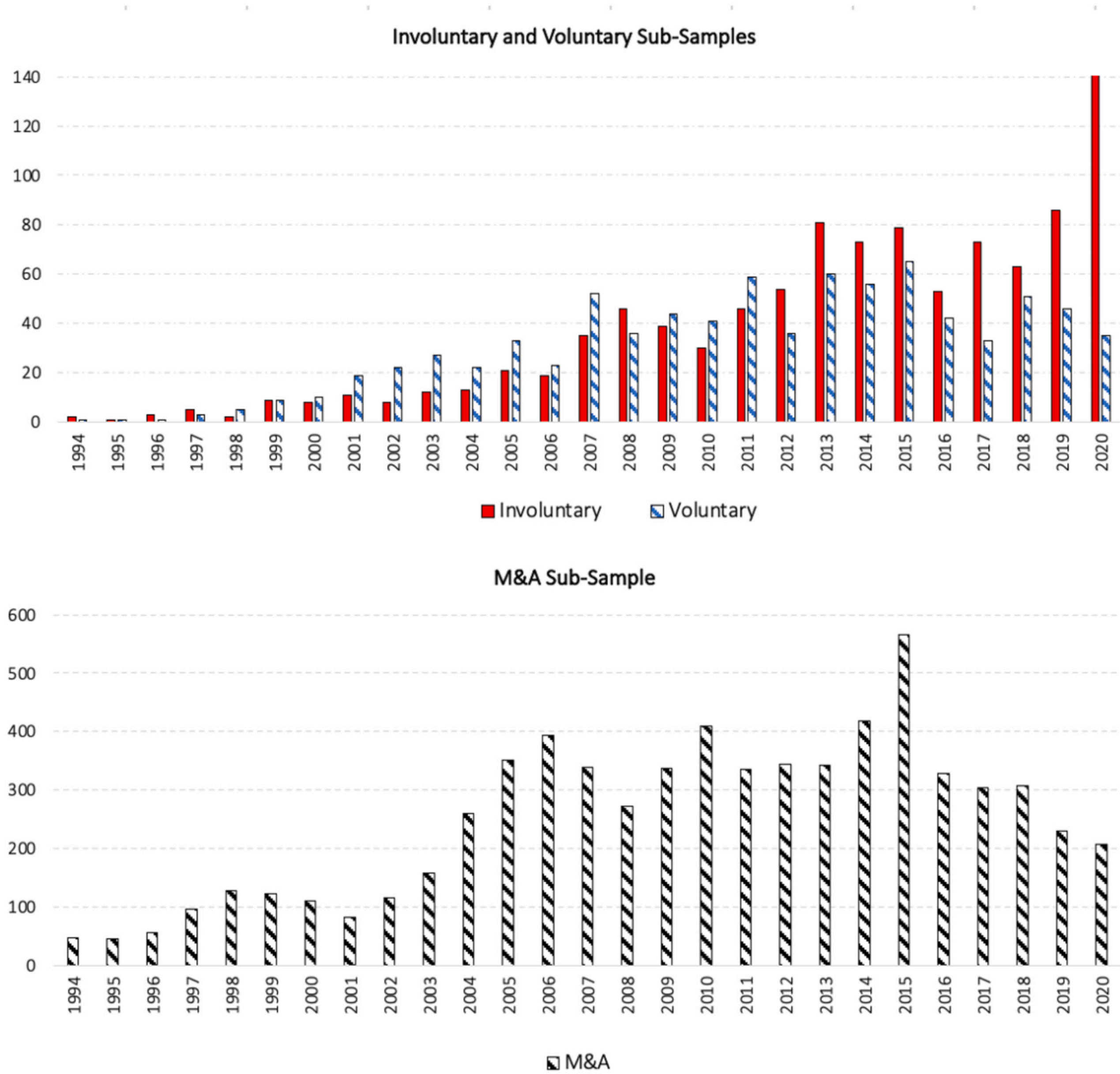
As a final screening criterion, we drop firm-year observations with missing values for important model variables (e.g., $\alpha$) and the controls used in the regressions. These exclusions leave us with information on 26,090 firms from 26 different countries. Of these firms, 832 have voluntarily delisted, 1,035 involuntarily delisted, and 6,708 of them delisted due to an M&A. Table 1 has the details on the breakdown of our final delistings sample that is constructed using different data sources and the related sample selection criteria. Online Appendix provides further details about our sample selection procedure.

Fig. 2 shows the number of delisted firms, by type, over our sample period. The number of voluntary delisted firms increases over time with substantial variation from year to year; particularly near well-known economic, financial, and regulatory-related events. For instance, voluntary delistings increased after the dot.com bubble in the early 2000s and during the 2007-2009 financial crisis.

### 3.3.2. *Variable construction*

From the CRSP database we extract daily trading information for US firms, and from Compustat and DataStream we obtain corporate financial data. For the sample of firms outside of the US, we use Compustat Global, Datastream, and Worldscope databases to extract daily stock prices, financial, and auditing information. We use the World Bank database to retrieve the macroeconomic indicators used in this study (see Table A.1 of Appendix B for further details).

As mentioned in Section 3.1 (Equation (15)), our empirical testing relies on the variables comprising the vector $X_n$. Next, we describe the construction of these variables. Our model variable $b$ captures the expropriation penalty parameter in a country and it is approximated by the Anti-Self Dealing Index of Djankov et al. (2008). The dividend payout $d$ is calculated as the ratio of a firm's dividends over its revenues (sales). A firm's growth rate $\mu$ and business risk $\sigma$ are calculated from




This figure shows the number of firms that delisted from the main exchanges of 26 countries over the period between 1994 and 2020. This is based on our final sample of 832 voluntary, 1,035 involuntary, and 6,708 M&A related delistings. Firms are organized into three delisting categories (voluntary, involuntary, and M&A) as described in Section 3.3. The plot starts in 1994 because our theoretical model relies on business risk estimation ($\sigma$, which is the standard deviation of the firm's growth rate) and for a more accurate estimation of standard deviation we need several years (more than three years) of observations to first calculate the growth rate and then to calculate the standard deviation of the growth rate (see our sample selection criteria described in Section 3.3). Panel A shows the fluctuations in the number of voluntary and involuntary delistings over time. Since the number of M&A delistings is relatively larger than the other types of delistings, in Panel B we create a separate plot for this type of delistings.

**Fig. 2.** Delistings over time.

the yearly changes in firm's revenues. See Table A.1 for formal definitions of these variables.

Since it is an important variable for our theoretical model, we carefully collect information on insider ownership ($\alpha$) for each firm by using the Worldscope database for our sample of 26 countries. The Worldscope data has some missing observations on this variable. Thus, we complement any missing observations for $\alpha$ using Thomson-Refinitiv's EIKON database that has information on the same variable for the firms located in the aforementioned 26 countries. The remaining missing values of insider ownership (around 9.4% of our sample) are replaced with the firm's mean value during our sampling period. As we show in Table OA2 of the Online Appendix, our results are robust to dropping from the sample the observations with missing $\alpha$.

Our study is the first to introduce listing expenses $l$ as one of the determinants of voluntary delistings. A good proxy for this determinant are the audit fees (scaled by firm's sales), which reflect the costs associated with filing periodic earnings statements due to the public status of the firm. To obtain information on audit fees, we use Worldscope (variable name: auditor fees) and Audit Analytics (variable name: TotalFees). For some international firms in some years, the information on audit fees is missing and for some firms the scaled variable $l$ shows extreme variation from year to year due to drastic drop in their sales. Therefore, to better approximate the listing expenses $l$ based on firm's country and size group, we utilize a portfolio approach whereby all the firms in the same country and size tercile are assigned the mean value of this variable in their corresponding portfolio.

