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Article (Accepted Version)

Colak, Gonul, Fu, Mengchuan and Hasan, Iftekhar (2020) Why are some Chinese firms failing in the US capital markets? A machine learning approach. Pacific Basin Finance Journal, 61. a101331 1-22. ISSN 0927-538X

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Why are some Chinese firms failing in the US capital markets?
A Machine Learning Approach

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April 2, 2020

Why are some Chinese IPOs failing in the US capital market?

A Machine Learning Approach

Abstract

We study the market performance of Chinese companies listed in the U.S. stock exchanges using machine learning methods. Predicting the market performance of U.S. listed Chinese firms is a challenging task due to the scarcity of data and the large set of unknown predictors involved in the process. We examine the market performance from three different angles: the underpricing (or short-term market phenomena), the post-issuance stock underperformance (or long-term market phenomena), and the regulatory delistings (IPO failure risk). Using machine learning technique that can better handle various data problems, we improve on the predictive power of traditional estimations, such as OLS and logit. Our predictive model highlights some novel findings: failed Chinese companies have chosen unreliable U.S. intermediaries when going public, and they tend to suffer from more severe owners-related agency problems.

Keywords: initial public offerings, machine learning, China, underpricing, delistings, long-run returns, cross-listings, prediction

JEL Classification: C4, C53, C54, G30, G32, G33,

1. Introduction

As the World's largest equity markets, the U.S. stock exchanges have attracted many international companies seeking cross-listing opportunities. Although, for many foreign companies, going public under the supervision of the U.S. Securities and Exchange Commission (SEC) means new and arduous cross-listing processes with heavy regulatory burden (Doidge, Karolyi, and Stulz, 2009), the companies that ultimately succeed in this endeavor tend to enjoy better stock liquidity, more analyst coverage, higher market awareness, and higher valuations (Doidge, Karolyi, and Stulz, 2003; Lang, Lins, and Miller, 2003). The foreign firms may be motivated to list in the U.S. also to gain greater investors recognition (Foerster and Karolyi, 1999), greater product market visibility (Pagano, Roell, and Zechner, 2002), and lower cost of capital (Karolyi, 2006).

The firms headquartered in China (briefly “the Chinese firms”) are among the most prominent cross-listing examples in the U.S. The phenomenon of Chinese companies issuing shares in the U.S. exchanges began in the mid-1990s. Most of the early listed companies were large state-owned enterprises (SEOs) who chose to cross-list overseas to expand their investor base and modernize their corporate governance. They were considered a relatively safe investment because they were supported by the local or federal governments, and often enjoyed privileged and protected status within their industries. The success of these early listings has increased investor recognition of Chinese companies. The so-called “China concept” stocks have attracted large number of investors, which later on paved the way for smaller and riskier Chinese stocks.

While some Chinese companies have experienced dramatic growth within the U.S. markets, many U.S.-listed Chinese IPOs and ARDs struggled and even failed (Ang, Jian, and Wu, 2016). Further problems like the escalation of trade tensions between China and the United States

may exacerbate the underperformance of U.S. listed Chinese companies in the future. Due to such real and perceived problems with the Chinese IPOs, many successful U.S. listed Chinese companies (e.g., Baidu Inc. and Trip.com Group Ltd.) already trade at a discount to their Mainland and Hong Kong listed peers (Liu, Jiang, and Sathye, 2015). The large valuation discrepancy of Chinese stocks that recently enlisted in the U.S. exchanges puzzles many investors and thus, understanding the reasons behind their underperformance is a valuable academic endeavor. We shed light on this issue by utilizing machine learning techniques to pinpoint the important predictors of short- and long-term underperformance of the Chinese IPOs.

The decision to issue shares abroad is not an easy one (Hasan, Kobeissi, and Wang, 2011), because of the extra cost of issuing equity in an international setting (e.g., increased asymmetric information costs that have to be paid to the investors in the form of increased underpricing of shares) as well as the stricter scrutiny the foreign firms face when seeking approval for an IPO (Huddart, Hughes, and Brunnermeier, 1999). However, when a Chinese company ultimately ends up getting listed in a major U.S. exchange, it receives an implicit SEC approval seal. This implicit approval by U.S. regulators is claimed to be a valuable commitment (or bonding) mechanism, and it is theorized to carry a valuation premium (Siegel, 2005; Stulz, 2009).

However, due to reasons such as internal control weaknesses that result in corporate fraud (Baker et al., 2012; Ang et al., 2016), existence of many Chinese reverse mergers with heavy earnings management problems (Zhu, et al, 2015), and various negative stock spillover effects originating from Chinese reverse mergers (Darrough et al., 2019), the delisting of recent Chinese IPOs have become an increasingly common occurrence in the U.S. stock markets. Between 1993 and 2019, a total of 278 Chinese companies were listed in a U.S. exchange, 84 of which were delisted at different times either voluntarily or due to inability to meet exchange requirements.

This frequent occurrence of exchange delistings (i.e., IPO failures) is indicative of the greater and rising obstacles facing the Chinese companies who are trying to survive in the U.S. capital markets. Being forcefully dropped from an exchange is usually accompanied by a major decline in the stock price.¹ Thus, delisting is considered an ultimate and most consequential underperformance of an IPO (Demers and Joos, 2007, Yung, et al., 2008).

While the poor market performances of some U.S. listed Chinese stocks have been well noted in the literature (He et al, 2012; Chen et al, 2013; Lee et al, 2013), we still have only a very limited set of explanations behind this delisting phenomenon, with many crucial issues, such as the role of intermediaries, still left unresolved. One of the most important reasons why many other factors driving the delisting decision still remain uncovered is due to the scarcity of data (only 278 Chinese cross-listings between 1993 and 2019) and the large number of potential predictors involved in the process (e.g., various valuation ratios and their interactions). The traditional parametric models (such as OLS and logit), which are commonly used by the aforementioned studies, cannot properly identify most or all of the drivers of delisting due to the inherent constraints of their statistical features (Kleinberg et al, 2017; Mullainathan and Spiess, 2017). When the number of observations is limited and the number of parameters become large, traditional statistical models that are based on the classical asymptotic theory suffer from the curse of dimensionality, and thus become less stable and more prone to overfitting (Jones, 2017; Athey and Imbens, 2019). The objective of this study, thus, is to overcome this problem through machine learning techniques (such as gradient boosting) and uncover the main causes of the under-performance phenomenon of the U.S. listed Chinese firms.

¹ Except in the case of voluntary delisting (privatizations), which can involve a modest stock price appreciation (DeAngelo, DeAngelo, and Rice, 1984; Lehn and Poulsen, 1989; Bharath and Dittmar, 2010)

The gradient boosting (GB) machine learning technique has certain appeal for the purposes of this study. It can be shown empirically that the GB has predominance in high-dimensional data (Buhlmann and Yu, 2003), which better reflects the socioeconomic conditions of U.S. listed Chinese firms. Another advantage is that the GB procedures are invariant under all monotonic transformations of a single input variable (e.g. logarithm transformation). In other words, while variables in the studies have different scales, there is no need to normalize the input variables. In addition, the GB model is not sensitive to outliers and multicollinearity, and it is more robust due to better handling of uncorrelated inputs (Friedman 2001). Finally, in the corporate finance setting, GB technique seems to be the most practical machine learning method (Jones, 2017; Colak et al., 2019; Erel et al., 2019).

We examine the market performance of Chinese IPOs from three different angles: the underpricing (or short-term market performance), the stock underperformance (or long-term market performance), and regulatory delistings (IPO failures a la Demers and Joos, 2007). Using a machine learning technique, we provide a reliable way to study the U.S. listed Chinese firms in a high dimensional setting, which allows us to find the most reliable predictors among pre-listing firm characteristics and issuance characteristics of the market underperformers even when the number of non-missing observations is small. Our model shows very promising predictive ability with out-of-sample R-squared of 0.4 for prediction of underpricing and 0.05 for prediction of buy and hold abnormal returns (BHARs) within the 36 months window after the issuance. Moreover, our model has the ability to detect riskier Chinese firms that have higher probability of failure and has an out of sample predictive accuracy of 85% in prediction of regulatory delisting. Unlike traditional black box machine learning models (e.g. artificial neural network and support vector machine), the GB model we use is designed to generate transparent rules that are easily

interpretable by non-statisticians. This comprehensive model shows that, beside the well-known reasons for poor post-IPO performance (e.g., low firm quality), failed Chinese companies have chosen weak U.S. intermediaries (underwriters and audit firms). Furthermore, these issuing companies themselves were already suffering from various owners-related agency problems when they went public, which confounded with the intermediary agency problems (a la Liu and Ritter (2010) and Chang et al., (2017)) created a very unfavorable conditions for these firms. Finally, many of these unsuccessful IPOs originate from regions in China that have poor institutional environment (low marketization index of Fan et al, 2017) and/or low market power industries. These findings are novel to the cross-listing literature and are obtained through the application of advanced predictive methodologies, such as gradient boosting.

