Informing the Investor: A Comparative Analysis of the Importance of Pre-Initial Public Offering (IPO) Information on Stock Performance

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Abstract

This paper answers which available information about the company, macroeconomic and market environment, regulatory constraints, and offering before an IPO is most impactful on year-long buy-and-hold abnormal returns and how that changes across time while analyzing the IPO markets of 1999 and 2019. Data was gathered from predominantly company prospectuses and proprietary datasets to select a total of 419 IPOs across two samples and regress abnormal geometric returns against the aforementioned information using multivariate OLS regressions. There are a number of interesting findings. First, certain information or factors that act as signals of stock performance before an IPO that correlate with stock performance change across time. Second, there is evidence that companies abiding by more regulation pre-IPO tend to perform better on the stock market after the fact, particularly with the Sarbanes-Oxley and JOBS Acts. While the direction of causality is unknown, there is now a clear and quantified relationship between IPO regulation requirements and stock performance. Third, there is evidence that the IPO market has become more strong-form efficient when comparing 1999 to 2019.

JEL classification: G1; G12; G14; G18

Keywords: Initial Public Offerings (IPOs), information, information asymmetry, stock market

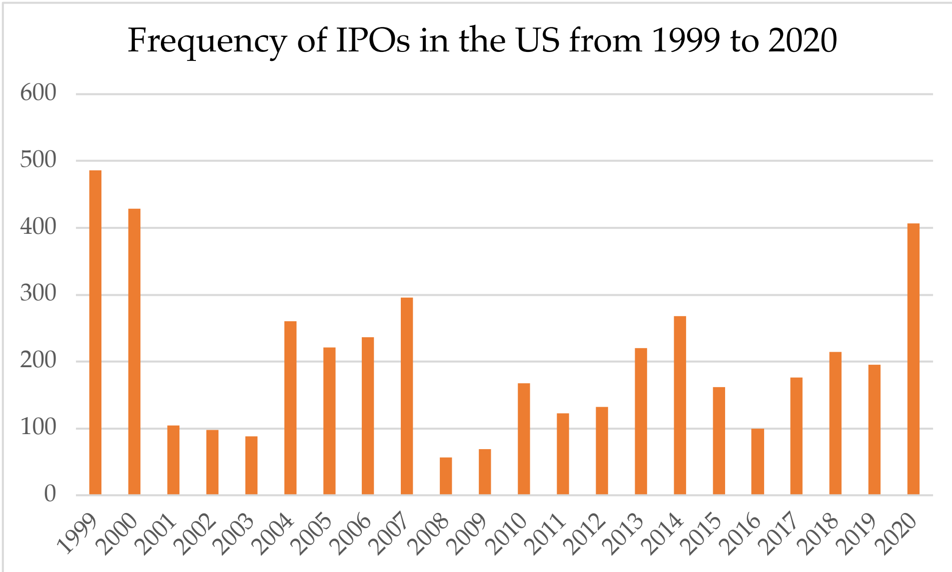
I. Introduction

Initial public offerings (IPOs) are defined as the action and process of a private company issuing shares to the general public, colloquially referred to as "going public," and has become engrained in strategies of capital accumulation. This study looks to test which information available before an IPO, like company characteristics, macroeconomic and capital market trends, and applications of regulation, are most associated with buy-and-hold stock performance post-IPO and comparing those relationships between the IPO markets of 1999 and 2019.

IPOs have been a part of modern business for centuries, with the first IPO in the United States debuting in 1783 with the Bank of North America (Mujalovic et al., 2018). However, interesting trends have arisen over the past few decades. The introduction of the Internet and the World Wide Web propelled "dot-com" companies into public markets, along with lower marginal capital gains taxes. IPOs rose in popularity within the coinciding bull market of the 1990s, breaking records of IPO volume or value nearly annually (Ghosh, 2006). IPO frequency in the United States peaked at over 500 in 1999, the record year in frequency, and over 400 in 2000 with many of these consisting of high-technology or Internet firms (Ghosh, 2006; Renaissance Capital, 2019; Ritter, 2021). Ritter (1984) classifies periods like these as "hot issue" periods, which are timeframes in which a relatively significant number of firms go public. Because the IPO market performance generally mirrors the performance of the broader stock market, periods of economic decline in the early- and late-2000s carried significantly fewer IPOs. Technology innovation, current macroeconomic state and market performance, and industry tends to correlate to IPO frequency.

Between 1999 and 2019, there have been an average of 178 IPOs in the United States per year. The IPO market in the United States has rebounded over the past few years following a

Figure 1: The number of firms going public in the United States between 1999 and 2020



strenuous decline in 2008 and 2009 but has not completely returned to the annual IPO frequency of the 1990s and early-2000s. However, a more unique trend than the volume of recent IPOs is the value of recent deals. As annual deal count declined nearly three-fold since the end of the 1990s and the IPO frenzy, average and cumulative deal value has grown, peaking over the course of the 2010s (Bloomberg Law, 2020). Investors in the 2010s saw a decline in the number of IPOs by a factor of three when compared to the decade of the 1990s, but cumulative deal value peaked in the 2010s at nearly $600 billion, a significant increase from nearly $500 billion in the 1990s. Although there may be fewer IPOs than in the 1990s, they are larger deals and still signify a rebound, or a structural change in composition of companies, within the market.

A contributing factor could be the advent of new "unicorn" company IPOs, which are IPOs of private companies exceeding $1 billion in valuation and seen by the likes of Snap and Dropbox. Between 2016 and 2018, the quarterly frequency of "unicorn" IPOs in the United States rose three-fold (Clabaugh & Peters, 2019). Given the rising values of companies, terms "decacorns" and "hectocorns" have been used to refer to private companies exceeding $10 billion and $100 billion in valuation, seen by companies like Uber. By example, Airbnb opened public trading with a market capitalization of over $100 billion in December of 2020, signifying that previous impossibilities or anomalies are becoming reality (Griffith, 2020). Many of these "unicorns" are high-technology, Internet, or software as a service (SaaS) companies, mirroring the trend of the late-1990s and early-2000s.

Involvement in hot issue markets tends to fluctuate by industry. Between 1985 and 2003, over 28 percent of IPOs were classified as consumer services, including software (Brau, 2012). Data provided by Dealogic shows that the share of money raised in IPOs has increased substantially for finance and healthcare companies (Driebusch, 2020). Meanwhile, IPO firms in computers and electronics have maintained supremacy, maintaining about one-fifth of the share of total money raised. Technology companies accounted for nearly 1,600, or 39 percent, of 4,090 IPOs in the 1990s compared to 370, or around 32 percent, of 1,174 in the 2010s displayed in Dr. Jay Ritter's dataset of IPOs (Ritter, 2020). This is because the technology sector and high-technology firms require heavy allocation into capital expenditures, such as research and development (R&D) and acquisitions. This paper will control for industry using a company's North American Industrial Classification System (NAICS) code rather than the more senior Standard Industrial Classification (SIC) system because the NAICS system is newer and was created to be more precise than the SIC system.

An elusive topic of research is to identify the drivers of returns after an IPO. Research surrounding quantitative indicators of what factors contribute to stock performance post-IPO and how those change across time is sparse. A reason for that is the inherent exogeneity of the process, making it difficult to make sure one is capturing all necessary variables as well as accounting for confounding variables and nuanced relationships. To be more specific, extrinsic factors could include the economic climate of the United States measure by gross domestic product (GDP); intrinsic factors could be the profitability of the IPO firm; and deal factors could be the size of the IPO offering in dollar value or a ratio of offering to market capitalization.

Some factors that ought to be included are difficult to measure, particularly when applying a regulatory framework. For example, a company in one time period may have to report more to the Securities and Exchange Commission (SEC) than in another. In this study, I employ the use of dummy and continuous variables to measure regulatory influences on post-IPO stock performance. These regulatory caveats will be explained further in this introduction. Also, financial analysts attempt to value companies based on intrinsic metrics, and many of those attempts affect the market capitalization of a company. Given that, research supporting or opposing the emphasis on intrinsic factors would be valuable to investors. This is particularly important because many "unicorns" are unprofitable, and investors may cry overvaluation.