**Table 2**
Model accuracy across countries.

| Country Name | Number Delistings | Number Accurate Predictions | Model Accuracy | Average $b$ | $\alpha$ | $d$ | $l$ | $\mu$ | $\sigma$ | Number Observ. |
|---|---|---|---|---|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| Brazil | 2 | 1 | 50% | 2.7361 | 0.4111 | 0.0297 | 0.0008 | 0.2641 | 0.2531 | 2,682 |
| Colombia | 2 | 2 | 100% | 5.7292 | 0.5018 | 0.0572 | 0.0009 | 0.1801 | 0.2081 | 482 |
| Greece | 2 | 2 | 100% | 2.1667 | 0.4294 | 0.0249 | 0.0016 | 0.0052 | 0.2721 | 300 |
| Russia | 3 | 3 | 100% | 4.4028 | 0.5641 | 0.0251 | 0.0277 | 0.2095 | 0.2200 | 103 |
| Ireland | 4 | 4 | 100% | 7.8889 | 0.2366 | 0.0116 | 0.0024 | 0.1410 | 0.2606 | 481 |
| Pakistan | 4 | 4 | 100% | 4.0833 | 0.2235 | 0.0261 | 0.0003 | 0.1503 | 0.2464 | 3,985 |
| Italy | 5 | 5 | 100% | 4.2083 | 0.4035 | 0.0188 | 0.0022 | 0.0370 | 0.2817 | 2,598 |
| Spain | 5 | 3 | 60% | 3.7361 | 0.3766 | 0.0261 | 0.0035 | 0.0810 | 0.2144 | 1,426 |
| China | 6 | 6 | 100% | 7.6250 | 0.3431 | 0.0482 | 0.0003 | 0.1460 | 0.2548 | 37,251 |
| Croatia | 6 | 6 | 100% | 2.4583 | 0.4198 | 0.0155 | 0.0004 | 0.0315 | 0.1912 | 893 |
| Belgium | 7 | 6 | 86% | 5.4444 | 0.3861 | 0.0239 | 0.0010 | 0.0545 | 0.2791 | 1,628 |
| Chile | 7 | 7 | 100% | 6.2500 | 0.5078 | 0.0543 | 0.0003 | 0.1009 | 0.2362 | 2,129 |
| Hong Kong | 7 | 7 | 100% | 9.6250 | 0.4376 | 0.0277 | 0.0072 | 0.0845 | 0.3324 | 15,079 |
| Mexico | 10 | 8 | 80% | 1.7222 | 0.2449 | 0.0254 | 0.0006 | 0.1487 | 0.1749 | 3,231 |
| Netherland | 11 | 3 | 27% | 2.0278 | 0.3156 | 0.0159 | 0.0028 | 0.0492 | 0.2282 | 2,246 |
| France | 17 | 16 | 94% | 3.7917 | 0.3861 | 0.0140 | 0.0018 | 0.0437 | 0.2518 | 7,197 |
| Japan | 24 | 24 | 100% | 4.9861 | 0.3465 | 0.0090 | 0.0005 | 0.0301 | 0.1155 | 53,122 |
| South Korea | 24 | 22 | 92% | 4.6875 | 0.3313 | 0.0081 | 0.0013 | 0.0914 | 0.2410 | 26,937 |
| Sweden | 24 | 21 | 88% | 3.3333 | 0.2646 | 0.0210 | 0.0019 | 0.1201 | 0.2513 | 4,950 |
| Singapore | 30 | 30 | 100% | 10.0000 | 0.4475 | 0.0277 | 0.0008 | 0.0530 | 0.2947 | 8,105 |
| Canada | 37 | 26 | 70% | 6.4167 | 0.2130 | 0.0229 | 0.0180 | 0.1589 | 0.3563 | 10,484 |
| India | 39 | 38 | 97% | 5.7917 | 0.4520 | 0.0130 | 0.0009 | 0.1737 | 0.2522 | 27,693 |
| Australia | 69 | 63 | 91% | 7.5694 | 0.3298 | 0.0189 | 0.0382 | 0.1379 | 0.6224 | 20,601 |
| USA | 120 | 105 | 88% | 6.5417 | 0.2079 | 0.0153 | 0.0045 | 0.1513 | 0.2174 | 71,455 |
| Germany | 136 | 100 | 74% | 2.8194 | 0.2603 | 0.0177 | 0.0109 | 0.1036 | 0.2762 | 33,420 |
| UK | 231 | 220 | 95% | 9.5000 | 0.2680 | 0.0144 | 0.0040 | 0.1334 | 0.2635 | 18,623 |
| Total | 832 | 732 | 88.15% | 5.2131 | 0.3580 | 0.0236 | 0.0052 | 0.1108 | 0.2614 | 357,101 |

This table provides the names of the countries considered in our data sample (column 1) and their respective statistics, including averages within and across countries. Specifically, columns 2, 3, and 4 show the number of voluntary delistings, the number of accurately predicted delistings by our model, and the accuracy of our model as a percentage of the total delisting events that occurred in that country over our sample time period. Columns 5 to 10 show the average of the key parameters considered by our theoretical delisting model, respectively, $b, \alpha, d, l, \mu, \sigma$, where $b$ is a penalty factor that measures the quality of the country's laws and regulations, $\alpha$ represents the insiders' ownership in the firm while it is listed, $d$ is the dividend payout, $l$ is the listing expenses, and $\mu$ and $\sigma$ represent the growth rate and the business risk of the firm, respectively. The last column (11) shows the number of firm-year observations. The countries are ordered based on the number of voluntary delistings during the sampling period of 1990-2020. At the bottom of the table, we show the sum (or the average) values across all countries.

The set of control variables ($Z_n$) used in our estimations are derived from the studies that examine the determinants of the firm's decision to go private (i.e., Marosi and Massoud (2007); Bharath and Dittmar (2010); Mehran and Peristiani (2010)). These control variables are the firm's size (Size), age (FirmAge), leverage (Leverage), market to book (MB), free cash flow (FCF), capital expenditure (CAPEX), research and development expenses (R&D), net equity issuance (NEI), stock turnover (Turnover), stock return volatility (ReturnVolatility), cross-listing dummy (CrossListing), and a country's stock market capitalisation to its gross domestic product (MCGDP). The definitions of the control variables are provided in Table A.1 of Appendix B.

### *3.4. Model validation across countries*

This subsection presents some preliminary model validation checks, while the simulation results are relegated to the Online Appendix. These validations are intended to verify how well our model fits the voluntary delisting patterns across various countries. Table 2 presents the model accuracy for each country separately together with the average values for the six key model parameters. Our model is very accurate (90% or higher) for 17 countries and it is less accurate (less than 50%) for only one country (the Netherlands). The average accuracy overall for all the countries is around 88%. This indicates that our model quite accurately reflects the real decision-making regarding the timing of the voluntarily delistings of firms around the World. The average values of our six key model parameters show substantial variation across countries which could potentially explain the delisting patterns from the public exchanges located in these countries.

Figure OA.1 in the Online Appendix shows the evolution over time of the accuracy of our model in predicting the voluntary delistings in the aggregated data across all countries. When plotting this figure, we use the observed outcomes (delisted or not) and the actual observed values of the parameters $(b, \alpha, d, l, \mu, \sigma^2)$ for each firm. We further assume that the entrepreneur believes that post-delisting values of the parameters $(\widetilde{\mu}, \widetilde{\sigma}^2)$ associated with the firm performance will converge to the industry sector averages. The accuracy of our model prediction of voluntary delisting is very high in the 1990s period (around 100%), but it drops slightly and fluctuates around 88% thereafter.

The Online Appendix presents simulations that help us gauge the parameters' sensitivities on the delisting decision. From those simulations, we can conjecture that the delisting decision appears to be most sensitive to the parameters $\alpha$ and $b$.[20] In the next section, we will formally investigate the role of all six model parameters in explaining the voluntary delisting decision.

[20] In untabulated tests, we reach qualitatively similar conclusions when we use pseudo-$R^2$s from multinomial logit estimations to gauge the economic importance of each variable. We essentially compare the magnitude of the changes in Pseudo-$R^2$ when each of the six model variables $(b, \alpha, d, l, \mu, \sigma)$ are separately included (one at a time) in the regression together with all the control variables $(Z_n)$.

**Table 3**
Univariate analysis.

| | Full Sample: n = 357,101 | | Voluntary: n = 8,745 | | Involuntary: n = 10,389 | | t-test | M&A: n = 71,533 | | t-test |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | (5)-(3) | Mean | Std. Dev. | (8)-(3) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| *Variables Related to Agency Motives:* | | | | | | | | | | |
| ExpropriationPenalty ($b$) | 6.0189 | 1.9871 | 6.3835 | 2.5781 | 5.9410 | 2.4191 | -12.2295*** | 5.9277 | 2.0774 | -18.8209*** |
| InsidersOwnership ($\alpha$) | 0.3143 | 0.1728 | 0.3513 | 0.1728 | 0.3190 | 0.1659 | -13.1541*** | 0.2871 | 0.1753 | -32.3959*** |
| DividendPayout ($d$) | 0.0193 | 0.0349 | 0.0156 | 0.0362 | 0.0099 | 0.0256 | -12.7637*** | 0.0138 | 0.0327 | -4.7254*** |
| ListingExpenses ($l$) | 0.0056 | 0.0126 | 0.0088 | 0.0155 | 0.0148 | 0.0216 | 21.6429*** | 0.0078 | 0.0123 | -7.4268*** |
| *Variables Related to Economic Motives:* | | | | | | | | | | |
| GrowthRate ($\mu$) | 0.1143 | 0.2178 | 0.1125 | 0.2618 | 0.1046 | 0.3200 | -1.8534*** | 0.1440 | 0.2489 | 11.1069*** |
| BusinessRisk ($\sigma$) | 0.2549 | 0.2902 | 0.3235 | 0.3348 | 0.4631 | 0.4228 | 24.9800*** | 0.2698 | 0.2969 | -15.7327*** |
| *Control Variables:* | | | | | | | | | | |
| Size (Millions USD) | 1527.7650 | 5887.9020 | 657.5859 | 3991.2890 | 229.4793 | 2177.1240 | -9.3973*** | 709.4502 | 2962.3630 | 1.4811*** |
| FirmAge (Years) | 17.2057 | 13.8263 | 13.4525 | 9.8472 | 11.6351 | 7.9436 | -14.1273*** | 14.9118 | 11.9238 | 10.9960*** |
| Leverage | 0.2149 | 0.1824 | 0.2179 | 0.1851 | 0.2475 | 0.2266 | 9.7859*** | 0.2096 | 0.1862 | -3.9221*** |
| MB | 1.0264 | 1.6425 | 0.8668 | 1.6693 | 0.5233 | 1.3505 | -15.7311*** | 0.9592 | 1.4929 | 5.3920*** |
| FCF | -0.0277 | 0.1420 | -0.0607 | 0.1781 | -0.1180 | 0.2265 | -19.2031*** | -0.0310 | 0.1559 | 16.5231*** |
| CAPEX | 0.0366 | 0.0450 | 0.0352 | 0.0448 | 0.0204 | 0.0423 | -23.5748*** | 0.0389 | 0.0501 | 6.5473*** |
| R&D | 0.0231 | 0.0583 | 0.0229 | 0.0607 | 0.0258 | 0.0613 | 3.3008*** | 0.0376 | 0.0754 | 17.5150*** |
| NEI | 0.0284 | 0.0943 | 0.0430 | 0.1105 | 0.0742 | 0.1488 | 16.2132*** | 0.0447 | 0.1100 | 1.3995 |
| Turnover (ratio) | 1.2750 | 2.0708 | 0.6543 | 1.6518 | 1.0238 | 2.0813 | 12.5295*** | 0.6531 | 1.5630 | -0.0648 |
| ReturnVolatility | 0.5622 | 0.3047 | 0.6871 | 0.3929 | 0.7756 | 0.4379 | 14.5834*** | 0.5916 | 0.3224 | -25.4924*** |
| CrossListing | 0.0332 | 0.1792 | 0.0593 | 0.2363 | 0.0103 | 0.1010 | -19.1798*** | 0.0292 | 0.1683 | -15.0499*** |
| MCGDP | 1.2161 | 1.7267 | 1.0085 | 0.7403 | 1.4583 | 2.2478 | 17.9136*** | 1.0090 | 0.7904 | 0.0531*** |