Prediction of market performance of U.S. listed Chinese firms can also be an economically consequential analysis. The Chinese firms account for 73.33% of the market share among all the foreign listings in the U.S. markets (Ritter, 2011). Also, the Chinese companies listed in the United States represent some of the best firms within China today. Because of its historical position, the U.S. market is attractive to the most promising Chinese growth companies. However, as more of their predecessors are undervalued and marginalized, some Chinese companies that have not yet listed in a U.S. exchange may worry about their prospects in the U.S. markets. U.S. investors can also benefit from knowing which Chinese IPOs are more prone to post-IPO failure. Thus, it is important, and of certain urgency, to find and document the predictors of some Chinese IPOs' poor performance in the U.S. markets.

The rest of the paper is organized as follows. Section 2 provides a literature review of the related theories. In Section 3, we briefly explain our machine learning methods we use in this

study. In Section 4, we discuss our data sources and our sample selection. In Section 5, all the empirical results are presented and discussed, and in Section 6 we summarize our conclusions.

2. Determinants of IPO Success and the Related Literature

While market share of Chinese firms is nearly $3/4^{\text{th}}$ of the market share among all the foreign listings in the U.S. market (Ritter, 2011), very few studies have examined specifically the market performance of U.S. listed Chinese firms, largely due to issues such as lack of detailed data and small sample size. In this section, we briefly go over the theories related to the market performance of IPOs, in general. This literature review is done with the purposes of pinpointing the known determinants of IPO success or failure, which then can be used to analyze Chinese IPOs' short- and long-term performance.

2.1. Asymmetric information

Disclosure and information exchange play vital roles in the valuation of companies in the capital markets. Overseas listings are known to trade at a heavy discount relative to the domestic market prices due to the lack of reliable information (Pagano et al., 2002; Liu et al., 2015). In the IPO literature, information asymmetry between different related parties and IPO firms (underwriters, issuers, and investors) explains the short-term underpricing (Loughran and Ritter, 2002) and the long-term underperformance (Ritter, 1991; Brav and Gompers, 1997) of IPOs. Specifically, to ensure that unwitting investors receive a fair rate of return and thus continue to participate in this market, the insiders need to underprice the issues on average (Rock, 1986; Beatty and Ritter, 1986). U.S. listed Chinese firms suffer more from information asymmetry because of the U.S.-China informational and cultural barrier (Ang, et al., 2016). In other words, the difference in legal system, language, and corporate governance hinders U.S. investors' understanding of the environment Chinese companies operate in (Chen et al., 2013). Consequently, Chinese issues

characterized by greater uncertainty are more likely to be underpriced to make up for the higher costs of information gathering and price discovery of the real value of these businesses. Due to similar problems, their long-term valuations can be discounted as well (Liu et al., 2015).

2.2. Signalling and bonding

Signalling strategy of private firms can affect various IPO outcomes (Grinblatt and Hwang, 1989; Welch, 1989). Most importantly, bonding and signalling incentives together play a crucial role in the decision of foreign companies to list in the U.S. (Siegel, 2005; Francis et al. 2010). In general, the U.S. exchanges provide unique gains to foreign firms regarding valuation effects due to more stringent listing requirements and accounting standards. Thus, foreign firms may be motivated to list in the U.S. to gain greater investors recognition (Merton, 1987), greater product market visibility (Pagano et al., 2002), and lower cost of capital (Karolyi, 2006). If a Chinese company is listed in the US, it has an implicit SEC approval seal. When overseas listed firms become bonded to the stricter regulations existing in the U.S., they tend to have better visibility and coverage in the financial press (Stulz, 2009; Doidge et al., 2004).

In the 90s, most Chinese companies traded in the United States in the form of ADRs with the intention of signalling the quality of state-owned enterprises (SOEs). As a foreign company, a Chinese company needs to signal its quality to the American investors in order to be recognized. Public attention, financial visibility, and investor interest are crucial factors over a firm's life cycle. Mehran and Peristiani (2010) suggest that IPOs that fail to attract investors' interest because of their lack of financial visibility tend to have higher stock price volatility and are more likely to delist. Asymmetric information between local investors and foreign managers create constraints to U.S. investors with regard to access to credible information about foreign firms. This reduces investor attention and trust towards such foreign firms' stock. Underpricing is a reasonable way

for high-quality Chinese firms to signal their quality to the U.S. investors. High-quality companies tend to underprice their issues to signal their quality to the market (Allen and Faulhaber, 1989). Higher underpricing allows them to raise more capital under more favourable conditions in the future (Welch, 1989).

2.3. Owners' agency problems (money left on the table)

Money left on the table theory interprets the underpricing and underperformance phenomenon as that certain firm owners have other more important incentives and thus, they care less about underpriced shares (Habib and Ljungqvist, 2001). These IPOs tend to offer only a small percentage of their shares during the offering (i.e., equity offer size is small) in order to achieve a major jump in the stock price during the first day of trading, which in turn increases the net value of the remaining shares the firm insiders own. The owners of the Chinese IPOs that plan on subsequent seasoned equity offering (SEO) would be less bothered by the money left on the table during the IPO event. Reportedly, this motive is especially prevalent among the Chinese reverse mergers (Chu et al., 2014; Ang et al., 2016), but it could be driving the cross-listing motive of some regular Chinese IPOs, as well.

Prospect theory assumes that issuers care about the change in their wealth rather than the level of wealth. Issuers will sum the wealth loss from leaving money on the table with the larger wealth gain on the retained shares from a price jump, producing a net increase in wealth for pre-issue shareholders (Loughran and Ritter, 2002). This incentive is part of the human nature of the firm owners, and thus it is likely true for all type of owners, including Chinese IPO owners.

2.4 Underwriter agency problems and other intermediary issues

Investment banks provide marketing, certification, and placement services (Ritter, 2011). They advise firm owners on the pricing of the IPO, help promote an IPO to increase investor

interest towards the stock, lead the distribution and placement efforts of the newly issued shares, and provide after-sales price support and analyst services. More succinctly, the underwriters are critical intermediaries that can affect the success of an IPO.

However, according to Hoberg (2007), Nimalendran et al., (2007), and Liu and Ritter (2011) some underwriters have a conflict of interest in that they convince the owners to accept underpricing of their stock shares, which then they allocate as a favor to preferred clients to generate short-term gains (underwriter agency problems).² Some issuers care less about the money left on the table, because they are more focused on post-IPO analyst coverage and favorable treatment during a subsequent SEO (Loughran and Ritter, 2004). An issuer may be willing to accept higher underpricing as a cost of receiving better analyst coverage in the post-IPO period. The less negotiating power an issuer has, the more likely it is that the underwriter can implement such selfish strategies. Thus, underwriter agency issues (Liu and Ritter, 2011; Chang et al., 2017) are expected to play a key role in the short-term performance (underpricing) of the Chinese IPOs, who are expected to have low negotiating power.

In the context of foreign listing, the problem of other intermediary issues could also arise, because Chinese firms have less experience with, and are less known to, U.S. financial markets. The choice of accounting auditor (e.g., choosing one of the Big 4 auditing firms)³ is reportedly an important indicator of the quality of a Chinese IPO (Chen et al, 2012; Ang et al., 2016). Some Chinese firms can choose to gradually build a positive reputation by avoiding earning management (Chu et al., 2014; Zhu et al, 2015), avoiding share-diluting large SEOs, and by hiring reputable

² Underwriters tend to use many other selfish strategies that, in one form or another, involve distorted short-term IPO pricing. Some of those strategies include IPO spinning (Loughran and Ritter, 2004; Liu and Ritter, 2010), laddering (Hao, 2007), favorable analyst coverage (Cliff and Denis, 2004; Dambra et al., 2018), and exchanging soft-dollar commission business in return for IPO allocation (Reuter, 2006).

³ *Big 4* refers to the four largest accounting and auditing firms: PricewaterhouseCoopers, Deloitte Touche Tohmatsu, Ernst&Young, and KPMG. These certified public accounting (CPA) firms perform most of the audits which are required from all the publicly listed U.S. firms.

auditors and investment bankers (Siegel 2005; Marosi and Massoud 2008). These intermediaries can monitor managers and improve the information environment of a foreign firm. These intermediaries can also help reconcile the cross-country differences in the earning reporting standards, and can help overcome the language and culture barrier.

2.5 Market timing

While there are many factors that affect the decision to conduct an IPO⁴, it is well established that the IPO activity, in general, depends on the current economic conditions (Lowry, 2003; Pastor and Veronesi, 2005). Thus, timing of an IPO event is usually considered important driver of its short- and long-run performance. Companies that successfully time their offerings for periods when valuations are high are more likely to have better after-listing market performance (Loughran and Ritter, 1995). IPO performance depends also on the prevailing investor sentiment for risky stocks during a given period (Derrien, 2005; Cornelli et al, 2006; Ljungqvist et al., 2006; Green and Hwang, 2012).

Furthermore, owners prefer to take their companies public when the expected cash flows are high, and firm's profitability is peaking and it is about to start declining (Benninga et al, 2005). Similarly, the quality composition of firms issuing during hot IPO markets is different than the ones issued during cold markets, which exacerbates the adverse selection costs during hot markets (Ritter, 1984; Helwege and Liang, 2004; Yung et al, 2008; Lowry et al, 2010). Evidence further shows that some high-quality companies may strategically postpone their initial public offerings dates until other issuers produce signals about the market conditions (Colak and Gunay, 2011).

⁴ The motives for conducting an IPO at a particular stage of a firm's life cycle are analyzed by various studies such as Chemmanur (1993), Zingales (1995), Pagano, et al. (1998), and Chemmanur and Fulghieri (1999), among others.