A significant field of thought in financial economics is Eugene Fama's efficient-market hypothesis (EMH) which elucidates that markets reflect all available information (Fama, 1970). While this study works to see if there is any information before an IPO that is predictive of stock performance after the fact, EMH would argue that pricing is constantly affected by information flows and information from a year before would have a smaller relative effect on market values. This study tests whether each of these are true among two different datasets across years of time.

Much of the research in this field subtracts the returns of an index from a stock's returns, generating abnormal returns that are more attributable to the IPO rather than broader market tendencies. However, there is no consensus about the proper timeframe to analyze after the IPO. There is a wide phenomenon of underpricing equities initially to inflate the share price and maximize returns shortly after the offering. Because this is short term, underpricing is mitigated in this paper by calculating returns from closing the day of the IPO to the same price one year following the offering.

Finally, there are few comparative analyses of the same IPO market over time. The United States IPO market has experienced volatility since the 1990s, just as the broader capital markets have, along with other certain trends, such as the return to pre-dot-com IPO frequency and the nature of the companies going public. Before the COVID-19 pandemic, the potential for another bubble similar to the dot-com bubble was there. The years of 1999 and 2019 represent similar periods of bullish markets and stable economic output in the United States. Each year has parallel macroeconomic environments, technological innovations, and regulatory shifts.

Regulations were implemented post-dot-com bubble that have increased the relative cost of IPO and decreased IPO frequency over time. Regulations like the Sarbanes-Oxley Act of 2002 aimed to increase financial disclosure, strengthen auditing of internal accounting controls, and is believed to increase the cost of IPO, requiring small companies to pay as much as $1 million dollars, which deterred companies from going public. This is not to say that these companies should have gone or needed to go public. The trend is supported by Ritter (2011) who documents that the median age of companies going public in the U.S. has increased from seven years during 1980 and 2000 to ten years during 2001 and 2010. Because of this and the reduction in IPO volume since the 1990s, it is reasonable to assume that regulation has become more robust on-net when compared to other deregulation tactics.

On the contrary, the Jumpstart Our Business Startups (JOBS) Act of 2012 changed reporting methods during the 21st century in favor of deregulation while also permitting equity crowdfunding for startups (GLI, 2020). In particular, the JOBS Act stipulated that private companies who earned less than $1.07 billion in annual revenue are classified as “emerging growth companies," or EGCs, and are relieved of certain disclosure requirements, such as a third-party audit of internal controls required by the Sarbanes-Oxley legislation, a reduction in fiscal years reported from three to two, and an extended disclosure period (SEC, 2017). The full extent of the JOBS Act went into effect in 2016, allowing us to analyze how that legislation along with the Sarbanes-Oxley Act affected the IPO market in 2019. Regulation is yet another example of how the IPO landscape and environment has changed, warranting further explanation.

Potentially, factors within the regulatory realm, along with company and offering characteristics, macroeconomic trends, and market sentiment, could drive returns post-IPO. They could also be dichotomized by the pre-dot-com IPO boom to the pre-COVID-19 "unicorn" IPO boom, especially given the difference in the composition of companies and surrounding regulatory frameworks, while explaining how and why shifts in stock performance post-IPO take place. Ultimately, there is an opportunity to define what makes a good candidate for an IPO and identify the similarities and differences in what information drives post-IPO buy-and-hold stock performance during the years of 1999 and 2019. This paper will contain helpful background about this area of study in the Literature Review followed by a description of relevant theories in a Theory section. The explanation of data logistics, execution of empirical specifications, and presentation of interpretive remarks in the Data, Empirical Specifications and Results, and Discussion portions, respectively.

II. Literature Review

Literature on IPOs is abundant and diverse because relevant proprietary data, like company financials, are readily and publicly available through sources like the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database. Furthermore, as identified earlier, IPOs have been nearly commonplace over the past four decades and are key indicators of business cycles. Under the umbrella topic of IPOs, a significant and *a priori* research subject is the presence of IPO underpricing. This is important to address because it is an application of key theoretical frameworks surrounding IPO strategy and sheds light on potential skewedness of data when calculating returns. Underpricing is the practice where an IPO is listed below its true market value, seen by the trend of private companies' immediate first day returns after floating their share price on the market and raising the question that companies are deliberately undervalued to feed off investor confidence while minimizing losses. There are three theoretical frameworks, with many sub-frameworks within, used to explain the phenomenon: information asymmetry theories, institutional theories, and ownership and control theories (Jamaani & Alidarous, 2019).

i. Information Asymmetry Theories

Applicable information asymmetry theories are delineated into three: principal agent, *ex-ante* uncertainty, and signaling. However, I would like to further address the efficient-market hypothesis introduced earlier.

EMH was elucidated by Eugene Fama in the Journal of Finance in 1970. Fama describes an efficient market as "[a] market in which prices always "fully reflect" available information..." This study takes an interesting approach at testing the EMH because we are already limited to pre-IPO information, whereas the EMH elucidates that constant flows of information lead to price fluctuation. In fact, Fama explains the difference between three types of efficient markets: weak form, semi-strong form, and strong form. Weak implies that all information from the past is available; semi-strong is where all publicly available information is available; and strong states all information, including private information, is available (Fama, 1970). This paper has a focus on the former two. Therefore, our study could highlight that current *ex ante* pricing and valuation methods, like the discounted cash flow analysis, is incorrectly applied to firms going public or that it becomes more unlikely to predict the success of a new offering as time moves on while limited to information that is available before the offering. Other studies, like James and Valenzuela (2019), have confirmed that the IPO market in the United States is, indeed, efficient. If the factors and variables addressed in this study do not drive returns, this could be evidence that the IPO market is strong-form efficient during that time period.

Now, we can offer perspectives that imply there are differences in information access among parties involved in an IPO. Baron and Holmstrom (1980) and Baron (1982) elucidate a "principal-agent" model of information asymmetry, explaining that underwriters have access to information from knowledge of capital markets and securities exchange to gauge demand while lowering the price to reduce marketing costs and benefit buy-side clients. Early buy-side clients are benefitted because they are theoretically able to garner more returns. However, this model excludes self-underwritten IPOs, as well as asymmetries in information between other IPO parties. This study will incorporate the analysis of IPO underwriters as agents and will be discussed and applied further in the Data section.

Ex-ante uncertainty captures the relationship between issuing firms and investors, stating that underpricing is explained by the degree of uncertainty in the fluctuation of share price. Beatty and Ritter (1986) showed there was a positive relationship between ex-ante uncertainty of a firm and its expected initial return, using the number of disclosed uses of IPO proceeds and the size of the IPO as proxies for uncertainty. They also argue that the disclosure of information, particularly information relevant to the SEC, is incentivized to lower uncertainty to inform investors. Under this lens, investors of firms with higher levels of uncertainty demand underpricing to maximize potential returns, which can be interpreted as a risk premium. This can also contribute to my research when judging how regulatory environments of two periods differ with respects to the change in disclosure mandates and regulations from the SEC.

Signaling, as in traditional signaling theories in other fields, refers to the relationship between the issuer and the investors and is explained by discrepancies in access to private company information. Allen and Faulhaber (1989) articulate this by modeling a consistent relationship between a company's prospective favorability and underpricing. This is because it is ideal for issuers with better prospects to signal their performance and underprice with intentions to "separate" themselves to investors. This is because good companies would be more likely to recover from an initial undervaluation, which also benefits prospective investors. Ritter (1984) confirms this while also noting that in certain hot issue periods underpricing tends to occur in select industries. This is helpful for my prospective research because I must consider that hot issue periods of the dot-com boom and the current one could carry a confounding variable in underpricing in select industries. As stated, this paper utilizes a company's NAICS to identify industry. A technology firm dummy variable will be used to control for industry, and it is explained later in the **Data** section.

ii. Institutional Theories

An institutional theory to note is one of lawsuit avoidance. Lawsuit avoidance, explained by Ibbotson (1975), is the belief that companies underprice to mitigate the chance of litigation stemming from losses due to gaffes in the process, like prospectus errors, by inducing a better initial floating performance. Although this framework can be criticized because it is United States-centric, it is worth noting because I intend to focus on the United States IPO market. That said, there are not an insignificant number of IPO-related lawsuits, with the proportion of IPO-related lawsuits rising over two-fold over the past decade (Fortune, 2019). While this may be explained by the relative increase in IPO frequency, the rate of increase for lawsuits has been much higher than the rate of increase for IPOs. This also overlaps with the general premise of information exchange. The exchange of accurate information is institutionally reinforced by regulatory and legal action, which installs further interest in determining what information matters most when persuading investors to buy into a newly public company. Furthermore, lawsuits about misleading prospectus or filings can be a reputation-tarnishing signal from companies to investors.