This table displays summary statistics on firm characteristics for the entire sample as well as the subsamples of firms corresponding to delisted firms (voluntary, involuntary, and M&A). Variables are defined in Table A.1. The sample consists of 26,090 (357,101 firm-year observations) firms over the 26 countries from 1990 to 2020 of which 832 (8,745 firm-year observations) voluntarily delisted firms, 1,035 (10,389 firm-year observations) involuntarily delisted, and 6,708 (71,533 firm-year observations) delisted due to a merger. The rest of the firms (17,515 firms; 266,434 firm-year observation) belong to the stay-listed firms. All continuous variables included in our main empirical model are winsorized at the $1^{st}$ and $99^{th}$ percentiles (except for ExpropriationPenalty ($b$)). $t$-tests are conducted to test for differences in means between voluntary delisted subsample and involuntary and M&A subsamples; columns 7 and 10 present the $t$-values from this test. The superscripts ***, **, and * indicate that the coefficients are significant at the 1%, 5%, and 10% level, respectively.

## 4. Empirical results

### 4.1. Univariate analysis

In Table 3, we provide a univariate analysis for the variables used in our empirical testing. Specifically, we report the means and standard deviations for the full sample of listed and delisted firms for the subsamples of voluntary, involuntary, and M&A delistings. We also report the $t$-test results for the differences in means between the voluntary delisted subsample and each of the other two subsamples. More detailed summary statistics for each subsample are provided in Table OA1 of our Online Appendix.

On average, voluntarily delisted firms are mostly located in countries with the highest expropriation penalty measure ($b$) compared to other delisted firms. The average value of $b$ for the group of voluntarily delisted firms is 6.3835 (out of maximum of 10) versus 5.9410 (5.9277) for the involuntary (M&A) subsample. This value provides initial support for our Hypothesis H1A. Further, we find that firms in the voluntary delisting subsample have the highest ratio for insider ownership with an average of 35.13%. The mean of the listing expenses ($l$), as a percentage of the annual revenue, differs significantly between the voluntary subsample (0.88%) and the other two subsamples.

As for the variables that are related to the firm's economic performance, we find that the growth rate and business risk, are 11.43% and 25.49%, respectively, for an average firm in our full sample that comprises of both listed and delisted firms. On average, the involuntarily delisted firms have very high business risk at around 46.31%, followed by the voluntary subsample at 32.35% and the M&A subsample at 26.98%. The growth rate is the highest for the M&A subsample (14.40%) and is followed by the voluntary (11.25%), and the involuntary (10.46%) subsamples. The $t$-tests of the growth rate ($\mu$) and the business risk ($\sigma$) variables shows that the mean differences between the voluntary delisted subsample and each of the involuntary and M&A delisted subsamples are statistically significant at the 1% level.

Further, the $t$-test results show statistically significant differences in the means of the control variables between the voluntary delisted subsample and the other subsamples. Some notable findings about voluntarily delisted firms around the World are as follows. These firms, on average, are 13.4525 years old, have total assets equivalent to USD657.5859 million, have a leverage to total asset ratio of 21.79%, have a stock return volatility of 68.71%, and 5.93% of them are cross-listed on other exchanges. Their market-to-book and R&D ratios are 0.8668 and 0.0229, respectively.

These statistics provide some insights into the nature of voluntary delisted firms in our cross-county sample. Overall, the univariate comparisons are in line with our model's predictions in that the average values of $b$, $\alpha$, $d$, $l$, $\mu$, and $\sigma$ are substantially different for voluntary delistings than the other types of delistings.

### 4.2. Multivariate analysis: competing risk and multinomial logit models

Model (1) of Table 4 provides the results from estimating our competing risk sub-hazard model. The focus is on the six theoretical variables that relate to the agency motives ($b$, $\alpha$, $d$, $l$) and the economic motives ($\mu$ and $\sigma$) for delisting. Model (1) shows the coefficient estimates, while Model (2) gives the sub-hazard rates.

Following Austin and Fine (2017) approach, we interpret the results as follows. As shown in Model (1), we find that the coefficients for the variables that represent the agency motives and economic motives to have the signs as predicted by our theory. As per Model (2), the sub-hazard rate of voluntary delisting increases with the expropriation penalty variable ($b$), insider ownership ($\alpha$), listing expenses ($l$), and business risk ($\sigma$), but it decreases with the dividend payout ($d$; albeit statistically insignificant) and growth rate ($\mu$). The positive coefficient for $b$ indicates that firms located in countries that are classified as having a higher anti-self-dealing index are more likely to delist voluntarily - the sub-hazard ratio is 1.2161 that means that the sub-hazard rate of delisting changes by 21.61% (= 1.2161 − 1) for each unit increase in

**Table 4**
Prediction testing analysis - competing risk subhazard & multinomial logit models.

| | Competing Risks Model | | Multinomial Logit Model | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | M&A | | Involuntary | | Voluntary | |
| | Coefficient | SHR | Coefficient | RRR | Coefficient | RRR | Coefficient | RRR |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Variables Related to Agency Motives:* | | | | | | | | |
| ExpropriationPenalty ($b$) | 0.1957*** | 1.2161 | 0.0297*** | 1.0302 | -0.0308 | 0.9697 | 0.1921*** | 1.2118 |
| | (0.0285) | | (0.0084) | | (0.0214) | | (0.0280) | |
| InsidersOwnership ($\alpha$) | 1.7471*** | 5.7378 | -0.3990*** | 0.6710 | -0.4442** | 0.6413 | 1.7908*** | 5.9942 |
| | (0.2372) | | (0.0844) | | (0.2015) | | (0.2476) | |
| DividendPayout ($d$) | -2.0801 | 0.1249 | -2.9529*** | 0.0522 | -8.0167*** | 0.0003 | -2.8606** | 0.0572 |
| | (1.4229) | | (0.5233) | | (1.9043) | | (1.4584) | |
| ListingExpenses ($l$) | 0.1269*** | 1.1354 | 0.1151*** | 1.1220 | 0.1112* | 1.1177 | 0.1385*** | 1.1486 |
| | (0.0345) | | (0.0235) | | (0.0572) | | (0.0362) | |
| *Variables Related to Economic Motives:* | | | | | | | | |
| GrowthRate ($\mu$) | -0.9153*** | 0.4004 | -0.5892*** | 0.5548 | -1.6737*** | 0.1875 | -0.9887*** | 0.3721 |
| | (0.1435) | | (0.0613) | | (0.1330) | | (0.1670) | |
| BusinessRisk ($\sigma$) | 0.2240** | 1.2511 | 0.3606*** | 1.4342 | 1.1557*** | 3.1762 | 0.2927** | 1.3400 |
| | (0.1025) | | (0.0470) | | (0.0757) | | (0.1153) | |
| *Control Variables:* | | | | | | | | |
| Size | -0.0023 | 0.9977 | -0.0184*** | 0.9817313 | -0.0955*** | 0.9089 | -0.0167 | 0.9835 |
| | (0.0161) | | (0.0067) | | (0.0143) | | (0.0167) | |
| FirmAge | 0.6067*** | 1.8344 | 0.3465*** | 1.4142 | 0.2846*** | 1.3292 | 0.3643*** | 1.4395 |
| | (0.0495) | | (0.0202) | | (0.0506) | | (0.0521) | |
| Leverage | 0.2757* | 1.3174 | 0.2191*** | 1.2450 | 1.3033*** | 3.6814 | 0.2979* | 1.3470 |
| | (0.1657) | | (0.0739) | | (0.1267) | | (0.1743) | |
| MB | -0.1619*** | 0.8505 | -0.1760*** | 0.8386 | -0.0834** | 0.9200 | -0.1744*** | 0.8399 |
| | (0.0598) | | (0.0168) | | (0.0371) | | (0.0632) | |
| FCF | -1.0318*** | 0.3564 | 0.2325* | 1.2617 | -1.3350*** | 0.2632 | -1.3966*** | 0.2474 |
| | (0.2352) | | (0.1376) | | (0.2020) | | (0.2530) | |
| CAPEX | -2.2357** | 0.1069 | -0.2563 | 0.7739 | -7.7417*** | 0.0004 | -2.9454*** | 0.0526 |
| | (1.0460) | | (0.3936) | | (1.5192) | | (1.0735) | |
| R&D | 1.5212** | 4.5777 | 3.8680*** | 47.8479 | 0.5243 | 1.6893 | 1.7271*** | 5.6245 |
| | (0.6625) | | (0.2186) | | (0.5900) | | (0.6700) | |
| NEI | -1.4916*** | 0.2250 | -0.4618** | 0.6301 | -2.9266*** | 0.0536 | -1.7407*** | 0.1754 |
| | (0.4513) | | (0.1858) | | (0.3580) | | (0.4770) | |
| Turnover | 0.0240 | 1.0243 | 0.0262*** | 1.0265 | 0.0093 | 1.0093 | 0.0286* | 1.0290 |
| | (0.0173) | | (0.0047) | | (0.0102) | | (0.0167) | |
| ReturnVolatility | 0.4791*** | 1.6146 | -0.7936*** | 0.4522 | -0.0303 | 0.9701 | 0.3250*** | 1.3840 |
| | (0.1026) | | (0.0646) | | (0.0991) | | (0.1132) | |
| CrossListing | 1.2505*** | 3.4921 | -0.0809 | 0.9223 | -0.0141 | 0.9860 | 1.2263*** | 3.4085 |
| | (0.1597) | | (0.0828) | | (0.2786) | | (0.1600) | |
| MCGDP | -0.3308*** | 0.7183 | -0.1196*** | 0.8873 | 0.0210 | 1.0212 | -0.3291*** | 0.7195 |
| | (0.0530) | | (0.0100) | | (0.0188) | | (0.0462) | |
| Constant | | | -4.5157*** | | -4.9145*** | | -8.5794*** | |
| | | | (0.3350) | | (0.5289) | | (0.7794) | |
| Industry FE | Yes | | | | Yes | | | |
| Wald $\chi^2$ | 14,368.69 | | | | — | | | |
| LPLR | -8,068.18 | | | | -43,410.44 | | | |
| Pseudo $R^2$ | — | | | | 0.0609 | | | |
| Observations | 357,101 | | | | 357,101 | | | |