Product market competition and first mover advantages can also affect the IPO timing decision (Maksimovic and Pitchler, 2002; Chod and Lyandres, 2011).

2.6 Local institutional environment and market power

The cross-listing literature has emphasized the operating institutional environment as a key motivation behind the foreign firms' choice to list in U.S. (Siegel, 2005; Karolyi, 2006; Stulz, 2009; Francis et al. 2010). Specifically for China, several studies by He et al. (2012), Jindra et al. (2012), Siegel and Wang (2013) have claimed that one of the main reasons for underperformance of Chinese IPOs is the cultural and institutional differences between the U.S. and China. Givoly et al. (2014) pinpoint the openness and disclosure to the market participants as the main difference between failed Chinese IPOs and matched U.S. IPO firms.

Beside the historical, cultural, and institutional differences between U.S. and China, the differences across local regions within China make Chinese cross-listings a suitable sample to study the relative explanatory power of various IPO theories explained above. Chen et al., (2013) and Ang et al (2016) note that the severity of the institutional and cultural barriers between U.S. and China show major variation across various Chinese regions, which can explain why some Chinese IPOs are more successful than the others. In other words, the domestic regional markets in which Chinese companies operate in can help explain why some of them suffer from more severe intermediary and owner-related agency problems.

In light of the above claims, we consider the regional differences within China as a potential explanation for the quality differences among Chinese IPOs. The marketization level of each region can potentially explain which companies are more familiar with US-style market-driven institutional environment that fosters openness, disclosure, and fair practices. The marketization index by Fan et al. (2017), referred to as NERI Index, can capture such local marketization

differences between various regions in China. The five major components of the NERI Index are: (1) “relationship between government and market”, capturing the size of the government in the regional economy; (2) “development of non-state economy (ownership structure)”, which affects the growth of the non-state sector and provincial-level reform of state enterprises; (3) “goods market development”, measuring the trade barriers and the regional-level price controls; (4) “factors market development”, capturing the nature of the relationship between capital and labor; and (5) “legal frameworks”, which characterizes the legal framework for property-rights protection and contract enforcement of the region.

In addition to marketization, we also consider the importance (or market power) of the firm’s industry within the Chinese economy. When a firm operates in a large industry, it becomes a vital part of the Chinese economy and thus it is less likely to fail as an IPO. Such firms have more market power to affect the local business practices and the way institutions operate.

3. Methodology

3.1 High dimensional statistics

According to statistical theory, a high-dimensional data is the one whose dimension is larger than the dimensions considered by classical multivariate analysis. The main difference between the high-dimensional model and the traditional model (low-dimensional model such as OLS) is that the traditional statistical model is based on the classical asymptotic theory, which assumes that the number of parameters is a few and the number of observations is infinite, while the high-dimensional models usually involves a large set of variables with a fixed sample size. For example, the number of Chinese IPO samples is limited (our sample includes 278 Chinese IPO cases from 1993 to 2019), but the number of potential predictors (alternative measures and their interactions) is immense.

3.2 Ensemble machine learning

Ensemble methods are meta-algorithms that combine several machine learning techniques into one predictive model. This is a very powerful and widely adopted class of techniques. The subset of models that are combined is sometimes referred to as “weaker models,” since the results of these weaker models need not completely fulfil the expected outcome in isolation. There are two general kinds of the ensemble procedures – bagging and boosting. Bagging stands for bootstrap aggregation (to reduce the variance). Boosting refers to the process of converting weak learners to strong learners (to reduce bias).

The statistical framework describes boosting as a numerical optimization problem whose goal is to minimize the loss of the model by adding weak learners using gradient descent-like process. Boosting refers to the general problem of producing very accurate forecasting rules through a combination of rough and modest inaccurate empirical rules. In the boosting process, samples that can be estimated relatively correctly using previous base learners will be less emphasized in the following learners. Unlike other ensemble methods, such as random forests, the gradient boosting model provides relatively more useful information for the previous continuous model through a strategically re-sampling method to select examples in training data. In simple terms, the weights of selection of the training data set for the latter learners are not equal. Samples with larger multinomial deviance have higher weights. The latter learners are adjusted based on the deviance made by the previous learners.

3.3 Predictive models

In this paper, we consider two base models (weak learners) in constructing the boosting model, namely generalized linear model and regression/decision trees. In order to fully explore the predictive capabilities of the ensemble method, we also construct a bagging model based on

decision trees, namely random forest. We compare the predictive performance among four predictive models – generalized linear model (GLM), boosted generalized linear model (BGLM), gradient boosted trees (GBT), and random forest (RF).

In Boosted Generalized Linear Model (BGLM), a generalized linear model is fitted using a boosting algorithm based on component-wise univariate linear models (Buehlmann and Yu, 2003; Buehlmann, 2006). Like BGLM, gradient boosted trees (GBT) combines weak learners into a single strong learner in an iterative fashion. The difference is that GBT use regression/decision trees as base learners while BGLM use linear models as base learners. Random forest (RF) uses a bagging approach to create a set of regression trees with a random subset of the data. A model is trained several times on a random sample of the dataset to achieve good prediction performance. Average vote of the forest is selected as the predicted output. Further details about our predictive models can be found in Appendix A.

3.4 Interpretability

Accuracy and interpretability are two basic goals of predictive learning. However, these goals are not always consistent. While most sophisticated statistical learning methods provide predictions with very high accuracy, they sacrifice the ability to interpret the results. Compared to other popular machine learning techniques, such as artificial neural networks and support vector machines, the gradient-boosting model is designed to generate transparent rules that are easily interpretable by non-statisticians. Although gradient boosting models can be quite complex and involve many potential nonlinearities and the interactions between predictor variables, various standard outputs are available, making it easier to interpret the effects of different predictors. These outputs include (1) the variable important (VI) measure and (2) the partial dependence (marginal effect) plot.

The VI is a generic term for the degree to which a predictive model relies on a particular variable. It is a relative measure of how each predictor contributes to the model. Specifically, the VI is calculated as mean decrease in impurity (see, e.g., Friedman, 2001), which is the sum over the number of splits that include the feature, proportionally to the number of samples it splits. Typically, the VI is expressed as a scale between 0 and 100, where the most important variable gets assigned 100, and all other variables are readjusted to reflect their relative importance in comparison to the top variable.

Since our ML models are mostly nonlinear, the effect of each predictor on underpricing is complicated, and their coefficients cannot be represented by constants. One way to investigate the non-linear relationships is with partial dependence plots (PDP). These plots are graphical visualizations of the marginal effect of a given variable on underpricing. The slope of the graph, which depicts the non-linear relationship between each of the predictor and the underpricing value, can be understood as a dynamically changing coefficient as the value of the predictor changes.

4. Data and Sample

We start by retrieving Chinese American Depositary Receipts (ADRs) and other IPOs between 1993 and 2019 that listed on three major U.S. exchanges (NASDAQ, Amex, and NYSE) using the U.S. Common Stock Data File of Securities Data Company (SDC). From SDC we obtain various issuance-related features of the IPO firm, including the filing and issuance dates, the offer price, the first-day closing price, the total proceeds it raised, the total shares offered, the number of primary shares offered, the price revision before the IPO date, the name of the lead underwriter, whether the firm is backed by venture capital, and whether or not the firm is from a high-tech industry. The founding year of the IPO firm is from Field-Ritter dataset of company founding dates (downloaded from Jay Ritter's website), as used in Field and Karpoff (2002) and Loughran and

Ritter (2004). Underwriter reputation is the lead underwriter's reputation ranking at the time of the IPO, which is based on the updated Carter and Manaster (1990) classification. Our IPO market's heat indicator (Yung, Colak, and Wang, 2008) utilizes the quarterly IPO volume data going back to 1960, which in turn is retrieved from Jay Ritter's website.

From Compustat we obtain various annual fundamentals for our sample firms. Based on the fundamentals, we computed different accounting ratios used as predictor. Details are provided in Appendix B. We then merge our dataset of listed firms from Compustat with security prices (CRSP). CRSP provides delisting codes which allow us to determine the reason for delisting. Delisting code is a 3-digit integer code. It either (1) indicates that a security is still trading or (2) provides a specific reason for delisting. All coded delistings are categorized by the first digit of the delisting code. We follow Fama and French (2004) to classify CRSP delist codes 200-399 as a merger, code 570 and 573 are classified as voluntary delisting, and then classify the other codes that are 400 and above as involuntary delisting. A full list of involuntary delisting Chinese firms are provided in Appendix C. Also, from the daily CRSP data, we obtain the daily closing prices of the stock during the first few days of trading. The stock's monthly trading volume, the monthly stock returns, and the monthly CRSP index returns are obtained from the monthly CRSP data; as is the total shares outstanding of the IPO firm as of the end of the first trading month. The institutional holdings information is from Thomson 13F Institutional Holdings database. We get marketization index (Fan index) for each of the Chinese provinces for each year from Fan et al. (2017) and acquire the location of headquarter of each firm from bloomberg.com, and company's website. Additionally, we retrieve all Chinese companies' annual assets, revenue, and sales from Global Compustat.