Another institutional theory of underpricing is the tax argument. Guenther and Willenborg (1999) evaluated prices of small IPOs by comparing the actual issue price to a benchmark unaffected by capital gains taxation to test whether 1993 legislation lowering capital gains taxes affected underpricing. They find that the tax change was associated with a significant increase in the prices received for small IPOs, showing that underpricing was encouraged by a decrease in capital gains.

A contribution is that capital gains tax rates affect the prices of equity securities. While this would be interesting to include as a macroeconomic variable, the capital gains tax rates do not change regularly and there would be no variability during the years of 1999 and 2019. This is a topic that can be considered in future research.

iii. Ownership & Control Theory

Ownership and control theories state that an IPO, and underpricing, is a means to constructing the shareholding base to crowd out external investors from managing their firms. These theories are identified by either entrenchment management, which argues that managers of the issuer underprice to create demand and disperse ownership to reinforce their control, and the agency costs argument, on the contrary, which states that underpricing is used to attract large shareholders to minimize control discrepancies between mangers and shareholders because there are fewer investors (Ghosh, 2006; Jamaani & Alidarous, 2019). While each of these competing frameworks are worth perusing, I do not believe this will be useful for my research because there are other easier alternatives to consolidate control to substitute for pricing strategies, such as issuing non-voting shares.

An important theory regarding broader ownership theory in finance is the free cash flow (FCF) hypothesis by Jensen (1986), similar to entrenchment management, stating that managers waste free cash flow to consolidate power in operations rather than issue payouts and lower firm value in turn. Given that an IPO would increase shareholder's equity and, thus, cash in assets on the balance sheet, it is helpful to note this theory to analyze whether the intended use of proceeds are frivolous or effective and this study tests this directly.

Each of these selected theories are important for a myriad of reasons. These theories are foundational in understanding not only underpricing, but broader IPO strategy. There are multiple parties in play, and it is worth noting how they interact with each other while balancing intrinsic factors of the company, external economic and market forces, and regulatory environments. The impact of underpricing is mitigated in this research because I calculate returns based on the closing value of the first day of trading, rather than the listed offering or opening price, and the same value one year after.

iv. IPO Performance Predictors

It is important to consider literature surrounding the identification of success indicators of IPOs. There have been multiple independent analyses by established institutions, like Goldman Sachs or McKinsey, or media outlets, like Forbes, to identify niche indicators in broad datasets. However, these sources focused on international datasets or data of other individual countries (Business Insider, 2019; McKinsey, 2020; Forbes, 2019).

It is well documented that IPOs are generally underpriced in the short run, as explained above, but are overpriced in the long run. If EMH holds true, this could mean that IPO firms may share a characteristic or information that lowers market prices in the long run. Ritter (1991) proved that a firm's abnormal returns were negative on average 36 months after an IPO while their raw returns, or unaltered returns, rose by over forty percent. While this was only an analysis of IPOs from 1975 to 1984, the trend has remained. A similar analysis of Ritter's dataset from 1980 to 2016 by Draho and Gourd (2019) with UBS revealed that absolute and excess returns for companies going public were negative on average five years after the IPO. This study analyzes one-year returns post-IPO, but it can be expected that stock performance for a security is generally worse following the period of underpricing once the market catches up.

A range of techniques have been applied to define a successful IPO or measure stock performance post-IPO. A study by van den Assem et al. (2017) surveyed CEOs and CFOs of companies that went public in Dutch markets between 1980 and 2008. After ranking a series of explanatory variables by importance, such as "Changes in visibility and credibility in general" and "Access to equity finance," they used a probit regression to decipher relationships between the scores and whether the surveyed executives rated an IPO as successful on a five-scale rating from "Very Good" to "Very Poor." They found no significant relationships. This form of research is inherently subjective. Also, I would rather analyze other quantified metrics to depict operational success and the market environment.

Pagano et al. (1998), Brau et al. (2014), Brycz et al. (2017), and Amor and Kooli (2017) employ regression techniques to predict IPO success and the probability of the occurrence of an IPO, while making other empirical contributions to this study. Pagano et al. looked to predict the probability of IPO, which is different than what this paper will address. They proxied for profitability using return on assets (ROA), because profitability could be collinear with occurrence of an IPO due to listing requirements, and defined it as earnings before interest, taxes, depreciation and amortization (EBITDA) over total assets. This study incorporates a similar definition but instead employs net operating profit as the numerator because most all companies report operating profit rather than EBITDA. They find the two most important determinants of whether a firm goes public is the market-to-book ratio at which firms in the same industry trade and the size of the company – both positively associated with the occurrence of an IPO. Limitations of Pagano et al.'s contributions to this study include determining the success of IPO, since they only look at the occurrence of one, and the use of *ex post* information in their modeling. The purpose of this study strictly focuses on *ex ante* information.

While the purpose of Brau et al. is different than this paper, it is important to address contributions. The study draws upon the Rolls' hubris hypothesis, in which Roll argues that acquiring managers become overconfident in their ability to select targets, so they destroy wealth by overpaying for acquisitions (Roll, 1986). They found that IPO firms that acquire within the first year of going public experience significantly worse five-year performance after the first year than IPO firms that do not acquire in the first year. There are a number of contributions to this study. First, they control for the reputation of the underwriter using the Underwriter Reputation rank codified by other researchers (Loughran & Ritter, 2004). We will use the same underwriter reputation used and augmented by these researchers. Second, they take the natural log of company age to asymptotically measure the age of the company. Third, they employ abnormal returns, defined as asset returns subtracted by a benchmark, and use the CRSP index that we will use in this study. While the purpose of the study is different than this one, it offers an example of regressing multiple variables to abnormal returns in the context of an IPO, offering encouragement for the future.

Brycz et al.'s analysis mirrors the work of this paper. With a focus of analyzing the impact of firm operating and exchange performance on IPO success, defined as the percentage increase in shareholders' equity per each percentage of firm ownership sold during the IPO, they employ a number of variables. These variables were categorized into six groups of variables: size, profitability, leverage, terms of issue, economic conditions, and investor optimism. They cited signaling in that high levels of pre-IPO profitability would send positive messages of firm value to investors. This yields many takeaways for further research, especially with regard to the identification of specific balance sheet and income statement data along with the use of ratios. It is important to note that this study did not consider the industry of firms. In my analysis, I would include this to answer whether a certain industry fared better during a certain time period and how that may have changed over time.

Similar to Beatty and Ritter (1986), Salma Amor and Maher Kooli explored the importance of *ex ante* uses of proceeds listed in IPO prospectus on long-run stock performance after the IPO. They classified uses into four categories: investment, debt repayment, marketing and sales promotion, and general corporate purposes. Investment was defined as uses involving acquisition, R&D, and capital expenditure, and general corporate purposes are ambiguous reasons. To calculate cumulative abnormal returns for the 36 months after the IPO, they employ the Fama and French (1992) three-factor model, which will be touched on further in the Data section, to measure monthly returns. While they find that long-run stock performance is generally negative post-IPO, firms that primarily invest their proceeds perform better than all other categories, followed by sales and marketing, general purposes, and debt repayment (Amor & Kooli, 2017). I look to employ the exact same categories into my own research to include as a regulatory variable across a different sample.