This table presents two sets of estimates. The first set provides the estimates of the competing risk sub-hazard model, based on maximum likelihood estimation, using the method of Fine and Gray (1999). The competing risk model posits a specification for the sub-hazard function as per Equation (14). The dependent variable is the time to voluntarily delist, which measures the time between the IPO date and the voluntarily delisting date. When the IPO date is not available, we use the first available observations in Compustat and Global Compustat. The coefficients measure the partial impact of each variable on the likelihood of voluntary delisting conditional on the duration. A set of control variables is used as explained in Section 3.3. While Model (1) reports the coefficient estimates, Model (2) reports the Sub-Hazard Ratios (SHR). The sub-hazard ratio gives an estimate of how much the sub-hazard of voluntary delisting increases for a unit change in the variable. The second set provides the estimates of the multinomial logit model. The dependent variable equals zero if a firm did not delist. It equals one for delistings because of merger, two for involuntary, and three for voluntary. While Models (3), (5) and (7) report the coefficient estimates, Models (4), (6), and (8) report the Relative Risk Ratios (RRR). The relative risk ratio gives an estimate of how much the risk of the outcome falling in the comparison group (i.e., M&A, Involuntary, and Voluntary) compared to the risk of the outcome falling in the reference group (i.e., Listed) changes with the variable in question. All models include industry fixed effects using the two-digit SIC industry code, 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. Our sample includes 26,090 listed firms over the 26 countries from 1990 to 2020 of which 832 voluntary delisted firms, 1,035 involuntary delisted firms, and 6,708 delisted due to M&A. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. LPLR denotes to Log-pseudolikelihood ratio. All variables are defined in Table A.1.

anti-self-dealing index. This coefficient supports our Hypothesis H1A. Similarly, the sub-hazard ratio of the insiders ownership is 5.7378 which indicates that a unit increase in insiders ownership increases the likelihood of a voluntary delisting by a multiple of 5.7378 relative to the normal value of a hazard rate of one.[21] The sub-hazard ratio of listing expenses is 1.1354 that indicates the sub-hazard rate of delisting changes by 13.54% (= 1.1354 − 1) for each unit increase in listing expenses. The coefficient for the dividend payout ratio is statistically insignificant; hence, we cannot meaningfully interpret its sub-hazard ratio and its effect on the probability of voluntary delisting. The weak result for that ratio is consistent with our simulation results in the Online Appendix. Overall, these results provide supporting evidence for our main Hypotheses 1 and 2.

Further, the negative coefficient for the growth rate indicates that firms with lower revenue growth are more likely to delist; the sub-hazard ratio is 0.4004 that means it changes by -59.96% (= 0.4004 − 1) for each unit increase in growth rate. This supports our Hypothesis H2A. Moreover, the higher the business risk, the more likely the delisting is; the sub-hazard ratio of 1.2511 indicates that a one unit increase in business risk changes the probability of delisting by 25.11% (= 1.2511 − 1) which is in line with Hypothesis H2B. Based on these results, we can sort the main theoretical variables based on their economic significance as per the following: insider ownership, firm's growth rate, business risk, country's expropriation penalty parameter, listing expenses, and dividends.

The effect of the control variables on the probability of voluntary delisting is as follows: the sub-hazard rate decreases with the market to book ratio, free cash flow, capital expenditure, net equity issuance, and stock market capitalisation to GDP; while it increases with the firm's age, leverage, research and development, stock return volatility, and cross listing.

In our second set of results, we use a multinomial logit estimation model. Models (3), (5), and (7) provide the coefficient estimates for M&A, involuntary, and voluntary delistings, respectively, compared to the reference group of listed firms. Models (4), (6), and (8) present the Relative Risk Ratios (RRR) of the multinomial logit model which are obtained by exponentiating the multinomial logit coefficients. The relative risk ratio gives an estimate of how much the probability of the risk of the outcome falling in the comparison group compared to the risk of the outcome falling in the reference group (i.e., listed firms) changes with the variable in question. A RRR value higher (lower) than one indicates that the risk of the outcome falling in the comparison group relative to the risk of the outcome falling in the referent group increases (decreases) as the variable increases.

In Models (3) to (8), we find that firms located in countries with a higher expropriation penalty measure ($b$) are associated with higher probability of delisting for M&A or voluntary reasons. Unlike the results from the voluntary delisted subsample, firms with higher percentages of insider ownership ($\alpha$) are less likely to delist due to M&A and involuntary reasons. Firms paying higher dividend ratios ($d$) are associated with a lower risk of M&A, involuntary, and voluntary delistings. Higher listing expenses ($l$) are associated with higher probability of delisting for merger, involuntary, and voluntary reasons. Firms with higher growth rates ($\mu$) are less likely to delist because of merger, involuntary, or voluntary reasons. Higher business risk ($\sigma$) is associated with higher probability of M&A, involuntary, and voluntary delistings.

In summary, using the multinomial logit estimation instead of the competing risk model does not meaningfully alter our qualitative conclusions regarding our model's predictions.

### 4.3. Alternative estimation methods

In this subsection, we check the validity of our main empirical results under alternative estimation specifications.

[21] With competing risk survival models, such large multiples are common; see Table 3 of Fos and Jiang (2015).

#### 4.3.1. Different regression estimations

First, we address potential problems with left censoring, as studies have shown that it biases the estimation of the parameters (Ongena and Smith, 2001). We follow Heckman and Singer (1984) and remove from our sample all the left-censored observations and then reestimate Equation (14). The results are provided in Model (1) of Table 5. 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. Under Model (2), we also check whether changing the starting date of our sample time period to 1994 affects our results. Furthermore, the previous literature on firms' delisting decisions has highlighted the differences in incentives between domestic and foreign firms' decisions to list, delist, or deregisters from the home market (see Leuz et al. (2008) and Marosi and Massoud (2008)). We rerun our main model after excluding cross-listed firms from our sample and report the results in Model (3). To verify that our main results are not affected by countries with a small number of voluntary delisted firms (see Table 2), under Model (4) we rerun our main model after excluding all firms in countries with less than five voluntarily delisted firms throughout the sample period. The results reported in Models (1) through (4) of Table 5 are qualitatively similar to our main findings in Table 4.

Our next robustness test addresses the unobserved heterogeneity at the firm and industry levels. For this issue, we use a parametric model to estimate the hazard rates. Survival analysis studies typically assume that the population is homogeneous. In our context this assumption means that firms have the same risk of experiencing a delisting event, conditional on a set of control variables, and that the delisting times are independent. However, the former assumption may not hold because firms can have different risks and sub-hazards. Also, an association between the event times of some subsamples 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 the duration dependence (Heckman and Singer, 1984). Therefore, to reduce this bias, we control for an unobserved random factor ($\phi_{i,n}$) known as "frailty." This factor multiplicatively modifies the hazard function of each firm, or a cluster of firms, according to Equation (16):

$$h(n|X_{i,n}) = h(n|0)(\omega_{i,n})e^{\beta X_{i,n}} \tag{16}$$

where $\omega_{i,n} = e^{\phi_{i,n}}$. According to Mehran and Peristiani (2010), it is computationally easier to specify the heterogeneity using a parametric model than using a semi-parametric model. In order to test our parametric model with heterogeneity, we use the following equation:

$$h(n|\beta X_{i,n}; \gamma, \theta) = \gamma e^{\beta X_{i,n}+\phi_{i,n}}(ne^{\beta X_{i,n}+\phi_{i,n}})^{\gamma-1} \tag{17}$$

where $\phi_{i,n}$ is an unobserved heterogeneity factor that is assumed to be normally distributed with a zero mean and a variance of $\theta$. The variance $\theta$ is the frailty variance that is estimated from our data sample and measures the variability of the frailty across various groups of firms and industries groups. The rest of the variables are as defined in Equation (14). Models (5) and (6) of Table 5, show our results for the parametric models that consider the existence of a shared frailty at the industry $\phi_{i,n} = \phi_j$ ($j$ = two-digits SIC) and firm $\phi_{i,n} = \phi_i$ ($i$ = firm) levels. Overall, the qualitative conclusions are unchanged after adjusting for heterogeneity.

Survival analysis depends heavily on the censoring assumptions. Competing risk models utilise cause-specific hazard functions and are particularly appropriate when the possible failure events are known as a complete set. In addition, they are theoretical superior in presence of covariate information that may influence the censoring time. The competing risk models we employ in our paper follow Fine and Gray (1999) and they are a direct analog to Cox regression hazard rate models. Our competing risk models are still semiparametric in the sense that the baseline subhazard has no particular functional form while the effects of covariates are assumed to be proportional, see Van Cleave (2016).