The above screening criteria leave us with a sample of 278 Chinese IPOs during the period of 1993 to 2019. The yearly distribution of total numbers of IPO and numbers of regulatory delistings over the sample period can be found in Panel A on Table 1 and the distribution of headquarters can be found in Panel B on Table 1. A visualized yearly distribution of IPOs and average underpricing is plotted on Figure 1. A more detailed description of all the variables used in this study is provided in the Appendix B.

Insert Table 1 and Figure 1 Here

5. Empirical Analyses

5.1. Construction of predictors

As opposed to traditional parametric model where very few variables can be included in the baseline regression to prevent overfitting, machine learning is capable to deal with high dimensional data where large number of variables are included. In this study, we incorporate 25 pre-listing variables that measures different aspects of firm- and issuance-related characteristics.

Information asymmetry measures are drawn from the literature that have been proved to explain IPO performance. Specifically, we include firm age, institutional holdings (Loughran and Ritter, 2002), venture capitalists dummy (Liu and Ritter, 2011), high-tech dummy (Colak, Durnev, and Qian, 2017), intangible ratio and R&D to sales (Marosi and Massoud, 2008). To measure the quality of a firm, we use the ratios related to companies' profitability and earnings that have been widely captured by the market as signals. Specifically, the set of quality indicators includes: cash flow volatility, ROA volatility, cash to asset, earnings ratio, liquidity ratio, CAPEX to sales, free cash flow to assets, and tax ratio. Owners' agency issues are measured by equity offer size, institutional holdings, proportion of primary shares, and dividend dummy. Underwriter agency problems and other intermediary issues are captured by underwriter reputation, underwriter agency

measure, Big 4 auditor dummy. Market timing is measured by market return and market heat degree. Additionally, we measure the market power of the industry in which each company operates based on the ratio of the industry's total assets to the total assets of all Chinese firms (mktpower1), the ratio of the industry's total revenue to the total revenue of all Chinese firms (mktpower2). Also, institutional environment is measured by the yearly Fan index of each province where the company's headquarters is located.

The definition and related predictor variables are presented in Table 2. A more formal definitions of the variables used in this study, including the data source are in Appendix B. The descriptive statistics are presented in Table 3.

Insert Table 2 and Table 3 Here

5.2 Construction of model

We divide the samples into a training set and a testing set according to the chronological order of the IPOs. Specifically, IPOs that occurred from 1993 to 2015 were assigned to the training set, and IPOs that occurred after 2015 were assigned to the testing set⁵.

We train machine learning models using all 25 predictors introduced above to examine the market performance of U.S. listed Chinese firms from three different angles: the underpricing (or short-term market performance), the underperformance (or long-term market performance), and regulatory exchange delistings (IPO failure).⁶ The objective of this study is to test the predictability of the market performance of U.S. listed Chinese firms during and after the IPO event in order to find out the most reliable predictors of this performance.

⁵ In the models of predicting regulatory delisting, we use 2007 as the cut-off point to have enough delisting cases in the test set.

⁶ Data pre-processing was performed before training the models, where missing values were imputed based on the cross-sectional median.

We compare the predictive performance among three machine learning models, including boosted generalized linear model (BGLM), gradient boosted trees (GBT), and random forest (RF). As the baseline model, we also train a generalized linear model (GLM) using the same sample. The paper uses 3-folds cross-validation method to select the best model parameters. We allow up to 3 way of interaction of the predictors. Models are selected based on the minimized loss function, which is mean squared error for the case of predicting the underpricing and underperformance and logistic loss for the case of predicting the regulatory delisting. Variable relative influence scores are computed on the training sample, and the model performances are evaluated on the testing set.

5.3. Prediction of short-term market performance

To measure the short-term market performance, we use the first day return, computed as the first trading day closing price over the offer price, minus one. In our sample, Chinese listing are on average underpriced by about 21.3%. However, the level of underpricing differs a lot across different Chinese firms. To test the predictability of first day return, we run the four predictive models on the sample. The comparison of predictive performance of all models on the testing sample can be found in Panel A on Table 4.

Insert Table 4 Here

GLM has the worse out-of-sample performance, with R-squared of 0.01. This is a clear sign that GLM has over-fitted the training samples and the model is not very effective in out of sample prediction. Applying the boosting algorithm and fit linear models via component-wise boosting improves the predictive performance as the BGLM has a R-squared of 0.026. It can be interpreted as the boosting process helps combining weak GLM into a strong GLM that better captures the trend of out-of-bag data. Adding flexibility by replacing the base learner with regression trees further improves the performance substantially, as GBT has an out-of-sample R-

squared of 0.404. It shows that the regression tree that captures the non-linear characteristics of the relationship is more suitable for use as a basic learner to reflect the nature of IPO underpricing. RF also use tree-based learner, but it differs from GBT in the way the trees are built. While GBT build trees one at a time where each new tree helps to correct errors made by previously trained tree, RFs train each tree independently, using a random sample of the data. Based on the out-of-sample R-squared, RF performs worse than GBT with R-squared of 0.21.

To get a more thorough understanding of the predictive accuracy, we also test the out of sample root mean squared error (RMSE) and mean absolute error (MAE). Whereas R-squared is a relative measure of fit, RMSE and MAE is an absolute measure of fit. RMSE is the square root of the average of squared differences between prediction and actual observation and MAE is the average of the absolute differences between prediction and actual observation. Still, GBT outperforms other models with the lowest RMSE and MAE (RMSE of 30.109 and MAE of 21.377). It is not surprisingly that GBT model has the best predictive performance since the GBT model inherit the merits from both boosting process and non-linear tree base learner.

Next, we investigate the relative importance of individual covariates for the performance of the model. Instead of searching for highly significant variables using *t*-stats (or *p*-values), machine learning focuses on locating highly predictive variables using relative ranking by variable importance. Panel A in Table 5 reports the variable importance for the top 10 most influential variables selected by GBT.

Insert Table 5 Here

As discussed in Section 3.4, a variable's importance (VI) is calculated as mean decrease in impurity (see, e.g., Friedman, 2001), which is the sum over the number of splits that include the feature, proportionally to the number of samples it splits. Essentially, the VI represents a variable's

relative predictive ability of the first day return. While predictors representing all different aspects have some level of predictive power, the most reliable predictors are measures related to intermediary issues and owners' agency issue. The underwriter agency problems measure, in particular, sticks out as being a clear number one predictor of underpricing with a VI of 100. owners' agency issue measures of equity offer size and institutional holding ranked the second and the third with VIs of 29.38 and 20.11 respectively. Information asymmetry measure and market timing measure also play a role in predicting an IPO's underpricing, but they are much less powerful than the underwriter agency problem measure (R&D to sales and market return have VIs of 15.48 and 13.51, respectively). Thus, the results in Panel A highlight certain novel findings for the literature: underwriter agency issues are the most reliable predictor of a Chinese IPO's underpricing. This result is consistent with the findings of Chang et al. (2017).

Since GBT model is a nonlinear model, the marginal effect of each predictor on the first day return cannot be represented by a constant. One way to investigate the non-linear relationships is, thus, with partial dependence plots. These plots are graphical visualizations of the marginal effect of a given variable on first day return. The slope of the graph, which depicts the non-linear relationship between each of the predictor and the first day return, can be understood as a dynamically changing coefficient as the value of the predictor changes. The dependence plot for the top-ranked four predictors is reported in Figure 2.

Insert Figure 2 Here

As we reported in Panel A of Table 5, the best predictor is the underwriter agency measure, indicating that the choice of underwriter has a strong predictive power to first day return. Those firms who chose underwriter with long history of underpricing is more likely to underprice their shares when listing. As can be seen from the first plot, while between the first and third quartile,

underwriter agency measure substantially increases the underpricing (very steep curve), increase in the underwriter agency measure has little incremental effect to the underpricing in the latter quartile (the curve is fairly flat). Similarly, the second plot (*equity offer size*) reveals the non-linear nature of the dependence of underpricing on the equity offer size. The general trend shows a negative dependence of underpricing on equity offer size. This indicates that underpricing is concentrated in the issues where firm issues only a tiny fraction of their shares during the IPO. Such decisions may have been made with the intent of rewarding investors with a higher first-day return in order to issue more shares later on in the post-IPO market (seasoned equity offering), which confirms that owners' agency issue is a serious problem for the Chinese cross-listings.

To illustrate some of the differences between GBT and OLS, we run OLS on the full sample using top 10 variables that have highest VIs in the GBT model. Panel B in Table 5 displays the regression results.⁷ As OLS must perform regression on observations where all variables are not missing (observations with missing value are removed case-wise), only 58 observations are included even when we take the whole sample into account. Such a requirement of all variables being non-missing will not only greatly reduce the sample size, but more importantly, this non-random sample selection prevents the regression sample from representing the population, which in turn, can lead to misleading statistical inference and wrong economic conclusions. As can be seen from Panel B, with these 58 observations, OLS find most variables to be statistically insignificant. Nine out of ten variables are not significant even at 10% level, suggesting they contribute very little to overall model performance. This, in turn, prevent us from making reliable

⁷ R-squared reported in this table is in-sample R-squared where model is built and evaluated using the full sample. It is different from the out of sample R-squared reported earlier where model is built in the training sample and R-squared is computed on testing sample using the fitted model.

economic conclusions about the true drivers of underpricing in Chinese IPOs when OLS is used as our analytical tool.