There have been other empirical methods used that strays from the regression technique. Boubekeur Baba and Güven Sevil looked to apply the random forest machine learning technique to IPOs debuting on the Borsa Istanbul Exchange (BIST) to take into account outliers excluded by traditional regression techniques. The random forest is an algorithm that "constructs" decision trees to create a "bagging" method, which means that more observations mean a more reliable result. The way it is able to generate "splits" is by randomly applying features from a subset to find the best one. The main result was that the size of the offering is the main predicting metric (Baba & Sevil, 2020). Important takeaways for my own and future research that the nature and size of the IPO must be evaluated. The researchers used an IPO size ratio variable, which is the size of the offering divided by the market capitalization of the company at the time of the offering, and this study incorporates this. While the simulation technique is interesting, regressions seem to be the prevailing method of analysis and I employ the same.

Clearly, it would be incomplete to say only one variable or group of variables is responsible for the performance of a company's stock following an IPO. That it is important to assess and measure just how much company, sector, macroeconomic, and regulatory data affects post-IPO returns. This is a worthwhile subject because this has not been discussed and articulated in the context of the United States, especially in the cases of comparing two different time periods and regulatory environments.

III. Theory

Because this study focuses on both pre-IPO intrinsic and extrinsic determinants of a successful IPO, the theoretical framework must synthesize a few aforementioned theories. These two are signaling and *ex ante* uncertainty as applications of information asymmetry. Recall the two definitions. Signaling refers to the discrepancy in private company information an issuing firm has over potential investors, motivating firms to convey viability and quality by disclosing information to send messages of success to IPO investors. It is less costly for low-risk firms to signal because firms that may not feel fit to achieve a successful IPO will either postpone their offering, release favorable information to bolster its prospects, or delist post-IPO. The second option is risky because it risks legal action and delisting is inherent failure, incentivizing transparency. Theoretically, high-risk firms would not possess the signals of a low-risk firm. With regards to underpricing, underpricing signals to investors whether a firm is able to cope with initial underpricing due to the confidence in their knowledge of the firm's present value and future growth prospects.

Ex ante uncertainty refers to the discrepancy in private company information especially with regards to growth prospects between issuers and investors as it pertains to future share price fluctuation. Disclosure requirements have reduced uncertainty, but there is a continuum of how transparent a company can be when undertaking an IPO. With regards to underpricing, investors would demand underpricing to create artificial returns if they are uncertain of future prospects. In a simpler sense, investors would demand more information about operational, financial, and prospective plans if they are uncertain of future price fluctuations.

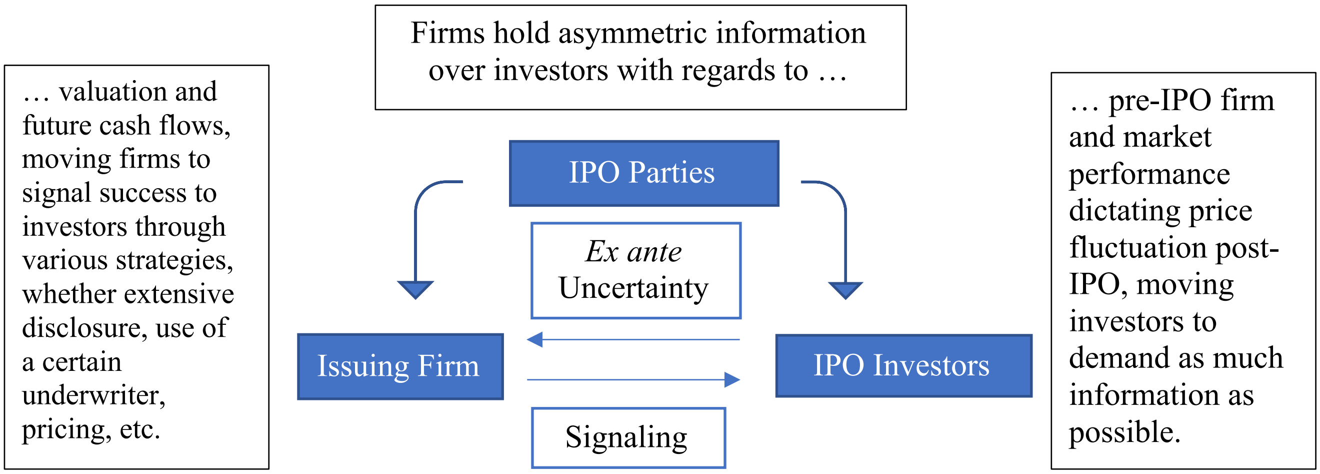
Both theories of asymmetry complement each other by highlighting pre-IPO uncertainty for the investor. *Ex ante* uncertainty can be proposed as the reduction in expected utility of the investor due to uncertainty about a firm's fitness for public markets or a market for a product. This causes the market clearing IPO price to be lower than it would be without this uncertainty, empirically supported by underpricing. In essence, the risk premium of an investment into an IPO for an investor is characterized by the level of underpricing. However, information about the market or firm, like operational or macroeconomic metrics, and other signals would reduce uncertainty and contribute to an increase in share price of the IPO firm, because it illustrates how well the company has managed this uncertainty. The purpose of this study is to test whether there is a relationship, and the strength of it, between those various metrics and returns post-IPO.

These signals and the demand for information may change for 1999 and 2019, making this framework structured but flexible. In essence, we are trying to quantify the importance of pre-IPO signals and information disclosure, whether intrinsic firm information or extrinsic data, in determining the performance of an IPO. Using this theoretical framework of information asymmetry to remedy signaling and *ex ante* uncertainty, we can see that disclosure of information, in whatever form, is in the best interest of the firm if the firm believes they are fit to IPO.

This intuition has been elucidated empirically by Brau and Fawcett (2006) to explain the compromise between signaling and *ex ante* uncertainty. They surveyed a sample of 336 CFOs stratified into three groups: 212 had not attempted an IPO, 87 had successfully completed one, and 37 had withdrawn their IPO between January 2000 and December 2002 in the United States. Drawing upon signaling theory, the CFOs ranked "past historical earnings" on average as the most important signal of IPO success. Furthermore, the respondents categorized uncertainty from the lack of perfect information as the most important factor determining underpricing.

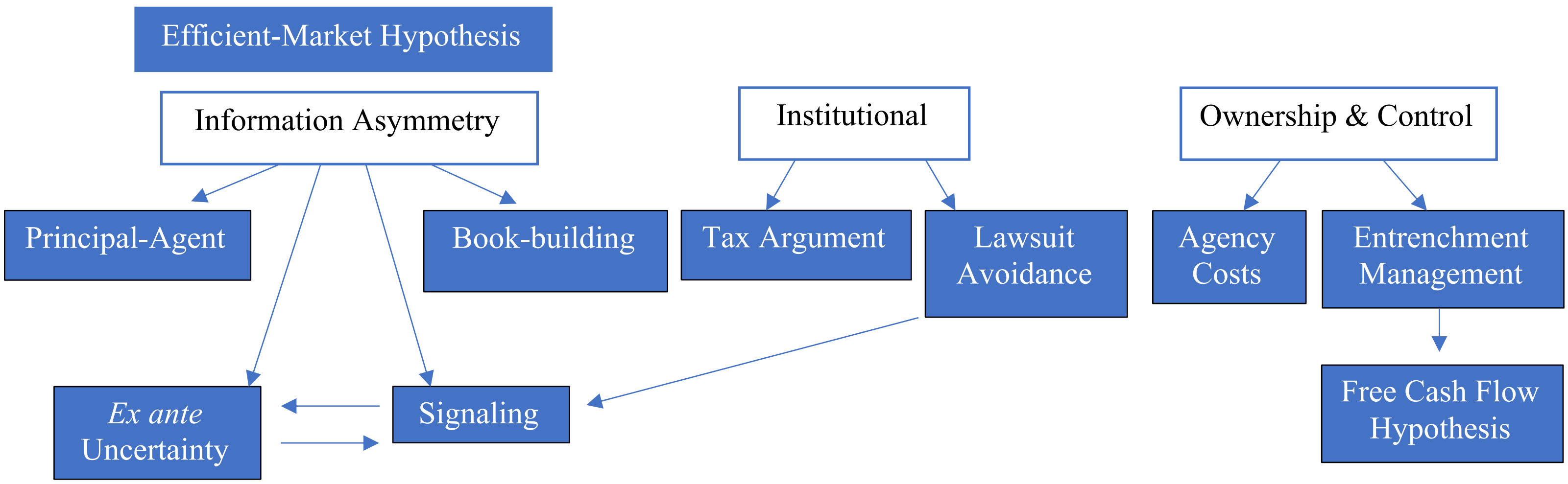
Brau and Fawcett remedy these fields of thought important to IPO performance from the perspectives of business leaders. While the aforementioned study proves the ideological importance of the exchange of information to IPO performance, this study attempts to test these fields of thought relying on company, IPO, and extrinsic data, rather than relying on the experiences and opinions of those involved with IPOs.