**Table 5**
Prediction testing analyses - alternative estimations.

| | Left Censoring | | Different Subsample | | Unobserved Heterogeneity | | Different Estimation Methods | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Variables Related to Agency Motives:* | | | | | | | | | |
| ExpropriationPenalty ($b$) | 0.1401*** | 0.1957*** | 0.2123*** | 0.1953*** | 0.1967*** | 0.2188*** | 0.4492*** | 0.2324*** | -0.0010*** |
| | (0.0341) | (0.0285) | (0.0289) | (0.0291) | (0.0205) | (0.0232) | (0.1063) | (0.0302) | (0.0001) |
| InsidersOwnership ($\alpha$) | 1.3137*** | 1.7471*** | 1.6827*** | 1.6777*** | 1.7500*** | 1.9920*** | 2.3756*** | 1.5246*** | -0.0058*** |
| | (0.2667) | (0.2372) | (0.2485) | (0.2408) | (0.2221) | (0.2600) | (0.2278) | (0.2406) | (0.0010) |
| DividendPayout ($d$) | -2.2408 | -2.0801 | -1.6840 | -1.7104 | -3.7646*** | -3.8341*** | -1.2450 | -3.0115** | 0.0147** |
| | (1.5771) | (1.4229) | (1.4969) | (1.4242) | (1.2787) | (1.3571) | (1.2342) | (1.4932) | (0.0066) |
| ListingExpenses ($l$) | 0.1176* | 0.1269*** | 0.1286*** | 0.1697*** | 0.1168*** | 0.1138*** | 0.0241** | 0.1580*** | -0.0007*** |
| | (0.0623) | (0.0345) | (0.0352) | (0.0386) | (0.0245) | (0.0254) | (0.0113) | (0.0383) | (0.0002) |
| *Variables Related to Economic Motives:* | | | | | | | | | |
| GrowthRate ($\mu$) | -0.7337*** | -0.9153*** | -0.9366*** | -0.8674*** | -0.8384*** | -0.8380*** | -0.8610*** | -0.9690*** | 0.0036*** |
| | (0.1571) | (0.1435) | (0.1481) | (0.1429) | (0.1577) | (0.1653) | (0.1480) | (0.1411) | (0.0006) |
| BusinessRisk ($\sigma$) | 0.2765** | 0.2240** | 0.2138** | 0.2265** | 0.2322* | 0.2754** | 0.2051* | 0.1998** | -0.0007* |
| | (0.1148) | (0.1025) | (0.1060) | (0.1031) | (0.1220) | (0.1341) | (0.1063) | (0.0997) | (0.0004) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Wald $\chi^2$ (LR $\chi^2$) | 29,499 | 14,369 | 14,665 | 14,150 | (709.71) | (343.83) | 25,362 | 822 | 2,083 |
| LPLR (LL) | -6,025 | -8,068 | -7,527 | -7,873 | -3,608 | -3,601 | -7,749 | -7,866 | 587 |
| Observations | 263,146 | 350,232 | 345,238 | 349,068 | 357,101 | 357,101 | 357,101 | 357,101 | 357,101 |

This table provides the results of our alternative regression estimations. Models (1), (2), (3), (4), and (7) provide the estimates of the competing risk sub-hazard model, based on maximum likelihood estimation, using the method of Fine and Gray (1999) as per Equation (14). Models (1) and (2) report the results after addressing the left censoring problem. Model (1) shows the results based on Heckman and Singers (1984) estimation strategy, and Model (2) shows our results when we change the first year of the sample from 1990 to 1994. Models (3) and (4) report the results using different subsamples. Models (3) and (4) report the results after removing all the cross-listed firms from the sample and excluding all firms in countries with less than five voluntary delisted firms throughout the sample period, respectively. Models (5) and (6) report the results based on maximum likelihood estimation of the proportional hazard model using Weibull distribution as the baseline hazard rate as per Equations (17), while taking the effect of industry and firm unobserved heterogeneity into consideration. Models (5) and (6) are estimated under the assumption of shared frailty effects at the industry and firm levels using the two-digit SIC codes ($\phi_{i,n} = \upsilon_j$ where $j$ = SIC code) and ($\phi_{i,n} = \phi_i$ where $i$ = firm), respectively. Models (7), (8), and (9) report the results using different estimations. Model (7) is estimated while controlling for both industry and country fixed effects. Model (8) is estimated using the Cox proportional hazard model. Model (9) is estimated using the Accelerated Failure Time (AFT) model drawn from a Weibull density distribution. For all models, 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. All models include industry, at the two-digit SIC code, fixed effects. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. LPLR denotes to Log-pseudo likelihood ratio, LL denotes to Log Likelihood, and LR Chi$^2$ denotes to Likelihood Ratio Chi$^2$. All variables are defined in Table A.1.

Finally, to check whether our main results hold under different specifications, we reestimate our competing risk model: (i) with industry and country fixed effects, (ii) by using the semi-parametric Cox proportional hazard model; and (iii) by applying the Accelerated Failure Time model (AFT) drawn on a Weibull density distribution to parametrize the baseline survivor function.[22] Note that, the signs of the coefficients estimated from the AFT model are the exact opposite of those reported by the competing risks models. The change in sign is because the competing risks models use variables to model the hazard rate, while the AFT models use variables to model the survival times. In other words, in an AFT model, estimated parameters quantify whether the survival time accelerates (if it is positive) or decelerates (if it is negative) for a one unit change in the variables values. As per Models (7), (8), and (9), the results remain qualitatively similar.

#### 4.3.2. Matching estimators

According to Wheelock and Wilson (2000), the competing risk estimation inherently benchmarks and compares several different competing outcomes, and in doing so effectively adjusts for the counterfactual (in our case any outcome other than voluntary delisting serves as a counterfactual).[23] Such adjustments for counterfactuals are known to ameliorate the endogeneity bias (Roberts and Whited, 2013), which strengthens our confidence in the results provided in Table 4.

Nonetheless, we take additional care to improve the identification of our main tests using two techniques. First, a method that has been shown to reduce endogeneity bias without needing an instrument is the matching estimation approach (Dehejia and Wahba, 2002; Çolak and Whited, 2007). In particular, we use a regression analysis but by first applying propensity score matching (PSM). Other studies have used this dual approach before (Drucker and Puri, 2005). Table OA3 in the Online Appendix provides the details of our PSM approach. Model (1) presents the results for the pre-matching logistic regression without the six theoretical variables. Model (2) shows the same estimates for the post-matching sample. All regression coefficients for the post-matching sample are statistically insignificant, which implies that our PSM technique successfully removes any differences in the observable characteristics other than the difference in the six variables of interest. Next, in Model (3), we use the matched sample to re-estimate our baseline model from Table 4. Our conclusions regarding six theoretical variables are qualitatively similar except for the coefficient for business risk.

Our second technique is more suitable for the cases when there are multiple endogenous variables. In our paper's context, there are several endogenously chosen variables by the entrepreneur (see Section 3) and each one of them is an important variable for our model. Thus, endogeneity bias may originate from any of the six theoretical variables. In such cases of multi-variable endogeneity, Wintoki et al. (2012) recommends using the system generalized method of moments (GMM) of Blundell and Bond (1998). Our IV-style instrument is tax revenues (as

[22] We also consider other functional forms such as lognormal, loglogistic, and exponential. All these models provide qualitatively similar results.

[23] The power of such tests derives from the ability to reject the null (voluntary delisting) when it is false. Our theoretical model should not apply to firms who continue to stay listed or delist due to other reasons. As such, these outcomes can serve as a proper control sample or as a counterfactual.

% of GDP) that is prevalent in a country during a given year (shortly *Taxes*; see Table A.1). We argue that this variable is relevant for the entrepreneur when they determine the optimal levels of the endogenous variables like the ownership stake ($\alpha$) and the dividend ratio ($d$), but we are not aware of any economic argument (or academic study) that claims that government's tax revenues are important for voluntary delisting decisions. Using this IV-style instrument together with the lagged values of the control variables, we implement the GMM. As shown under Model (4), our qualitative conclusions regarding all theoretical variables are unchanged.

## 5. Macroeconomic shocks and the delisting decision

In this section, we test Hypothesis 3 that claims that macroeconomic shocks can disproportionately affect certain firms and make it optimal for them to voluntarily delist. The economic motives for delisting ($\mu$ and $\sigma$) can play a mediating role and through them external shocks could impact the delisting decision. We first test whether a country's political and regulatory uncertainties affect the delisting choices of the local firms and then, we focus on the mediating role of $\mu$ and $\sigma$.

### 5.1. Does uncertainty affect the delisting outcomes?

We first test for an important consequence of rising political and regulatory uncertainties within a country. Specifically, we test Hypotheses 3A and 3B by using proxies for the uncertainties generated by rapidly changing economic and regulatory policies within a country.

Our measure of political uncertainty is the economic policy uncertainty index (*PolUncertainty*) of Baker et al. (2016); this index is a country-specific measure constructed based on newspaper articles published on policy uncertainty. The economic policy uncertainty database (www.policyuncertainty.com) provides the data for various national economic policy uncertainty indices.[24,25] Our regulatory uncertainty measure (*RegUncertainty*) is obtained from the World Bank's World Governance Indicators and it is one of the six major governance indicators (Regulatory Quality) in that database.[26] It captures the perceptions of the economic agents in that country regarding the abilities of the government to formulate and implement sound policies and regulations that permit and promote private sector development.

To capture the direct effects of uncertainty variables on the delisting outcome, we essentially rerun our analyses from Table 4 but by adding the uncertainty variable(s) to the list of determinants of the voluntary delisting outcome. As estimation methods, we again use both the competing risk sub-hazard and the multinomial logit models. The results are reported in Table 6. Both, *PolUncertainty* and *RegUncertainty*, are positively and significantly associated with the probability of voluntarily delistings. This result is novel to both the public listing and uncertainty literatures as it shows that political uncertainty not only reduces the number of private firms willing to conduct an IPO (Çolak et al., 2017), but it also increases public firms' probability of voluntary delisting. That is, it squeezes the number of public firms from both sides. In short, these findings indicate that rising policy uncertainties (Baker et al., 2016) and regulatory restrictions (Doidge et al., 2017; Kalmenovitz, 2023) in some countries can be one reason for declining numbers of public firms as claimed by Doidge et al. (2017) and Stulz (2020).