5.3. Prediction of long-term market performance

Newly listed firms, in general, typically experience a significant under-performance relative to their peer firms in the subsequent 3 years after issuance (Ritter, 1991; Loughran and Ritter, 1995). However, Chinese firms in the U.S. generally underperform relative to a typical IPO and relative to their industry peers in the post-IPO period of 3 years. To examine the predictors of this long-run underperformance of the Chinese IPOs and ADRs, we construct the buy and hold abnormal returns relative to the benchmark index of CRSP equally-weighted index during the 36 months period after the issuance. We define the buy and hold abnormal return (BHAR36) for each stock as the geometric average abnormal rate of return over the time periods of 36 months relative to the benchmark index.

We use the four models to predict the BHAR36 for all listed Chinese firms. Again, GBT model has a better performance than the other three models. As shown in Panel B on Table 4, the GBT model produces a decent predictive accuracy with out of sample R-squared of 0.054, RMSE of 170.94 and MAE of 135.91. GLM technique, on the other hand, has a much worse performance with out of sample R-squared of 0.03, RMSE of 965.45 and MAE of 475.32. GBML and RF have out-of-sample performances in between GLM and GBT. Again, to investigate their relative importance, we compute the variable importance of each variable in optimizing the model. Panel A in Table 6 reports the variable importance for the top 10 most influential variables. The dependence plot for the top-ranked predictors is reported in Figure 3.

Insert Table 6 and Figure 3 Here

The top predictors of BHAR36 differ from the first test (underpricing), as other measures of firm quality become important. The best predictor of BHAR36 is underwriter agency measure, which again emphasizes the fact that Intermediary issues are important issues that affect Chinese firms' long-term market performance. Firm quality measures have a good predictive power of the long-run performance. Variables such as free cash flow to asset, cash to asset, cash flow volatility, liquidity ratio, earnings ratio, and tax ratio rank high in the list of most reliable predictors (Panel A of Table 6), which confirms the power of signaling theory in explaining long-run returns. In the environment where investors have less information about the firms' true value, they rely more on some general operational indicators. Market power of the industry in which each company operates matters when predicting the long-run market performance, as market power measured by revenue and assets ranked the eighth and the tenth. The firms in industry that has higher market power are more recognized by the investors. As oppose to the GBT model, regression results for the OLS model reported in Panel B of Table 6 shows insignificant coefficient for most variables, indicating OLS is not capable to find the relationship between these predictors and long-run market performance with this sample.

5.4. Prediction of regulatory delisting

An extreme case of an IPO failure is the regulatory delisting within short period of time following the issuance date (Demers and Joos, 2007; Yung et al, 2008). Such a forced delisting almost always implies a failed business model, which is associated with rapid and sharp declines in stock returns. Over the sample period, 25 Chinese firms involuntarily delisted due to inability to meet exchange requirements.

Again, we use four models to predict the likelihood of regulatory delisting of the Chinese firms. Panel C of Table 4 indicates that our GBT is still the best model that shows very promising

predictive power, with out-of-sample predictive accuracy (the fraction of right predictions) of 0.85. The other three models do worse jobs in predicting which firm got regulatory delisting, with out-of-sample predictive accuracy of 0.76, 0.66, and 0.68 respectively. More importantly, GBT has outperformed the other models in both recognizing those firms that got delisted and those that stayed listed. Specifically, our GBT model has sensitivity of 0.88 and specificity of 0.40.⁸ As the sample distribution of listed Chinese firms is very skewed (compared to listed firms, firms that experience regulatory delisting are very few), we test the area under ROC (receiver operating characteristics) curve (AUC), which is threshold insensitive measure of the model (Fawcett, 2006). Specifically, AUC tells how much model is capable of distinguishing between different classes. The AUC of GBT model is 0.72, indicating that the model has a decent classification ability to diagnose firms who will experience regulatory delisting. On the contrary, GLM and BGLM model have AUC of 0.50 and 0.41 respectively, representing failed classification models. Similar to previous analysis, we test the variable importance of the GBT model. Panel A in Table 7 reports the variable importance for the top 10 most influential variables in the GB model and Figure 4 plots the dependence plot for the top-ranked predictors. Panel B in Table 7 shows the results of logistic regression using full sample.

Insert Table 7 and Figure 4 Here

The measures of owners' agency issues are the most important variables in the prediction of a Chinese IPO's likelihood of failure in the post-issuance period (3 years). The top two predictors are equity offer size (VI of 100) and institutional holding (VI of 98.69). This emphasizes how important are the agency issues relative to the financial performance of the IPOs. Those issuers

⁸ Sensitivity (or the true positive rate, the recall) measures the proportion of actual positives (regulatory delisting) that are correctly identified. Specificity (or true negative rate) measures the proportion of actual negatives (stay listed) that are correctly identified. Balanced accuracy is the average of sensitivity and specificity.

who intentionally keep equity offer size small in order to raise money through equity offering after the IPO are likely to end up getting delisted. Also, higher percentage of institutional holdings at initial offering is positively related to higher probability to survivorship. Pre-listing firm quality has a profound impact on a listed Chinese company. Pre-listing firm quality measures of free cash flow to asset, earnings ratio, cash flow volatility (ranked the third to the fifth) have predictive power to delisting. A listed Chinese firm with poor operating performance gives investors bad impression may eventually lead to a regulatory delisting from the U.S. exchanges.

6. Conclusion

Chinese companies listed in the United States represent some of the best values in China today. Because of its historical position and its size, the US market is attractive to the most promising Chinese growth companies. However, as more of their predecessors are undervalued and marginalized, some Chinese companies that have not yet listed in the US may worry about the US market. In this study, we show the reasons behind some Chinese companies' poor performance in the US market, which can provide very useful guidance for latecomers.

Chinese cross-listings a unique sample that allow for better testing of various IPO theories as many cross-firms and cross-regional differences within the domestic markets can be exploited using novel methodologies like machine learning. While machine learning models (e.g. gradient boosting) do not provide causal interpretation, they provide a better way to learn from the data (Kleinberg et al, 2017; Mullainathan and Spiess, 2017; Athey and Imbens, 2019). Compared to other econometric methods, which provide a means to interpret historical data, machine learning methods leave the task of learning from the data to the machine so that better predictive models can be implemented. That is, machine learning's good out-of-sample data prediction ability allows

us to predict the future by learning from historical data. people can focus on applying the knowledge learned from historical data to practical problems.

In this study, we find underwriter agency problems (Cheng et al, 2017) and other intermediary issues (not having prestigious auditors) to be among the most reliable predictors of the market performance of U.S. listed Chinese firms. Local regional differences in marketization and lower inherent firm quality also make it hard for some Chinese firms to survive. Equity offer size, which reflects owners' related agency problems (money left on the table), is also an important predictor of a Chinese IPO's performance. To survive and succeed in the U.S. market, it's important for a Chinese firm to choose the right intermediaries (underwriters and auditors), and to optimize the equity retention through reasonably choosing the equity offer size. Such considerations become even more important if the local regional market the firm operates in has weak market institutions and if the firm has lower market power at home.

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Figure 1: Yearly distribution of IPOs and average underpricing

Figure 1 plots yearly distribution of the total number of IPOs (left axis) and the average underpricing (right axis). Our sample includes 278 Chinese IPOs during the period of 1993 to 2019.

Figure 2: Partial dependence plot for top predictors of first-day returns

Figure 2 plots the partial dependence of top 4 predictors on underpricing. These plots are graphical visualizations of the marginal effect of a given variable on first day return. The y value (vertical axis) is the dependence of IPO underpricing on a specific predictor, marginalized over all other predictors. It calculates the importance of a feature by comparing what a model predicts with and without the feature.

Figure 3: Partial dependence plot for top predictors of BHAR36s

Figure 3 plots the partial dependence of top 4 predictors on BHAR36. These plots are graphical visualizations of the marginal effect of a given variable on BHAR36. The y value (vertical axis) is the dependence of BHAR36 on a specific predictor, marginalized over all other predictors. It calculates the importance of a feature by comparing what a model predicts with and without the feature. A negative y value indicates negative dependence which suggests that as the predictors increases, the target variable (BHAR 36) tends to decrease.

Figure 4: Partial dependence plot for top predictors of regulatory delisting

Figure 4 plots the partial dependence of top 4 predictors on regulatory delisting. These plots are graphical visualizations of the marginal effect of a given variable on regulatory delisting. The y value (vertical axis) is the dependence of regulatory delisting on a specific predictor, marginalized over all other predictors. It calculates the importance of a feature by comparing what a model predicts with and without the feature. The target variable (regulatory delisting) is a dummy variable that is 1 when delisted, and 0 otherwise.