Figure 2: Relationship of *ex ante* uncertainty and signaling theories



This framework is helpful because it integrates pre-IPO factors in the analysis of the prospective performance of an IPO which is the focus of this study. While both theories relate to intrinsic company performance and characteristics, they also account for other factors that can influence the results whether that be extrinsically or regarding offering itself. Those factors are interpreted in variables sets of the following groups: intrinsic company, macroeconomic, market, regulatory, and control. If this is confirmed, there should be certain pieces of information that are associated with stock performance post-IPO, and the predicted directions of these effects are better listed in the Data section. *Ex ante* uncertainty and signaling theories, however, conflict with the EMH that markets reflect all available information, making it hard to "beat" or out-predict the market in question in the long run, while the world has seen outliers like Warren Buffet beat the market for years. According to the strong form of EMH, no variables pre-IPO should be significant because constant flows of information adjust security prices accordingly. Ultimately, this study will rectify whether these theories manifest within the two samples. The following figure illustrates the relationships between relevant IPO theories:

Figure 3: Flowchart of relevant IPO theories



IV. Data

The Data section will consist of descriptions of the data, including the time period, important variables, size of the dataset, sources of data, and commentary on processes, limitations and challenges, and univariate analysis of each sample's variable distributions.

i. Time Periods

The time periods analyzed will be the IPO markets of 1999 and 2019 with each sample composed of companies going public between January 1 and December 31 of each year. The logic for these two periods is two-fold. First, both periods mirror major economic events and macroeconomic environments. The beginning of both periods marked an period of economic prosperity, each leading into a recession – the two being the Dot-com Bubble recession and the COVID-19 recession. Recessions are not included on the dataset to exclude potential bias, because each recession impacted different industries more than others, but the two years mark similar bullish environments prior to a recession. Second, while each period can be classified as hot issue during each decade, there is a significant difference in IPO frequency, probably due to regulatory changes in the early-2000s and late-2010s. The sample years selected straddle those regulatory changes. Third, in the same vein, 2019 allowed for the full extent of the JOBS provisions to come in place following its full passage in 2016. The two years of 1999 and 2019 straddle significant regulatory changes, like the Sarbanes-Oxley Act of 2002 and the JOBS Act.

ii. Variables

Before exploring necessary datasets, it is important to delineate the independent variables into four categories: intrinsic company, macroeconomic, market sentiment, and regulatory. I select variables within intrinsic company and regulatory that can best “signal” to investors, retail or institutional, the financial health of the company along with its ability to yield consistent returns post-IPO. Tables 1 through 5 include the variable name, along with the coded and italicized name used in the merged dataset, applicable calculations, commentary on the variable including its predicted impact on the dependent variable based on corresponding theory (signaling, *ex ante*, FCF, etc.), and source of data.

Intrinsic company variables are a blend of financial or structural company characteristics. Ratios will be used so that aggregate values will not be “rewarded” and thus skew the results, and this was taken from Brycz et al.’s logic. Although it would be preferable to measure ROA adjusted to use EBITDA as the numerator drawing upon Pagano et al. (1998), many firms do not report EBITDA and I want to ensure consistency across the sample. Finally, diverging from past studies, I will only analyze financials of firms’ most recent reporting period rather than focusing on strictly annual reporting. For example, a firm could go file their S-1 on June 1 of 1999, most likely indicating the most recent financials are of the first quarter in 1999 while reporting annual financials for the years up to and including 1998. This study accounts for the most recent available information before an IPO, and it can also examine whether it is in a company’s best interest to report the most recent financials or more favorable annual financials, especially assuming the latter is larger than the former. I am unable to predict some variables throughout the categories because of certain tradeoffs; higher age may proxy for experience and established revenue streams but also indicate lower growth potential. Names, calculations, descriptions, and sources of data for intrinsic company variables are included in Table 1.

Macroeconomic variables refer to broader metrics that tell the story about the domestic economy. The capital gains tax rate at the time of IPO as explored by Guenther and Willenborg (1999) would be ideal to include, but there is too little variation amongst the datasets. Monthly real GDP growth is used in the final analysis, listed in Table 2.

The market variable encompasses factors to diagnose the health of capital markets at the time of the IPO. As stated earlier, it is widely known that the IPO market closely follows broader equity markets, and these trends may be indicative of IPO success. This is reflected in Table 3. It is important to note that there will not be an explanatory variable with regards to overall market sentiment, like an exchange's returns. This is because the dependent variable already integrates this in the calculation for abnormal returns, which is explained further in this section.

Regulatory variables pertain to the various regulatory and institutional factors that impact the IPO process. There has been a trend towards regulation rather than away from it, and the dependent variable may change depending on the various regulatory environments. This will be the most difficult to measure qualitative regulatory variables, namely centered around the disclosure of uses of proceeds. However, it is even more important because regulatory changes may indicate a change in the difficulty of the IPO process, increasing literal or implicit "costs" of the process. Regulatory variables are in Table 4.

Quantity of disclosed uses are almost always in a section of the S-l filings, which will be explained later, labeled "Use of Proceeds." While I count the number of uses, I also elucidate between the types of uses. I look to replicate the criteria used by Amor and Kooli (2017) and delineate uses between investment, debt repayment, promotion, and general corporate purposes. This is to test whether increased transparency and a codified plan post-IPO is beneficial to driving returns over a year, and maybe one strategy is more beneficial than another.

Following other studies, like Ritter (1984), James and Valenzuela (2019), Brau (2012), and others, this paper employs a technology industry dummy to control for industry. The definition for a technology firm is vast, and other studies use a company's SIC codes rather than NAICS codes. Each company is classified as a technology company or not using the Paytas and Berglund (2004) list of primary technology employers. Paytas and Berglund define a primary technology generator as "if they exceed the U.S. average for both research and development expenditures per employee ($11,297.00) and for the proportion of full-time-equivalent R&D scientists and engineers in the industry workforce (5.9%)" (Paytas & Berglund, 2004). I also deduce whether the product or service offerings of the company are in technology hardware or software. For example, NAICS code 541300 is classified as "Architectural, Engineering, or Related Services" and a primary technology employer in the reference list, but companies with that NAICS code in our sample are not considered technology companies. Underwriter reputation may be related to the size and nature of the offering or company while also highlighting how embedded perceptions of "prestige" can act as signals to investors and impact their confidence. These controls are listed in Table 5.