### 5.2. Mediation analysis

To test and establish the mediating role of $\mu$ and $\sigma$ in transforming the uncertainty shocks into delisting outcomes, we follow studies such as Baron and Kenny (1986) and MacKinnon (2012) and perform a formal mediation analysis. A mediation analysis (or pathway analysis) involves parsimonious specifications of structural equation modelling.[27] Some studies have used this method to establish direct evidence on the underlying economic channels in other settings that use OLS regressions (e.g., Tsang et al., 2019). However, our analyses involve a proportional hazard model that requires a more elaborate mediation analysis that has no precedence in the financial economics literature but has been used in the biomedical field (e.g., VanderWeele, 2011).

Section D of our Online Appendix formally describes the mediation analysis in the context of our proportional hazard model and it presents our findings. We demonstrate that the macroeconomic shock variables (*PolUncertainty* and *RegUncertainty*) affect the voluntary delisting hazard through several pathways. Most importantly, both the growth rate ($\mu$) and the business risk ($\sigma$) are strong mediators of the uncertainty shocks: individually, they can mediate between 41.96% to 42.72% of the total effect exerted by the uncertainty shocks. This finding supports our Hypotheses H3A and H3B. Thus, our model variables that relate to the firm's economic performance play an important role: they expose the firm's delisting decisions to external macroeconomic shocks. Not only the internal dynamics of the firm, but also the external macroeconomic conditions can make it optimal to voluntarily delist from an exchange.

## 6. Conclusion

In this paper, we develop a theoretical model of a publicly listed firm that is considering voluntarily delisting from a stock exchange. A large shareholder, or a syndicate of shareholders with perfectly aligned interests whom we refer to as the entrepreneur, controls the decision to voluntarily delist. Consistent with prior models of the exchange listing decision of an entrepreneur (e.g., Pagano et al., 1998; Shleifer and Wolfenzon, 2002; Stulz, 2009), our model assumes that the entrepreneur is inclined to expropriate the publicly listed firm's assets at a rate that is influenced by the quality and enforceability of the shareholder protection laws within the country where the firm is listed. This is the agency motive for voluntary delisting. There are also economic motives behind the entrepreneur's delisting decision that include relatively higher and/or smoother production returns. In equilibrium, the entrepreneur balances the agency motives and the economic motives. The model allows for heterogeneity across firms and across countries whereby the unique conditions of the firm's business and the environment the firm operates in (the country) make it optimal for some firms

[24] Please refer to the following studies for further details on the construction of each country's uncertainty index: Arbatli et al. (2017), Armelius et al. (2017), Baker et al. (2016), Cerda et al. (2016), Ghirelli et al. (2019), Gil and Silva (2018), Hardouvelis et al. (2018), Kroese et al. (2015), and Zalla (2017).

[25] The data series on economic policy uncertainty index is available at different time periods for different countries in our sample. The data series for each country is as follows: Brazil (1991-2020), Columbia (1997-2020), Greece (1997-2020), Russia (1994-2020), Pakistan (2010-2020), Italy (1997-2020), Ireland (1990-2020), Spain (1997-2020), Croatia (2003-2020), Belgium (2001-2020), China (1997-2020), Chile (1993-2020), Hong Kong (1998-2020), Mexico (1996-2020), Netherlands (1997-2020), France (1990-2020), South Korea (1990-2020), Canada (1990-2020), Japan (1990-2020), Sweden (1990-2020), Singapore (2003-2020), India (1997-2020), Australia (1997-2020), Germany (1993-2020), the United States (1990-2020), and the United Kingdom (1997-2020). After merging our sample with the economic policy uncertainty index (*PolUncertainty*), the sample size drops to 349,626 firm-year observations.

[26] When merging our sample with the regulatory uncertainty measure (*RegUncertainty*), we end up with a sample of 304,779 firm-year observations. When the missing observations for both policy and regulatory uncertainty variables are dropped, we end up with a final sample of 301,785 firm-year observations.

[27] Pathway analysis is a branch of structural equation modelling and it is used to examine the causal relationship between two or more variables. It is a method to discern the effects of several variables acting on a specified outcome via multiple causal pathways. Pathway analysis is an extension of regression analysis, and it is only useful in cases applying regression analysis techniques. It is just a series of regressions applied sequentially to data. For further details, please see MacKinnon (2012).

**Table 6**
The impact of macro factor on voluntary delisting.

| | Competing Risk | | | Multinomial Logit | | |
|---|---|---|---|---|---|---|
| | | | | M&A | Involuntary | Voluntary |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| PolUncertainty | 0.0018*** | | 0.0018*** | -0.0008*** | 0.0014*** | 0.0012*** |
| | (0.0002) | | (0.0002) | (0.0001) | (0.0002) | (0.0002) |
| RegUncertainty | | 0.0368*** | 0.0370*** | 0.0407*** | 0.0035 | 0.0394*** |
| | | (0.0037) | (0.0038) | (0.0015) | (0.0024) | (0.0038) |
| ExpropriationPenalty ($b$) | 0.1808*** | 0.1930*** | 0.1609*** | 0.0527*** | 0.0106 | 0.1912*** |
| | (0.0298) | (0.0306) | (0.0283) | (0.0084) | (0.0232) | (0.0305) |
| InsiderOwnership ($\alpha$) | 1.9346*** | 2.2518*** | 2.2976*** | 0.1077 | -0.2676 | 2.3359*** |
| | (0.2517) | (0.2476) | (0.2450) | (0.0872) | (0.2318) | (0.2577) |
| DividendPayout ($d$) | -3.9555** | -2.3000 | -2.5356* | -2.9325*** | -9.4904*** | -3.2926** |
| | (1.6604) | (1.4258) | (1.4432) | (0.5338) | (2.3188) | (1.4972) |
| ListingExpenses ($l$) | 0.1196*** | 0.0638** | 0.0621** | 0.0717*** | 0.0861 | 0.0715*** |
| | (0.0370) | (0.0262) | (0.0271) | (0.0198) | (0.0606) | (0.0277) |
| GrowthRate ($\mu$) | -0.9528*** | -0.7614*** | -0.7942*** | -0.3797*** | -1.5928*** | -0.8179*** |
| | (0.1468) | (0.1492) | (0.1471) | (0.0640) | (0.1480) | (0.1742) |
| BusinessRisk ($\sigma$) | 0.2457** | 0.1798 | 0.2130* | 0.2773*** | 1.1483*** | 0.2232* |
| | (0.1074) | (0.1115) | (0.1097) | (0.0513) | (0.0848) | (0.1230) |
| Controls | Yes | Yes | Yes | | Yes | |
| Industry FE | Yes | Yes | Yes | | Yes | |
| Wald $\chi^2$ | 27,776.98 | 29,087.90 | 27,410.53 | | — | |
| LPLR | -7,296.50 | -7,220.63 | -7,199.14 | | — | |
| Pseudo $R^2$ | — | — | — | | 0.082 | |
| Observations | 301,785 | 301,785 | 301,785 | | 301,785 | |

This table reports the results of the direct effect of macroeconomic shock, represented by political (*PolUncertainty*) and regulatory (*RegUncertainty*) uncertainty measures on firm's probability of voluntary delisting. The first three columns show the estimates of the competing risk sub-hazard model as in Table 4, where the dependent variable is the time to voluntarily delist. Models (1)-(3) report the coefficient estimates while adding the political (*PolUncertainty*) uncertainty, regulatory (*RegUncertainty*) uncertainty, and both political (*PolUncertainty*) and regulatory (*RegUncertainty*) uncertainty variables to the models, respectively. The coefficients measure the partial impact of each variable on the likelihood of voluntary delisting conditional on the duration. The second set provides the estimates of the multinomial logit model after adding both political (*PolUncertainty*) and regulatory (*RegUncertainty*) uncertainty variables to the model in Equation (14). The dependent variable equals zero if a firm did not delist. It equals one for delistings because of merger, two for involuntary, and three for voluntary. Models (4)-(6) report the coefficient estimates. As explained in Section 5, *PolUncertainty* and *RegUncertainty* variables have some missing observations for some countries in earlier years of our sample. Thus, in this table, we work with the squared sample whereby all the missing observations are removed, which leaves us with a sample of 301,785 observations. All models include industry fixed effects using the two-digit SIC industry code and the estimates are adjusted for right censoring. The standard errors are reported inside the brackets and are corrected for firm-level clustering effects. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Table A.1.

to delist but not the others. Furthermore, various micro (within firm) and macro (external to the firm) shocks can change the optimality of the delisting decision.

A model with such assumptions makes a number of predictions concerning the voluntary delisting patterns across different countries. First, it emphasizes the agency motives for voluntary delisting that in our model are parametrized by variables such as i) country's expropriation penalty parameter, ii) entrepreneur's insider ownership, iii) listing expenses (e.g., audit fees), and iv) dividend payouts to shareholders. Second, it shows that under certain assumptions about the production returns, the economic motives behind the delisting decision can be described by the growth rate and volatility of the firm's revenue stream in the years leading up to the delisting. Third, our model demonstrates how exogenous shocks generated by increasing economic policy and regulatory uncertainties in a country can make it more optimal for the firm to delist that year.