Table 1. Distribution of Chinese listings (1993-2019)**Panel A. Yearly distribution of Chinese listings**

Year	Total # of listings	# of IPOs that were eventually regulatory delisted	# of Regulatory Delisting this year
1993	1	0	0
1994	4	0	0
1995	1	1	0
1996	1	0	0
1997	2	0	1
1998	1	1	0
1999	1	1	0
2000	6	0	0
2001	2	0	0
2002	1	0	0
2003	2	0	0
2004	10	0	0
2005	8	2	0
2006	10	0	1
2007	32	10	0
2008	7	1	3
2009	15	4	4
2010	42	3	4
2011	14	2	2
2012	4	0	3
2013	8	0	4
2014	14	0	1
2015	10	0	1
2016	8	0	0
2017	20	0	0
2018	37	0	1
2019	17	0	0
Total	278	25	25

Panel B. Distribution of headquarter locations

Headquarters	# of listings
BEIJING	110
SHANGHAI	57
GUANGDONG	40
ZHEJIANG	19
JIANGSU	10
HONG KONG	8
SHANDONG	7
FUJIAN	5
HUBEI	4
LIAONING	4
HEBEI	2
HENAN	2
JILIN	2
ANHUI	1
CHONGQING	1
JIANGXI	1
SHAANXI	1
SICHUAN	1
TIANJIN	1
XINJIANG	1
YUNNAN	1
Total	278

Table 1 shows the distribution of Chinese listing over the sample period. Panel A includes the yearly distribution of total numbers of listings and numbers of regulatory delisting and Panel B shows the distribution of headquarters. Our sample contains 278 Chinese listing during the period of 1993 to 2019.

Table 2. The predictors and the related hypotheses

Variable	Description	Dimension
firm age	The number of years since founding year to the IPO year.	Information asymmetry
high_tech	A dummy variable equals one if the IPO is a hi-tech firm, zero otherwise	Information asymmetry
VC	A dummy variable equals one if the IPO firm is VC-backed, zero otherwise.	Information asymmetry
proportion of primary shares	Proportion of the primary shares within the pool of total offered shares.	Owners' agency issues
underwriter reputation	Lead underwriter reputation ranking at the time of the IPO, a value between 9 (best) and 0 (worst)	Intermediary issues
market heat degree	The ratio of current quarter's number of IPOs to the moving average of the number of IPOs during the past 10 years (40 quarters).	Market timing
market return	The buy-and-hold return of the S&P 500 Index during the 12-month period prior to the IPO date.	Market timing
cash flow volatility	The standard deviation of the quarterly cash flows of a company calculated over the prior 12 quarters. Compustat's Quarterly data is used. When matching with the annual data, we take the standard deviation values as of the fourth fiscal quarter (end of the fiscal year).	Firm quality
ROA volatility	The standard deviation of the quarterly return on assets (ROA) variable of a company calculated over the prior 12 quarters period. Compustat's Quarterly data is used. When matching with the annual data, we take the standard deviation values as of the fourth fiscal quarter (or the end of the fiscal year).	Firm quality
institutional holding	The fraction of the shares outstanding owned by institutional investors as of the end of the first quarter following the IPO date.	Owners' agency issues
equity offer size	The ratio of the number of shares issued at IPO date to the total number of shares outstanding after the public offering.	Owners' agency issues
underwriter agency measure	The moving average of the underpricing of all the IPOs issued by that Underwriter up to that point.	Intermediary issues
big 4 auditor dummy	A dummy variable equals one if the IPO is audited by the 4 largest accounting and auditing firms, zero otherwise.	Intermediary issues
intangible ratio	The ratio of total intangibles to total assets.	Information asymmetry
dividend	A dummy variable equals one if the firm distributed dividend during the IPO year, zero otherwise.	Owners' agency issues
CAPEX to sales	The ratio of capital expenditures to sales.	Firm quality
R&D to sales	The ratio of R&D expenses to sales.	Information asymmetry
tax ratio	The ratio of total income taxes to sales	Firm quality
cash to asset	The ratio of cash and short-term investment to total assets	Firm quality
free cash flow to asset	Operating income before depreciation minus income taxes minus interest expense minus dividends scaled by total assets.	Firm quality
earnings ratio	The ratio of EBIT to total assets.	Firm quality
liquidity ratio	Current assets minus equity scaled by current liabilities.	Firm quality
mktpower1	The ratio of the industry's total assets to the total assets of all Chinese firms	Market power
mktpower2	The ratio of the industry's total revenue to the total revenue of all Chinese firms	Market power
marketization	The yearly Fan index of each province where the company's headquarters is located.	Institutional environment

Table 2 lists the predictors used in our GB models. We also show the definitions and the related hypotheses that these measures represent. Information asymmetry measures include firm age, institutional holding, venture capitalists dummy, high-tech dummy, intangible ratio and R&D to sales. Firm quality measures include cash flow volatility, ROA volatility, cash to asset, earnings ratio, liquidity ratio, CAPEX to sales, free cash flow to asset and tax ratio. Agency issues are measured by equity offer size, institutional holding, proportion of primary shares and dividend dummy. Intermediary issues are captured by underwriter reputation, underwriter agency measure, big N auditor dummy. Market timing is measured by market return, and market heat degree. Market power1 is measured by the ratio of the industry's total assets divided by the total assets of all firms in China. Market power2 is measured by the ratio of the industry's total revenue divided by the total revenue of all firms in China. Institutional environment is proxied by the yearly Fan index of each province where the company's headquarters is located.

Table 3. Univariate comparisons**Panel A. Positive first day return vs. negative first day return**

	<u>Negative first day return</u>		<u>Positive first day return</u>		<u>Dif. <i>t</i> test</u>
	Mean	N	Mean	N	Diff.
firm age	9.1290	31	6.8426	108	2.2864
high_tech_dummy	0.4746	59	0.4932	219	-0.0186
VC_dummy	0.5085	59	0.3973	219	0.1112
proportion of primary shares	0.8812	58	0.9814	214	-0.1002
underwriter reputation	6.4342	30	5.0528	77	1.3814*
market heat degree	0.9379	59	0.9808	219	-0.0428
market return	10.2329	53	11.0583	208	-0.8254
cash flow volatility	0.0544	34	0.0656	82	-0.0112
ROA volatility	0.0521	34	0.0414	82	0.0106
institutional holding	0.0794	40	0.1516	118	-0.0722**
equity offer size	0.2384	40	0.2361	118	0.0023
underwriter agency measure	91.2969	54	46.5437	154	44.7532
big 4 auditor dummy	0.6271	59	0.4475	219	0.1796**
intangible ratio	0.0804	36	0.0467	103	0.0337
dividend dummy	0.0847	59	0.1324	219	-0.0477
CAPEX to sales	0.1425	27	0.1960	85	-0.0535
R&D to sales	0.0320	59	0.0390	219	-0.0070
tax ratio	0.0295	27	0.0267	85	0.0027
cash to asset	0.3255	29	0.3722	88	-0.0467
free cash flow to asset	0.0414	23	-0.1007	79	0.1421
earnings ratio	0.0308	27	-0.0134	84	0.0441
liquidity ratio	2.4031	29	3.3623	85	-0.9592
mktpower1	0.0042	36	0.0035	111	0.0007
mktpower2	0.0065	36	0.0048	111	0.0017
marketization	8.1121	57	8.9105	213	-0.7984***

Panel B. Positive BHAR36 vs. negative BHAR36

	<u>Negative BHAR36</u>		<u>Positive BHAR36</u>		<u>Dif. <i>t</i> test</u>
	Mean	N	Mean	N	Diff.
firm age	7.6337	101	6.6053	38	1.0284
high_tech_dummy	0.5798	119	0.4214	159	0.1584***
VC_dummy	0.5210	119	0.3459	159	0.1751***
proportion of primary shares	0.9060	118	1.0015	154	-0.0955
underwriter reputation	6.2430	64	4.2450	43	1.9980***
market heat degree	0.8837	119	1.0375	159	-0.1539***
market return	10.7634	119	10.9974	142	-0.2340
cash flow volatility	0.0645	87	0.0555	29	0.0090
ROA volatility	0.0497	87	0.0292	29	0.0205
institutional holding	0.1356	109	0.1281	49	0.0075
equity offer size	0.2207	109	0.2724	49	-0.0517
underwriter agency measure	62.0091	112	53.6743	96	8.3348
big 4 auditor dummy	0.7563	119	0.2830	159	0.4733***
intangible ratio	0.0496	96	0.0686	43	-0.0190
dividend dummy	0.1933	119	0.0692	159	0.1241***

CAPEX to sales	0.1963	75	0.1565	37	0.0397
R&D to sales	0.0468	119	0.0306	159	0.0161
tax ratio	0.0287	75	0.0247	37	0.0040
cash to asset	0.3665	79	0.3483	38	0.0182
free cash flow to asset	-0.0880	68	-0.0299	34	-0.0582
earnings ratio	0.0312	75	-0.0731	36	0.1043
liquidity ratio	3.3198	77	2.6990	37	0.6208
mktpower1	0.0038	72	0.0036	75	0.0002
mktpower2	0.0060	72	0.0044	75	0.0016
marketization	8.7837	117	8.7100	153	0.0737