I would like to use a dependent variable indicating a change in share price one year after the IPO. This is different than traditional methods of measuring same day returns, because I would like to minimize the impact of underpricing without looking too far in the future. I will calculate returns of IPOs by change in share price over a one-year period, defined as the closing price after the first day of trading, called P_0, and the closing price a year from the IPO date,

Table 1: Intrinsic Company Explanatory Variables

Variable Name	Calculation or Definition	Commentary & Prediction	Source
Revenue (*revenue2*)	Revenue for the most recent filing period	Positive effect on returns	Company S-1 filings on EDGAR or Capital IQ
Net Income (*netincome*)	Net income or loss for the most recent filing period	Positive effect on returns	Company S-1 filings on EDGAR or Capital IQ
Revenue Growth (*revenueg*)	$\frac{(Revenue_{t-n} - Revenue_{t-2n})}{Revenue_{t-2n}}$	Calculated for both one and two periods prior to IPO; Positive effect on returns	Company S-1 filings on EDGAR or Capital IQ
Net Operating Profit Margin (*margin*)	$\frac{Operating\ Profit\ (Loss)_{t-n}}{Revenue_{t-n}}$	Also interpreted as return on sales (ROS); Positive effect on returns	Company S-1 filings on EDGAR or Capital IQ
Risk Size (*risk_size*)	$\frac{Shareholders'\ Equity_{t-n}}{Market\ Capitalization_{t}}$	Size of risk for pre-IPO investors, or the book-to-market ratio; Market Capitalization is calculated with the initial offer price multiplied by the number of shares outstanding; Unknown effect on returns	Equity: company S-1 filings on EDGAR or Capital IQ; Offering price: company 424 filings on EDGAR or Capital IQ; Shares outstanding: Ritter's dataset
Return on Equity (*roe*)	$\frac{Net\ Income_{t-n}}{Shareholders'\ Equity_{t-n}}$	To measure a firm's management of equity; Positive effect on returns	Company S-1 filings on EDGAR or Capital IQ
Return on Assets (*roa*)	$\frac{Operating\ Profit\ (Loss)_{t-n}}{Total\ Assets_{t-n}}$	Positive effect on returns	Company S-1 filings on EDGAR or Capital IQ
Company Age (*adj_age)*	$\ln\ (Year\ of\ IPO - Year\ of\ Founding)$	Evaluates firm age asymptotically; Unknown effect on returns	Both years available on Ritter's dataset

Assume *t* to be the IPO date and *n* to be each period is the reporting period of the company.

Table 2: Macroeconomic Explanatory Variables

Variable Name	Calculation	Commentary & Prediction	Source
U.S. Real Gross Domestic Product (*gdp*)	N/A	N/A	YCharts
U.S. Real Gross Domestic Product Growth (*outputg*)	$\frac{(GDP_{t-1} - GDP_{t})}{GDP_{t-1}}$	Monthly; decimal; Positive effect on returns	YCharts

Assume *t* to be the IPO date and *n* to be each period is the reporting period of the company.

Table 3: Market Sentiment Variable

Variable Name	Commentary	Source
IPO Frequency (*freq*)	Quarterly; proxies for IPO activity in a given period; Positive effect on returns	Counted using all IPOs 91 days preceding an IPO in the sample from Ritter's dataset

Table 4: Regulatory Variables

Variable Name	Calculation	Commentary & Prediction	Source
Quantity of Disclosed Uses (*uses, invest, debt, promo, general*)	N/A	Delineated by investment, debt repayment, promotional, and general uses and summed for total uses; Unknown effect on returns	Company S-1 filings on EDGAR or Capital IQ
IPO Size Ratio (*ipo_ratio*)	$\frac{Offering}{Market\ Capitalization}$	Ratio to show the IPO relative to the company size in dollar value; not impacted as strongly by large aggregate IPOs; Drawn from Baba et al.; Negative effect on returns	Offering price and shares offered: company 424 filings on EDGAR or Capital IQ; Shares outstanding: Ritter's dataset
Application of the Sarbanes-Oxley or JOBS Acts (*sox, jobs*)*	N/A	Dummy variable whether these laws regarding disclosure applied to a company; Positive effect on returns for both SOX and JOBS	Company S-1 filings on EDGAR or Capital IQ

*Only applies to 2019's sample

Table 5: Control Variables

Variable Name	Commentary & Prediction
Technology Industry (*tech*)	Used by NAICS code; NAICS codes classified as technology provided by Paytas & Berglund (2004); Unknown effect on returns
Underwriter Reputation (*under_rank*)	Ritter ranks this; Only classify the primary underwriter; Positive effect on returns

called P_1. These security prices were compiled using COMPUSTAT.

Arithmetic returns, called R, are defined:

(1) $$R = \frac{(P_0 - P_1)}{P_0}$$

used to calculate geometric returns to account for compounding and reduce bias. These returns, called r, were found by:

(2) $$r = \ln(1 + R)$$

Then, rather than calculating only blanket returns, I will compare this to a benchmark by employing the abnormal returns strategy used by Ritter, Brycz, Brau, Amor and Kooli, and others to isolate returns to separate variables. I subtract the CRSP returns over the same period using the same calculation, giving us abnormal returns for each security over a buy-and-hold period of a year.

iii. Size of Dataset

Upon reviewing Jay Ritter's database, there are 476 IPOs in the United States in 1999 and 112 IPOs in 2019. Ritter's list excludes some unit offers, Special Purpose Acquisition Companies (SPAC), real estate investment trusts (REITS) and close-end funds and all offerings initially priced under \$5, which would be required in my research anyways due to the nature of the filing for these IPOs. I will also screen for the previously mentioned offerings including SPACs, as the process of the offering is different and subject to other procedural and regulatory factors and achieve a different purpose to stakeholders (Cumming, 2014). Companies involved in the SPAC IPO process are fundamentally different, defined by the SEC as a "development stage company that has no specific business plan, or purpose, or has indicated in its business plan is to engage in a merger or acquisition with an unidentified company, other entity, or person" (Shachmurove & Vulanovic, 2016). There were 59 SPAC IPOs in 2019 and none in 1999 since the first SPAC came about in 2003.

Banks and financial institutions were excluded because of excessive skewness to the samples and different filing procedures. I removed companies that do not have the proper financials available in their S-1 filings, essentially classified as "missing observations." Examples would be biotechnology firms going public pre-revenue, offering little information. I also only use United States-based companies because the filing is recorded in a different currency and, thus, would require an approximation of data using the exchange rate.

The total number of IPOs in the sample for 1999 was 361, although one IPO had zero shareholder's equity and will excluded from the final analysis involving that term. The number of IPOs in 2019's sample was 58, bringing the total number of IPOs in this analysis to 419.

iv. Sources & Commentary

There are a multitude of data sources required. First, I referenced the IPO database curated by Jay Ritter at the University of Florida, comprised of IPOs in the US between 1975 and 2020. Relevant information listed on Ritter's dataset is the following: name of the company, date of the offering, offering ticker symbol, CUSIP unique identifier, CRSP permanent identifier number, post-issue shares outstanding, and the year of company founding.

The Wharton Research Data Services (WRDS) provides access to many datasets in one place. The two that apply to this study are The Center for Research in Security Prices (CRSP) and COMPUSTAT. This service can be available to students if the subscribed institution's representative approves the research request. The Duke University Library System provides access to online databases that are helpful for this research, particularly S&P Capital IQ. Capital IQ can only be accessed on-campus, prompting me to download Cisco AnyConnect available on the Ford Library website. These sources are important for different reasons. As stated, the CRSP value-weighted index is used as the benchmark for calculating abnormal returns. I have programmed in SAS Studio using SQL within WRDS to pull the share prices at closing on the day of the IPO, to mitigate the effects of underpricing, and a year after the IPO for all companies in the sample from COMPUSTAT. The prices for the 1999 sample are slightly rounded to the nearest $1/16^{th}$ of a dollar only because that is what COMPUSTAT provided.

One can then select the information they would like in the tables, from company name to ticker to dividends dates to prices. Pricing data not included in this query was manually pulled using COMPUSTAT's Security Daily query tool in WRDS. Once prices and values were attained, returns calculations from the Variables section were used.

Capital IQ consolidates filings to the United States SEC, similar to the EDGAR database provided by the SEC, but it is easier to navigate. Prior to an IPO, a company is required to submit an S-1 filing detailing the offering, company commentary, and performance metrics for the past 2 to 3 years. This answers most of the intrinsic company and regulatory answers. I have compiled information, such as company financials, the listed number and uses of proceeds, underwriters, and offering details, manually from these prospectuses. Directly referencing these filings ensures accurate data but the format of prospectuses is almost impossible to digitally scrape reliably without risking corrupting data, posing a major obstacle in efficient data aggregation. While this task may be cumbersome and time-consuming, causing a comparatively smaller sample than what could be achieved, the dataset is vetted for accuracy. The challenge of manual aggregation was the most difficult to overcome and required most of my time. Macroeconomic data are more widely available. Data on GDP for each time period was taken from YCharts, which aggregates data from the Bureau of Economic Analysis (BEA), because it was listed monthly, whereas sources like FRED only aggregate quarterly. Monthly intervals are preferable to include more variation among the samples; by example, quarterly growth rates would mean only up to four values would be used for all companies in each sample.