We show that our theoretical model's delisting condition has a reduced form which can be approximated by a hazard rate model, or alternatively, by a multinomial logit. Thus, the empirical tests of our model are conducted with the help of a competing risk hazard rate model that contrasts voluntary delistings to involuntary and acquisition-related delistings to better discern the determinants of the voluntary delisting decision in many countries. The competing risk model enhances the power of our tests as it allows for rejecting the null of voluntary delisting by contrasting it to firms that delist involuntarily or due to an M&A.

To test our model's predictions, we collect delisting data from 26 countries spanning three decades between 1990 and 2020. We then read the news around the delisting events and manually sort them into subsamples of voluntary, involuntary, and M&A delistings. This sorting yields the largest known cross-country dataset of delisted firms that includes 832 voluntary, 1035 involuntary, and 6,708 acquisition-related delistings across 26 different countries with different economic and regulatory conditions. Working with such a multi-country dataset is essential, since our model makes various general statements of principals that should be tested universally to be convincing. Using this data, we show that our model is broadly consistent with the voluntary delisting patterns around the World. The results from our competing risk model indicate that among the six key parameters that our model emphasizes, economically and statistically the most important ones are (in order of economic significance): insider ownership, firm's growth rate, business risk, country's expropriation penalty parameter, listing expenses, and dividends.

Furthermore, the related mediation analyses show that economic policy uncertainty affects the voluntary delisting odds by curtailing the firm's growth and by increasing its sales volatility (business risk). Similar analyses for regulatory uncertainty indicate that increasing regulatory requirements for the listed firms raise the attractiveness of the voluntary delisting decision by affecting both the growth rate and business risk. These findings can help explain the rising trend towards voluntary delisting we observe in many countries (Doidge et al., 2017; Stulz, 2020). The uncertainty in US economic policy has been rising in recent decades (Baker et al., 2016) and many additional business regulations and reporting guidelines have been imposed on listed firms since the early 2000s (Doidge et al., 2017; Kalmenovitz, 2023).

Overall, our model provides valuable insights into the key determinants of the decision to voluntarily delist and the external factors that affect the timing of that decision. Further, this model can potentially inspire other models on the decision to delist. For instance, one can consider the delisting decision as a real option held by the entrepreneur from the moment the firm is listed to the moment it is optimal to delist it from the exchange, possibly also considering the entrepreneur's option to completely abandon the business. Such a real option model would have the advantage of providing the entrepreneur with not only the optimal threshold to delist the firm from the exchange (as our model does), but also with the values of the options to delist and to abandon, and to see how they evolve over time and how they react to exogenous shocks. Another related model to ours could study the optimal delisting decision from the perspective of the policymaker (or social planner), for instance through a welfare analysis, with the aim of guiding the social planner on the optimal regulatory policy to be followed over time to enhance IPOs and minimize voluntary delistings. A different model could explicitly focus on regulatory uncertainty and analyse whether the ability to lobby politicians reduces or increases the value of the delisting option. This model extension would be of particular relevance for countries where there is high regulatory policy uncertainty.

## CRediT authorship contribution statement

**Alcino Azevedo:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Gonul Colak:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Izidin El Kalak:** Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Radu Tunaru:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation.

## Declaration of competing interest

The authors declare that they have no conflict of interest.

## Data availability

Data will be made available on request.

## Appendix A. Proposition proofs

**Proof of Proposition 2.** (i) First, let us notice that the $\Psi(b_n, v_n)$ factor is given by $1 - bv + \frac{1}{2}bv^2$. Since $v = \frac{1-\alpha d(1-l)}{b}$ it follows that $v'(b) = -\frac{1-\alpha d(1-l)}{b^2} = -\frac{v}{b}$. Then,

$$\begin{aligned}\frac{\partial \Psi}{\partial b} &= -[v + bv'] + \frac{1}{2}[v^2 + 2bvv'] = -v + b\frac{v}{b} + \frac{1}{2}[v^2 - 2bv\frac{v}{b}]\\ &= -v + v + \frac{1}{2}[v^2 - 2v^2] = -\frac{v^2}{2} < 0\end{aligned}$$

This means that when $b\uparrow \Longrightarrow \Psi(b,v)\downarrow$ and when $b\downarrow \Longrightarrow \Psi(b,v)\uparrow$.

In order to assess how changes in $b$ may impact the likelihood of delisting, we need to consider the function $\Gamma(b) = \frac{\Psi(b,v)}{\alpha}$, which reflects the entrepreneur's behaviour.

*The case of $\alpha$ being determined exogenously*

In this case, $\alpha$ is not linked to $b$ and because $\Gamma(b) = \frac{1}{\alpha}\Psi(b,v)$ it follows that $\Gamma$ has the same monotony with respect to $b$ as $\Psi$. Therefore, when $b\uparrow \Longrightarrow \Gamma(b)\downarrow$ and when $b\downarrow \Longrightarrow \Gamma(b)\uparrow$.

*The case of $\alpha$ being determined endogenously*

In this case, recall that $\alpha = \frac{1-bv}{d(1-l)}$. Because $\Gamma(b) = \frac{1-bv+0.5bv^2}{\frac{1-bv}{d(1-l)}} = d(1-l) + \frac{1}{2}d(1-l)\frac{bv^2}{1-bv}$ it follows that

$$\begin{aligned}\frac{\partial \Gamma}{\partial b} &= \frac{0.5d(1-l)}{(1-bv)^2}\left[(v^2 + 2bvv')(1-bv) + (v+bv')bv^2\right]\\ &= \frac{0.5d(1-l)}{(1-bv)^2}(v^2 + 2bv(-v/b))(1-bv) + bv^2(v + b(-v/b)))\\ &= \frac{0.5d(1-l)}{(1-bv)^2}(v^2 - 2v^2)(1-bv) = -\frac{0.5d(1-l)}{(1-bv)}v^2 < 0\end{aligned}$$

But $\alpha > 0$ implies that $1 - bv > 0$ so then $\frac{\partial \Gamma}{\partial b} < 0$. Therefore, when $b\uparrow \Longrightarrow \Gamma(b)\downarrow$ so if $\hat{E}(R_{n+1})$ and $E(R_{n+1})$ stay fixed then delisting is more likely. Similarly, when $b\downarrow \Longrightarrow \Gamma(b)\uparrow$ and if $\hat{E}(R_{n+1})$ and $E(R_{n+1})$ stay fixed then delisting is less likely.

(ii) Let $\Gamma = \frac{\Psi(b,v)}{\alpha} = \frac{1-bv+0.5bv^2}{\alpha}$. Recall that $v = \frac{1-\alpha d(1-l)}{b}$ and hence $1 - bv = \alpha d(1-l)$, $v'_\alpha = -\frac{d(1-l)}{b}$. Then,

$$\begin{aligned}\frac{\partial \Gamma}{\partial \alpha} &= \frac{[-bv'_\alpha + bvv'_\alpha]\alpha - [1 - bv + 0.5bv^2]}{\alpha^2}\\ &= \frac{-v + bv^2 - 0.5bv^2}{\alpha^2} = \frac{v[0.5bv - 1]}{\alpha^2}\\ &= -\frac{v}{2\alpha^2}[\alpha d(1-l) + 1] < 0\end{aligned}$$

The left-hand side of the delisting condition decreases when $\alpha$ increases and delisting becomes more likely.

(iii) We can calculate $v'_d = -\frac{\alpha(1-l)}{b}$. Similar calculations lead to

$$\begin{aligned}\frac{\partial \Gamma}{\partial d} &= \frac{1}{\alpha}[-bv'_d + bvv'_d] = \frac{1}{\alpha}[\alpha(1-l) - \alpha(1-l)v]\\ &= (1-l)(1-v) > 0\end{aligned}$$

Hence, the left-hand side of the delisting condition increases when $d$ increases and delisting becomes less likely.

(iv) Since $v'_l = \frac{\alpha d}{b}$, we get

$$\begin{aligned}\frac{\partial \Gamma}{\partial l} &= \frac{1}{\alpha}[-bv'_l + bvv'_l] = \frac{1}{\alpha}[-\alpha d + \frac{\alpha d(1-\alpha d(1-l))}{b}]\\ &= \frac{1}{\alpha b}[\alpha d(1-b) - \alpha^2 d^2(1-l)]\end{aligned}$$

The condition $\frac{\partial \Gamma}{\partial l} < 0$ is satisfied if $\alpha d(1-b) - \alpha^2 d^2(1-l) < 0$ which is equivalent to $1 - l > \frac{1-b}{\alpha d}$ or $l < 1 + \frac{b-1}{\alpha d}$. If $b \geq 1$ as it is the case in our paper, because $l < 1$, the last condition is always true. Therefore, $\frac{\partial \Gamma}{\partial l} < 0$ always holds in this case, which means that when $l\uparrow$ it follows that $\Gamma\downarrow$ and the entrepreneur is more likely to delist the company. □

**Proof of Proposition 3.** It is well-known (see Luenberger, 1998, Section 11.7) that, for a Geometric Brownian motion, the conditional connection between the value of $S_n$ and the value of $S_T$ at some future time $T$ is described by $S_T = S_n \exp\{(\mu - \frac{1}{2}\sigma^2)(T-n) + \sigma W_{T-n}\}$ where $\{W_n\}_{n\geq 0}$ is the Wiener process associated with the geometric Brownian motion. Thus, $Y_{[n,T]} \equiv \ln(\frac{S_T}{S_n}) = (\mu - \frac{1}{2}\sigma^2)(T-n) + \sigma W_{T-n}$ and since for yearly $R_{n+1} \approx 1 + Y_{[n,n+1]}$, it follows that $E(R_{n+1}) \approx 1 + \mu - \frac{1}{2}\sigma^2$.