Panel C. Regulatory delisted Chinese IPOs vs. other Chinese IPOs

	<u>Stay listed & Other Delistings</u>		<u>Regulatory delisted</u>		<u>Dif. <i>t</i> test</u>
	Mean	N	Mean	N	Diff.
firm age	7.5776	116	6.2174	23	1.3602
high_tech_dummy	0.4980	253	0.4000	25	0.0980
VC_dummy	0.4269	253	0.3600	25	0.0669
proportion of primary shares	0.9487	247	1.0720	25	-0.1233
underwriter reputation	5.3903	86	5.6438	21	-0.2534
market heat degree	0.9947	253	0.7386	25	0.2561***
market return	10.7857	236	11.8824	25	-1.0967
cash flow volatility	0.0662	98	0.0411	18	0.0250
ROA volatility	0.0412	98	0.0625	18	-0.0213
institutional holding	0.1346	137	0.1249	21	0.0097
equity offer size	0.2465	137	0.1728	21	0.0736
underwriter agency measure	61.3889	185	32.2092	23	29.1797
big 4 auditor dummy	0.4704	253	0.6400	25	-0.1696
intangible ratio	0.0602	114	0.0340	25	0.0262
dividend dummy	0.1146	253	0.2000	25	-0.0854
CAPEX to sales	0.1922	96	0.1289	16	0.0633
R&D to sales	0.0405	253	0.0080	25	0.0324
tax ratio	0.0259	96	0.0367	16	-0.0108
cash to asset	0.3774	100	0.2615	17	0.1160*
free cash flow to asset	-0.0989	87	0.1068	15	-0.2057
earnings ratio	-0.0381	95	0.2079	16	-0.2460*
liquidity ratio	3.3540	98	1.6742	16	1.6798
mktpower1	0.0035	130	0.0048	17	-0.0012
mktpower2	0.0046	130	0.0100	17	-0.0054*
marketization	8.7561	247	8.5896	23	0.1665

Table 3 shows the univariate results for three different comparisons. Panel A shows the comparison between firms with positive first day return and firms that have negative first day return. Panel B shows the comparison between firms that have positive BHAR36 and firms with negative BHAR36. Panel C shows the comparison between firms that experienced regulatory delisting and the other firms. Information asymmetry measures include firm age, institutional holding, venture capitalists dummy, high-tech dummy, intangible ratio, and R&D to sales. Firm quality measures include cash flow volatility, ROA volatility, cash to asset, earnings ratio, liquidity ratio, CAPEX to sales, free cash flow to asset, and tax ratio. Agency issues are measured by equity offer size, institutional holding, proportion of primary shares, and dividend dummy. Intermediary issues are measured by underwriter reputation, underwriter agency measure, big N auditor dummy. Market timing is measured by market return, and market heat degree. Market power1 is measured by the ratio of the industry's total assets divided by the total assets of all firms in China. Market power2 is measured by the ratio of the industry's total revenue divided by the total revenue of all firms in China. Institutional environment is captured by the yearly Fan index of each province where the company's headquarter is located.

Table 4. Comparison of out-of-sample performance

Panel A. Prediction of Underpricing					
			RMSE	R-squared	MAE
GLM			45.714	0.010	34.938
BGLM			40.752	0.026	31.231
GBT			30.109	0.404	21.377
RF			34.380	0.210	25.180
Panel B. Prediction of BHAR 36					
			RMSE	R-squared	MAE
GLM			965.447	0.003	475.322
BGLM			369.665	0.009	195.252
GBT			170.944	0.054	135.907
RF			172.701	0.001	135.013
Panel C. Prediction of regulatory delisting (IPO failure)					
	Accuracy	AUC	Sensitivity	Specificity	Balanced Accuracy
GLM	0.760	0.498	0.780	0.400	0.590
BGLM	0.658	0.405	0.683	0.200	0.441
GBT	0.852	0.716	0.876	0.400	0.638
RF	0.679	0.603	0.817	0.200	0.509

Table 4 shows the out of sample predictive performance for all models. Panel A presents the results for first day return prediction and long run market performance prediction. We use Mean Absolute Error (*MAE*) and Root mean squared error (*RMSE*) to measure the predictive accuracy. *MAE* measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight. *RMSE* is a quadratic scoring rule that also measures the average magnitude of the error. It's the square root of the average of squared differences between prediction and actual observation. Panel B present the results for regulatory delisting prediction. *Accuracy* is the fraction of right predictions. *Sensitivity* (or the true positive rate, the recall) measures the proportion of actual positives (regulatory delisting) that are correctly identified. *Specificity* (or true negative rate) measures the proportion of actual negatives (stay listed) that are correctly identified. *Balanced accuracy* is the average of sensitivity and specificity. *AUC* (or the area under receiver operating characteristics curve) is a threshold insensitive measure that tells how much model is capable of distinguishing between classes.

Table 5. Prediction of first-day return**Panel A: Top 10 predictors to first-day return using GBT**

<i>Dimension</i>	<i>Variables</i>	<i>Variable Importance Score</i>
Intermediary issues	underwriter agency measure	100.000
Owners' agency issues	equity offer size	29.380
Owners' agency issues	institutional holding	20.111
Information asymmetry	R&D to sales	15.484
Market timing	market return	13.513
Firm quality	ROA volatility	11.314
Market timing	market heat degree	8.783
Institutional environment	marketization	8.238
Firm quality	tax ratio	8.189
Firm quality	cash flow volatility	4.894

Panel B: Regression results of top 10 determinants to first-day return using OLS

<i>Dependent variable: Underpricing</i>	
underwriter agency measure	0.03 (0.72)
equity offer size	43.55 (0.92)
institutional holding	-8.25 (-0.13)
R&D to sales	10.74 (0.32)
market return	0.60 (0.82)
ROA volatility	25.26 (0.16)
market heat degree	4.63 (0.13)
marketization	-1.37 (-0.29)
tax ratio	-464.52* (-1.95)
cash flow volatility	67.27 (0.30)
constant	24.86 (0.42)
Observations	58
R-squared	0.14
Adjusted R-squared	-0.04
Residual Std. Error	63.24 (df = 47)
F Statistic	0.78 (df = 10; 47)

Table 5 shows the important predictors of the first-day returns. Panel A presents the variable's importance (VI) score for top 10 predictors selected by GBT. A variable's importance (VI) reflects the increase in the model's prediction error after we permuted the variable's values. Essentially, the VI represents a variable's relative predictive ability of the first day return. Panel B shows the regression results of the top 10 predictors to the underpricing using OLS (the numbers in parentheses are *t*-statistics). Detailed variable definitions and sources are in Appendix B. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6. Prediction of long-run market performance**Panel A: Top 10 predictors to BHAR36 using GBT**

<i>Dimension</i>	<i>Variables</i>	<i>Variable Importance Score</i>
Intermediary issues	underwriter agency measure	100.000
Firm quality	free cash flow to asset	95.040
Firm quality	cash to asset	95.021
Firm quality	cash flow volatility	92.037
Firm quality	liquidity ratio	80.249
Firm quality	earnings ratio	80.011
Firm quality	tax ratio	60.054
Market power	mktpower2	54.016
Market timing	market return	32.129
market power	mktpower1	29.137

Panel B: Regression results of top 10 determinants of BHAR36 using OLS

	<i>Dependent variable: BHAR36</i>
underwriter agency measure	-0.003 (-0.71)
free cash flow to asset	-31.37** (-2.13)
cash to asset	-10.12** (-2.11)
cash flow volatility	-7.95 (-0.37)
liquidity ratio	-0.04 (-0.23)
earnings ratio	-8.61 (-0.65)
tax ratio	-41.20 (-1.19)
mktpower2	-97.29 (-0.24)
market return	-0.22** (-2.18)
mktpower1	1.48 (0.01)
constant	12.45*** (4.02)
Observations	42
R-squared	0.53
Adjusted R-squared	0.38
Residual Std. Error	665.08 (df = 31)
F Statistic	3.55*** (df = 10; 31)

Table 6 shows the important predictors of long-term market performance. Panel A presents the variable's importance (VI) score for top 10 predictors selected by GBT. A variable's importance (VI) reflects the increase in the model's prediction error after we permuted the variable's values. Essentially, the VI represents a variable's relative predictive ability of the first day return. Panel B shows the regression results of the top 10 predictors to the BHAR36 using OLS (the numbers in parentheses are *t*-statistics). Detailed variable definitions and sources are in Appendix B. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7. Top predictors to regulatory delisting**Panel A: Top 10 predictors of IPO failure (delisting) using GBT**

<i>Dimension</i>	<i>Variables</i>	<i>Variable Importance Score</i>
Owners' agency issues	equity offer size	100
Owners' agency issues	institutional holding	98.68720799
Firm quality	free cash flow to asset	89.18618113
Firm quality	earnings ratio	80.87851647
Firm quality	cash flow volatility	78.32762184
Market power	mktpower1	62.63300364
Firm quality	CAPEX to sales	56.40003562
Information asymmetry	firm age	55.44278187
Market timing	market heat degree	55.35167054
Intermediary issues	big 4 auditor dummy	54.36715012

Panel B: Regression results of top 10 determinants of IPO failure (delisting) using logit

	<i>Dependent variable: Delisted</i>
equity offer size	-1.70 (-0.24)
institutional holding	7.60 (0.52)
free cash flow to asset	2.23 (0.37)
earnings ratio	1.86 (5.09)
cash flow volatility	-0.78 (-0.09)
mktpower1	-536.41 (-0.53)
CAPEX to sales	-1.85 (-0.73)
firm age	-0.36 (-1.39)
market heat degree	-3.30 (-0.87)
big 4 auditor dummy	17.41 (0.005)
Constant	-13.56 (-0.004)
Observations	35
Log Likelihood	-10.69
Akaike Inf. Crit.	43.39

Table 7 shows the important predictors of regulatory delisting. Panel A presents the variable's importance (VI) score for top 10 predictors selected by GBT. A variable's importance (VI) reflects the increase in the model's prediction error after we permuted the variable's values. Essentially, the VI represents a variable's relative predictive ability of the first day return. Panel B shows the regression results of the top 10 predictors to the regulatory delisting using logistic regression (the numbers in parentheses are *t*-statistics). Detailed variable definitions and sources are in Appendix B. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix A

A.1. Gradient Boosting in Details

Gradient boosting involves three elements: a loss function to be optimized, weak learners to make a prediction, and an additive model to add weak learners to minimize the loss function. The loss of the model measures the amount of deviation between the predicted and the observed values (e.g., the predictive value of underpricing vs. true value of underpricing). Decision trees are used as the weak learner. It should be noted that each decision tree deals with only one input variable. In this study, the modified version of the GB model is used to predict IPO performance.