The byproduct of using a variety of factors to indicate IPO success is the requirement to combine many datasets. While most datasets were exportable into Excel, I was still required to manually record cells of one spreadsheet to a central one to exclude irrelevant data, adding to the time commitment.

v. Techniques in Prior Research

The motivation for using abnormal returns is to account for an expected rate of return for the security. I emulate abnormal returns calculated by Brau, Ritter, and others, defined as some return as a difference to a benchmark, to isolate the returns of the company.

Brycz et al. and Brau et al. use a simple multivariate regression model. An applicable model that has been used extensively in portfolio pricing is the Fama-French Three Factor Model originally proposed by Eugene Fama and Kenneth French (1993) as an augmentation to the traditional capital asset pricing model (CAPM) and also employed by Brau et al. (2012). The model uses three factors of size of firms, book-to-market values and excess return of the market. Brau et al.'s description of Fama-French in their model is below:

$$R_{pt} - r_{ft} = AR_t + \alpha_1(R_{mt} - r_{ft}) + \alpha_2 SMB_t + \alpha_3 HML + \varepsilon_t, \tag{3}$$

where R_{pt} is the monthly return on an equal-weighted calendar-time portfolio of IPOs; r_{ft} is the monthly return on the 3-month United States Treasure note, AR_t is the intercept term denoting mean monthly abnormal returns for the portfolio; R_{mt} is the monthly return for the value-weighted market index; SMB_t is the monthly difference between returns of a value-weighted portfolio of large and small stocks purged of offerings; and HML_t is the monthly difference between returns of high and low book-to-market stock purged of offerings.

While this will not be used exactly, particularly because returns are evaluated on a security-level and not portfolio-level, some of the measurements, such as the risk size variable from book-to-market ratio, have inspired variables of this study. The risk-free rate, denoted by r_{ft}, is substituted for the return of the CRSP value-weighted index consistent with Amor and Kooli (2017). The Fama-French model lays the groundwork for a reliable model for equity pricing, but this study looks to remedy extrinsic factors as well. Furthermore, the error term would theoretically drop in absolute value by the inclusion of more variables.

vi. Summary Statistics & Univariate Analysis

a. Year 1999

Summary statistics for each variable used were coded into Stata using **`summarize varname, detail`** to interpret percentiles, variance, and skewness, with **`varname`** being the name of the variable of interest. The results are listed in Table 6 in Appendix A.

The first set of variables analyzed are intrinsic company variables. Revenues of the most recent reporting period for companies in the 1999 sample was listed in thousands of United States dollars ($). Since the lower bound of revenue is generally zero, it is unsurprising there is significant right skew. Most firms grew at a rate of at least 97 percent the year before the IPO and between rates of 45 and 265 percent. The range is extreme because one company's revenue grew 10,000 times over the year until the most recent filing period.

Most companies going public in the 1999 sample were unprofitable, and as few as 25 percent were profitable with one topping out at $366 million. Given that *margin* and ROA are quotients of profitability, it is unsurprising that most companies have negative operating profit margins and ROA (impactful outliers such as the minimum of -25.4). Interestingly enough, ROE was reasonably shaped. Because many firms had negative shareholders' equity, seen by the high number of negative book-to-market companies, and most were unprofitable, it is unsurprising that the median ROE was positive even when companies are unprofitable. There are only 360 observations for ROE instead of 361 because a company reported an equity value of 0, creating an undefined ratio.

A snapshot of the distribution for *age* is included to justify the aid of the natural logarithm adjustment. The average company going public in this sample was just over 10. However, recall that this sample excluded companies that did not have necessary financials for the necessary duration. Some new companies did not report two periods of financials (say, financials for Q1 1999 and Q1 1998) and were not included. It can be inferred that the true average is lower than the sample average for these reasons. Meanwhile, the natural logarithm makes the distribution much more normal.

Market sentiment is only measured by counting the number of IPOs a quarter before a given IPO, labeled *freq*. Most firms went public when at least 140 companies went public in the quarter prior. There was relatively significant fluctuation in IPO frequency throughout the year, showing hot issue trends during individual years.

The regulatory variables begin with the IPO size ratio, labeled *ipo_ratio*, for all companies in the sample. This is to measure the size of a company's offering compared to their market capitalization at the time of the offering. Most companies offered at least 21 percent of their market value in the offering. At least one firm in the sample offered their whole market capitalization in the offering.

Next are the distributions for the number of disclosed uses of IPO proceeds. I counted the number of uses in each of the four categories covered before: investment (*invest*), debt repayment (*debt*), sales and marketing promotion (*promo*), and other general corporate purposes (*general*). The sum of each category is the total number of listed uses, recorded as *uses*. Even though the lower bound for *uses* is tethered to zero, because a firm can only disclose as few as zero total uses, the distribution is slightly skewed left with the mean coming in at 4.64 and the median at 5. The range for *uses* is high compared to the standard deviation of the distribution. Most companies did not disclose a plan on debt repayment or promotional services, but most had allocated a portion to investment and general purposes. The ranges of each distribution were similar, as well.

The technology dummy was tabulated using the **`tabulate varname`** function in Stata. The distribution is relatively evenly split between technology (1) and non-technology (0) companies:

Table 7: Tabulation of companies that are classified as technology companies in 1999

TECH	Freq.	Percent	Cum.
0	197	54.57	54.57
1	164	45.43	100.00
Total	361	100.00	

Dr. Jay Ritter tabulates the number of technology IPOs per year in his "Initial Public Offerings: Technology Stock IPOs" source on his website and lists that technology firms accounted for 78 percent of IPOs in 1999 (Ritter, 2020). This discrepancy is because Ritter uses the SIC codes of companies, which is slightly less precise than the NAICS used in this analysis.

Underwriter reputation ranking, or *under_rank*, provided an interesting distribution. Over half of all IPOs in the sample were underwritten by top ranked underwriters, and at least 75 percent had an underwriter with a rank of 8 or 9. This alone may be the first confirmation of signaling with regards to using specific underwriters.

The explanatory variables for 1999 had mostly negligible correlations ($0 < \rho < |.3|$) at insignificant levels, seen in Table 8 in Appendix C. However, some trends had low positive correlations. Reported revenues and net incomes had a $\rho = .444$ significant to an α of .01. ROA and ROE were also relatively correlated at an *r* of .47 and significant to an α of .01. Both of these seem intuitive: companies that earn more are generally more profitable, and a firm's management of assets and equity is dependent on profitability.

The natural logarithm of company age and most recent total revenue shared a very significant relationship. While the magnitude was not strong (*r* of .29), the economic relationship between the two is intuitive: older firms have more established sources of income, allowing them to yield higher revenues. Because of this, the final models include an interaction term between the natural logarithm of company age and most recent total revenues. Unsurprisingly, the total disclosed use of proceeds, *uses*, had moderately positive correlations with the subsets of *uses*. Total uses correlated with *invest* and *promo* at levels of .631 and .585, respectively, and had weaker relationships with *debt* and *general* at correlations of .428 and .368, respectively. Each of these were significant at α equal to .01.

Monthly real GDP growth and quarterly frequency of IPOs had a measurable correlation of .318 significant at an α equal to .01. This makes sense, for as total economic output is or is forecasted to be relatively better, firms may increase demand for capital and expand through offerings.

b. Year 2019

The same command was executed for all accompanying variables in 2019 and results were indicated in Table 9 in Appendix B. Revenue for the most recent reporting period providing another right-skewed distribution for revenues, especially with Uber earning over $11 billion the period before its IPO. Firms in the 2019 sample possessed four times larger revenues than 1999 and the median was nearly seven times larger, even though UPS in 1999 was the largest IPO in both samples.