Replacing now in (12) the $\widetilde{E}(R_{n+1})$ and $E(R_{n+1})$ with the respective formula based on the approximation above we get (13). □

**Proof of Proposition 4.** The delisting condition can be rewritten[28] as

[28] This requires all quantities involved to be positive.

$$\frac{1+\mu_{n+1}-0.5\sigma^2_{n+1}}{1+\widetilde{\mu}_{n+1}-0.5\widetilde{\sigma}^2_{n+1}} < \frac{\alpha_n}{\Psi(b_n, \upsilon_n)} \tag{A.1}$$

Then, by adding the shock to business uncertainty we get

$$\frac{1+\mu_{n+1}-0.5(\sigma^2_{n+1}+\varepsilon)}{1+\widetilde{\mu}_{n+1}-0.5\widetilde{\sigma}^2_{n+1}} < \frac{\alpha_n}{\Psi(b_n, \upsilon_n)}$$

$$-\frac{0.5\varepsilon}{1+\widetilde{\mu}_{n+1}-0.5\widetilde{\sigma}^2_{n+1}} + \frac{1+\mu_{n+1}-0.5\sigma^2_{n+1}}{1+\widetilde{\mu}_{n+1}-0.5\widetilde{\sigma}^2_{n+1}} < \frac{\alpha_n}{\Psi(b_n, \upsilon_n)}$$

The last inequality is more difficult to hold when $\varepsilon < 0$ and it is more likely to hold when $\varepsilon > 0$. Likewise, by adding the shock to the growth rate we get

$$\frac{1+\mu_{n+1}+\varepsilon-0.5\sigma^2_{n+1}}{1+\widetilde{\mu}_{n+1}-0.5\widetilde{\sigma}^2_{n+1}} < \frac{\alpha_n}{\Psi(b_n, \upsilon_n)}$$

$$\frac{\varepsilon}{1+\widetilde{\mu}_{n+1}-0.5\widetilde{\sigma}^2_{n+1}} + \frac{1+\mu_{n+1}-0.5\sigma^2_{n+1}}{1+\widetilde{\mu}_{n+1}-0.5\widetilde{\sigma}^2_{n+1}} < \frac{\alpha_n}{\Psi(b_n, \upsilon_n)}$$

The last inequality is more difficult to hold when $\varepsilon > 0$ and it is more likely to hold when $\varepsilon < 0$. □

## Appendix B. Variables definition

**Table A.1**
Variables definition.

| Variable Name | Definition | Item Code | |
|---|---|---|---|
| | | CRSP/ Compustat | Datastream/ Worldscope |
| **Variables Related to Agency Motives for Delisting** | | | |
| ExpropriationPenalty ($b$) | Proxied by the Anti-Self Dealing Index of Djankov et al. (2008), which is originally defined to range between 0 and 1, however in our sample, there is no country with the value of 0. Furthermore, as described in Section 2.1, our model requires the proxy for the true country penalty parameter to be greater than 1 ($b \geq 1$). Thus, we multiply the Anti-self dealing index with 10 to ensure the $b$ values are between 1 and 10. | Djankov et al. (2008) | |
| InsidersOwnership ($\alpha$) | Firm's insiders ownership is measured as the natural logarithm of insiders ownership in the firm plus one. As per DataStream, WC08021 is defined as the number of closely held shares divided by common shares outstanding where closely held shares are those held by the insiders. For US firms, we complement the missing values of insiders ownership from DataStream with those obtained from shares Refinitiv Eikon Database (around 9% of the sample). The remaining missing values of this variable are replaced with the firm's mean value (around 9.4% of the sample). To smooth out the extreme observations just before delisting, we take five years moving average of the variable. | | ln(WC08021 + 1) |
| DividendPayout ($d$) | Dividend payout is a ratio of dividend paid (in millions of local currency) divided by total sales (in millions of local currency). To smooth out the extreme observations just before delisting, we take five years moving average of this variable. | DV/SALE | WC05376/WC01001 |
| ListingExpenses ($l$) | Listing expenses is a ratio of audit fees (from Refinitiv's Worldscope; in millions of local currency) divided by firm's total sales (in millions of local currency). For US firms, we complement the missing observations with data from Audit Analytics. We replace all observations in the sample with the mean values of this variable for the portfolio of firms sorted by country and firm size tercile. In some developing countries this variable shows extreme observations (above 100%) in some years, so we standardize this variable and we take five years moving average. | WC01801 and TotalFees (from Audit Analytics) | WC01801 |
| **Variables Related to Economic Motives for Delisting** | | | |
| GrowthRate ($\mu$) | The firm's growth rate is defined as the annual change in the natural logarithm of total sales (inflation adjusted). To smooth out the extreme observations just before delisting, we take five years moving average of this variable. | $ln(SALE_t)-$) $ln(SALE_{t-1}$ | $ln(WC01001_t)-$ $ln(WC01001_{t-1})$ |
| BusinessRisk ($\sigma$) | Firm's business risk is defined as the standard deviation of the firm's growth rate (GrowthRate) over the five years window. | Std.Dev. (Growth Rate) | Std.Dev. (Growth Rate) |
| **Control Variables** | | | |
| Size | The firm's size is defined as the natural logarithm of total assets (inflation-adjusted). To smooth out the extreme observations just before delisting, we take five years moving average of this variable. | ln(AT) | ln(WC02999) |
| FirmAge | Firm's age is defined as the natural logarithm of (1 + the number of years since the firm's IPO date). If the IPO date is not available, then we use the number of years since the firm's record first appears in the corresponding dataset. For USA firms, we also complement missing IPO dates with dates obtained from Jay Ritter's website as described in Appendix A of Loughran and Ritter (2004). | ln(FirmAge + 1) | ln(FirmAge + 1) |
| Leverage | The firm's leverage is defined as the firm's total debt divided by total assets. To smooth out the extreme observations just before delisting, we take five years moving average of this variable. | (DLTT+DLC)/AT | WC03255/WC02999 |
| MB | It is defined as the firm's market value divided by total assets. To smooth out the extreme observations just before delisting, we take five years moving average of this variable. | (AT-CEQ+ (CSHO*PRCC_F))/AT | MV/WC02999 |
| FCF | The firm's free cash flow. For firms in Worldscope this variable is already calculated. In the Worldscope manual, FCF is defined as Operating activities minus (capital expenditure, extraordinary items and discontinued operations, and total working capital change) divided by firm's total assets. To be consistent, for Compustat North America and for Compustat Global, FCF is defined using the same formula. To smooth out the extreme observations just before delisting, we take five years moving average of this variable. | (OANCF - CAPX - XIDOC - WCAPCH)/AT | (WC05507 * WC05301)/ WC02999 |
| CAPEX | The firm's CAPEX is defined as the firm's capital expenditure divided by total asset. To smooth out the extreme observations just before delisting, we take five years moving average of this variable. | CAPX/AT | WC04601/WC02999 |

(continued on next page)

**Table A.1** (*continued*)

| Variable Name | Definition | Item Code | |
|---|---|---|---|
| | | CRSP/ Compustat | Datastream/ Worldscope |
| R&D | The firm's R&D ratio is defined as the firm's research and development expenditure divided by total assets; missing values of R&D are replaced by zero. We take the five years rolling window to smooth out the extreme observations. | XRD/AT | WC01201/WC02999 |
| NEI | The net equity issuance ratio is defined as net equity issuance to total assets. To smooth out the extreme observations just before delisting, we take five years moving average of this variable. | (SSTK-PRSTKC)/AT | WC04251/WC02999 |
| Turnover | The firm's stock turnover is defined as the firm's natural logarithm of the annual number of shares traded divided by the number of shares outstanding. We take the five years rolling window to smooth out the extreme observations. | ln(CSHTR_F)/ln(CSHO) | ln(VO)/ln(WC05301) |
| ReturnVolatility | The firm's stock return volatility is defined as the annualized standard deviation of the daily stock returns. To smooth out the extreme observations just before delisting, we take five years moving average of this variable. | Std.Dev.(StockReturn) | Std.Dev.(StockReturn) |
| CrossListing | Cross listing is a dummy variable that equals one if a local firm is also cross listed in a foreign exchange and zero otherwise. | Authors' calculation | Authors' calculation |
| MCGDP | Stock market capitalisation to GDP ratio is the country's stock market capitalisation divided by its gross domestic product. | WorldBank Database | WorldBank Database |
| **Macroeconomic Variables** | | | |
| PolUncertainty | Political uncertainty index is a country specific measure constructed based on newspaper articles regarding policy uncertainty. We use the variable as defined. | Baker et al.'s (2016) economic policy uncertainty database: https://www.policyuncertainty.com/all_country_data.html | |
| RegUncertainty | The regulatory uncertainty measure is proxied by the World Bank's World Governance Indicators as one of the six major governance (Regulatory Quality) indicators. It captures perceptions about the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. | World Bank's World Governance Indicators database: https://info.worldbank.org/governance/wgi/ | |
| **Alternative measures of $b$** | | | |
| Revised Anti-director Index | The index is defined as the aggregate index of shareholder rights. The index is formed by summing: (1) vote by mail, (2) shares not deposited, (3) cumulative voting, (4) oppressed minority, (5) pre-emptive rights, and (6) capital to call a meeting. By definition, this index ranges from 1 to 5 (i.e., $b \geq 1$ is satisfied). | Djankov et al. (2008) | |
| Public Enforcement Index | Index of public enforcement if all disclosure and approval requirements have been met. By definition, it ranges from 0 to 1. We use the index for robustness checks and, thus, we do not apply any transformation to change the range of this index. | Djankov et al. (2008) | |
| **Instrumental Variable** | | | |
| Taxes | WDI defines this variable as: "Tax revenue refers to compulsory transfers to the central government for public purposes. Certain compulsory transfers such as fines, penalties, and most social security contributions are excluded. Refunds and corrections of erroneously collected tax revenue are treated as negative revenue." | World Development Indicator (WDI) and OECD Database | |

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

## Appendix C. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2024.103832.

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