Specifically, the GB model's iterative procedure works as follows. Give the data sample a distribution D . M stands for the total number of base models and determines the sample size, which is denoted by N . Define the initial training sample distribution as D_1 .

From $m = 1$ to M

- (1) Train a base model $f_m(x)$ from the training sample distribution D_m .
- (2) Compute the error of this model.
- (3) Adjust the distribution D_m to D_{m+1} and update the model.
- (4) Output the adjusted base model $f_m(x)$.

More formally, Friedman (2001) illustrate how the gradient boosting algorithm works. The pseudo-codes are as follow:

Initialize $f_0(x)$ to be a constant and $f_0(x) = \arg \min_{\rho} \sum_{i=1}^N L(y_i, \rho)$.

For $m=1$ to M do:

For $i=1$ to N do:

Compute the negative gradient
$$y_i = - \left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \right]_{f(x)=f_{m-1}(x)} \quad i = 1, N$$

Fit a decision tree $g_m(x)$ to predict the y_i from covariates x_i for all training data.

Compute a gradient descent step size as $\rho_m = \arg \min_{\rho} \sum_{i=1}^N L(y_i, f_{m-1}(x_i) + \rho g_m(x_i))$

Update the model as $f_m(x) = f_{m-1}(x) + \rho_m g_m(x)$

Output the final model $f_m(x)$

A.2. Random Forest in Details

The random forest (RF) model is a type of additive model that makes predictions by combining decisions from a sequence of base models. More formally we can write this class of models as: $g(x) = f_0(x) + f_1(x) + f_2(x) + \dots$, where the final model is the sum of simple base models f_i . Here, each base regressor is a simple regression tree. In random forests, all the base models are constructed independently using a different subsample of the data.

Appendix B: Variable definitions

Variable	Description
<i>Auditor</i>	The auditing firm (AU) of the IPO. Data is from Compustat annual files.
<i>CAPEX</i>	The total level of capital expenditures (CAPEX) made by the firm, scaled by total assets (AT), for the fiscal year prior to the IPO. Data is from Compustat annual files.
<i>Cash</i>	Cash and short-term investment (CHE) for the fiscal year prior to the IPO. Data is from Compustat annual files.
<i>Cash Flow</i>	The quarterly Cash flows (CF) variable is calculated as $CF = (IBQ + DPACTQ - DVY/FQTR) / ATQ$, for the fiscal year prior to the IPO. Data is from Compustat Quarterly files.
<i>Dividend</i>	Takes a value of one when the firm pays a common dividend (DVC) for the fiscal year prior to the IPO. Data is from Compustat annual files.
<i>Earnings</i>	Earnings before interest and taxes (EBIT) for the fiscal year prior to the IPO. Data is from Compustat annual files.
<i>Equity Offer Size</i>	The ratio of the number of shares issued at IPO date to the total number of shares outstanding after the public offering. Data is obtained from ThomsonOne database and the IPO prospectuses.
<i>Firm Age</i>	Firm age is the number of years since founding year to the IPO year. The founding year of the firm is obtained from Jay Ritter's website (from Field-Ritter database of company founding dates, as used in Field and Karpoff (2002) and Loughran and Ritter (2004)).
<i>Free Cash Flow</i>	Operating income before depreciation (OIBDP) – income taxes (TXT) – interest expense (XINT) – dividends (DVP+DVC), for the fiscal year prior to the IPO. Data is from Compustat annual files.
<i>Hi-Tech</i>	A dummy variable equals one if the IPO is a hi-tech firm, zero otherwise. In line with Loughran and Ritter (2004), hi-tech firms are defined as those with SIC codes 3571, 3572, 3575, 3577, 3578 (computer hardware), 3661, 3663, 3669 (communications equipment), 3671, 3672, 3674, 3675, 3677, 3678, 3679 (electronics), 3812 (navigation equipment), 3823, 3825, 3826, 3827, 3829 (measuring and controlling devices), 3841, 3845 (medical instruments), 4812, 4813 (telephone equipment), 4899 (communications services), 7371, 7372, 7373, 7374, 7375, 7378, and 7379 (software). Data is obtained from SDC database.
<i>Institutional Holdings</i>	Measures the fraction of the shares outstanding owned by institutional investors as of the end of the first quarter following the IPO date. Calculated following the procedure in Field and Lowry (2009). Data is from 13F files.
<i>Intangible</i>	Total intangibles (INTAN) for the fiscal year prior to the IPO. If the observation for the INTAN is missing, we assume it is 0. Data is from Compustat annual files.
<i>Liquidity Ratio</i>	Liquidity ratio = (current assets (AT) – equity (CEQ)) / current liabilities (LCT), for the fiscal year prior to the IPO. Data is from Compustat annual files.
<i>Market Heat Degree</i>	This measure of the IPO market's heat is calculated as the ratio of current quarter's number of IPOs to the moving average of the number of IPOs during the past 10 years (40 quarters). It is calculated by following the methodology in Yung et al., (2008).
<i>Market Return</i>	The buy-and-hold return of the S&P 500 Index during the 12-month period prior to the IPO date. Data is from CRSP files.
<i>Proceeds</i>	Proceeds are total IPO proceeds (net of all fees) raised in all markets in millions of U.S. dollars.
<i>R&D Spending</i>	The total level of Research and Development (XRD) reported by the firm for the fiscal year prior to the IPO. If the observation for the XRD is missing, we assume it is 0. Data is from Compustat annual files.
<i>ROA</i>	Quarterly ROA variable is calculated as $ROA = NIQ/ATQ$. Compustat's Quarterly data is used. When matching with the annual data, we take the standard deviation values as of the fourth fiscal quarter (or the end of the fiscal year prior to the IPO).
<i>Sales</i>	Sales (SALE) for the fiscal year prior to the IPO or 0, if missing. Data is from Compustat annual files.
<i>Tax</i>	Total income taxes (TXT) for the fiscal year prior to the IPO. Data is from Compustat annual files.
<i>Underpricing</i>	The Underpricing (first-day return) is the first trading day closing price over the offer price, minus one.
<i>Underwriter Reputation</i>	Underwriter reputation is the lead underwriter reputation ranking at the time of the IPO, a value between 9 (best) and 0 (worst). It is based on the updated Carter and Manaster (1990) classification, obtained from Jay Ritter's website.
<i>VC Dummy</i>	A dummy variable equals one if the IPO firm is VC-backed, zero otherwise (0 if missing). Data is obtained from ThomsonOne database.

Appendix C: Full list of involuntary delisting Chinese firms

<i>Company Name</i>	<i>Exchange</i>	<i>Issue Year</i>	<i>Delisting Year</i>	<i>Delisting Code</i>	<i>Main SIC Code</i>
HI-Q Wason	NASDAQ	1999	2000	580	4941
Qiao Xing Universal Tele Inc	NASDAQ	1999	2012	585	3661
China Medical Technologies Inc	NASDAQ	2005	2012	585	3845
Suntech Power Holdings Co Ltd	NYSE	2005	2013	580	3674
Fuqi International Inc	NASDAQ	2007	2011	584	3911
Xinhua Finance Media Ltd	NASDAQ	2007	2011	552	4833
Longtop Finl Tech Ltd	NYSE	2007	2011	584	7371
WSP Holdings Ltd	NYSE	2007	2014	552	3317
LDK Solar Co Ltd	NYSE	2007	2014	551	3674
China Sunergy Co Ltd	NASDAQ	2007	2016	560	3674
Agria Corp	NYSE	2007	2016	585	115
VisionChina Media Inc	NASDAQ	2007	2017	470	7312
China Dig TV Hldg Co Ltd	NYSE	2007	2017	561	7372
Yingli Green Energy Holding Co	NYSE	2007	2018	560	3674
China Mass Med Int Adv Corp	NYSE	2008	2012	584	7311
Duoyuan Printing Inc	NYSE	2009	2011	580	3555
Duoyuan Global Water Inc	NYSE	2009	2011	580	3589
ZST Digital Networks Inc	NASDAQ	2009	2012	584	3663
Tri Tech Holding Inc	NASDAQ	2009	2013	585	8711
SinoTech Energy Ltd	NASDAQ	2010	2011	584	5085
Ambow Education Holding Ltd	NYSE	2010	2013	580	8211
Andatee China Marine Fuel Svcs	NASDAQ	2010	2015	580	2911
IFM Investments Ltd	NYSE	2010	2015	584	6531
Prime Acquisition Corp	NASDAQ	2011	2013	560	6726
Zuoan Fashion Ltd	NYSE	2011	2015	582	2329