Tests of differences of means between 1999 and 2019 used the two-sample t-test functionality assuming unequal variances in Excel. The goal is to test whether the observations in each sample are significantly different than one another. The two-tailed hypotheses for most recent revenues were replicated throughout with all variables and are as follows:

$$H_0: \mu_1 - \mu_2 = 0$$
$$H_a: \mu_1 - \mu_2 \neq 0$$

with μ_1 being the mean for each variable in 1999 and μ_2 averaging 2019. Most recent revenues carried a p-value of .053. While this value misses the α of .05, it is still comfortably significant at an α of .1. We can favorably reject the null in favor of the alternative that the average revenues for the two samples are different.

The mean growth multiple for firms in the sample going public in 2019 is 1.175 and the median is .487. On the contrary to what was seen before, the two-sample t-test for the difference of means between 1999 and 2019 yielded a p-value of approximately .243. Regardless, it cannot be concluded that the means of proportional revenue growth are different. The mean and median net income in thousands of dollars for a firm in this sample were negative, showing that most companies going public in this dataset were not profitable in the most recent reporting period before the IPO, which is consistent with 1999's sample. While the t-test of differences yielded an insignificant result, 2019 had noticeably higher losses than 1999 and that could be because the companies were larger in 2019, seen by significantly higher revenues.

The mean for risk size is relatively close to the median, with the former listed at -.000011 and the latter being -.0000494. The fact that the median is a negative number means that most of the companies had negative shareholder's equity. Recall that the average *risk_size* for 1999 was positive, indicating that most companies in that period had positive shareholders equity. The t-test of differences yielded insignificant p-value, but this is an interesting characteristic of the two years.

Similar to net operating profit margin, it is unsurprising that ROA is negative due to the lack of total and operational profitability. The t-test of *roa* means results in a p-value of .01, so we can reject the null that the ROA means of both periods are the same.

While both ROE distributions of 1999 and 2019 yielded positive medians, the mean was higher for 2019. This could be because, as stated, more companies had negative shareholders equity in 2019 and that aligned with the negative distribution of the net income numerator in ROE.

The range for company age is 144, with companies like Levi Strauss & Co. holding the position on the upper bound and LMP Automotive Holdings at the bottom. The mean age of firms going public in the 2019 was two times higher than the 1999 sample, consistent with past research that tighter IPO regulations coincided with an increase in more experienced firms going public. Adjusting age by taking the natural logarithm of age, recorded as *adj_age*, accommodates for the excessive range of company ages. Both t-tests provided p-values below .01, signifying the means of the *age* and *adj_age* distributions among the two samples are probably not the same and confirming past research.

The rolling frequency of IPOs was much lower in 2019 than it was in 1999 because of the decrease in overall IPO frequency over the past two decades. The two-tailed t-test results in a p-value under .01, so it is reasonable to conclude the means of *freq* distributions are different.

The mean *ipo_ratio* of 2019 was a little smaller than 1999 (.235 to .196) and that is significant at an α of .05. Both samples contained at least one company offering their entire market capitalization in their IPO. The next set of regulatory variables of interest involve the listed uses of IPO proceeds a company discloses at the time of filing, recorded as *uses*.

The distribution also closely resembles the *uses* distribution of 1999. The means were 4.643 for 1999 and 4.724 for 2019, and the means are not significantly different. Recall that the number of uses in each of the aforementioned four categories were counted: investment (*invest*), debt repayment (*debt*), sales and marketing promotion (*promo*), and other general corporate purposes (*general*). While most companies did not report any uses of proceeds involving debt repayment, at least a quarter did and the highest topped out at three.

The distribution for *promo* was interesting, for companies in the 2019 sample did not disclose more than one use for sales and marketing promotion. Therefore, this variable was reclassified as a dummy variable for the 2019 model. Table 10 sheds light on this distribution:

Table 10: Tabulation of the uses of proceeds for promotional purposes (*promo*) in 2019

Promo	Freq.	Percent	Cum.
0	47	81.03	81.03
1	11	18.97	100.00
Total	58	100.00	

Only eleven companies declared a use of proceeds for promotional purposes, making up just under 19 percent of companies in the sample. General purposes, or *general*, carried the most interesting distribution. The firms in the 2019 sample disclosed more uses for general purposes on average than the offerings in 1999, and the two-tail t-test yields a p-value result of approximately .02, rejecting the null that the means are the same.

Other regulatory variables are measured as binary, like whether restrictions and requirements required by the SOX and JOBS legislations applied for a company going public:

Table 11: Tabulation of the companies that adhere to the Sarbanes-Oxley restrictions in 2019

SOX	Freq.	Percent	Cum.
0	50	86.21	86.21
1	8	13.79	100.00
Total	58	100.00	

The companies that did not experience the restrictions of the Sarbanes-Oxley Act while going public are "0" and those that were subject to them are "1" in this distribution. Companies listed as "0" were defined under the JOBS Act as an EGC, unless a company elects to avail themselves of this label in the prospectus. While this one is much more tipped in favor of emerging growth companies, the other distribution delineating between companies that took advantage of the JOBS adjusted filing and extended reporting measures was less skewed. In this case, over 36 percent of companies in the 2019 sample elected to avail themselves of lax reporting provisions in the JOBS Act:

Table 12: Tabulation of the companies that must adhere to JOBS Act requirements in 2019

JOBS	Freq.	Percent	Cum.
0	37	63.79	63.79
1	21	36.21	100.00
Total	58	100.00	

The technology dummy in this analysis was significantly more skewed than originally expected. Only eight, or 13 percent, of the sample were classified as primary technology generators. Perhaps this is because of the exclusions that took place in procuring this data. Clearly, the proportion of technology IPOs in the 2019 sample pales in comparison to 1999. This is consistent with Ritter's data showing 33 percent of IPOs in 2019 were technology firms:

Table 13: Tabulation of companies that are classified as technology companies in 2019

TECH	Freq.	Percent	Cum.
0	50	86.21	86.21
1	8	13.79	100.00
Total	58	100.00	

Underwriter rank (*under_rank*) in 2019 follows the results from 1999. Most IPOs in the sample were underwritten by an agent with the highest prestige score, and 90 percent had at least a score of seven, presenting a very skewed dataset. The practical interpretation is that most primary underwriters were of high prestige, making up the likes of Goldman Sachs, Morgan Stanley, JP Morgan, and a few others. This is consistent with the distribution of 1999, albeit the average underwriter rank for the 2019 sample is slightly higher than almost a half a point (confirmed with the one-tailed t-test p-value of .04, significant at α = .05).

Similar to 1999, there were little to no strong correlations among the distributions for explanatory variables in 2019 seen in Table 14 in Appendix D. An exception would be the correlation of whether a company was required to comply with the Sarbanes-Oxley Act, *sox*, and company revenues, *revenue2*, which was .7129 and significant at an α of .01. This is unsurprising because of the annual revenue limit for companies that are classified as EGCs and exempt from SOX requirements.

There are other notable significant moderate correlations between variables. The distributions for *uses* and *invest* were correlated with *revenueg* at correlation coefficients of .366 and .398 significant at an α of .01. These ρ were slightly higher than the variable distributions of 1999 which carried negligible significant correlations of approximately .12, but they were both positive. Therefore, there is evidence growth prospects and strategic uses of proceeds are relatively related. The variables of *outputg* and *revenueg* also shared a moderate relationship with a significant correlation of .417. This is intuitively logical, but proportional real GDP growth had a negligible correlation with essentially all other company financial variables in both samples. This is because real GDP growth was at the time of the IPO and not at the time of filing.

The variable *uses* correlated with *invest*, *promo*, and *general* at significant positive coefficients of .75, .298, and .619, respectively. However, *uses* and *debt* carried an insignificant relationship, another difference firms in 2019 has with 1999. Recall that *promo* is a dummy in this sample. Because both samples provided comparatively stronger and more significant correlations with *uses* and other sub-categories and due to the practical relationship between these categories, I chose to include two- and three-way interactions of these variables in the final regressions to strengthen the robustness of the test.

ROA for 2019 was moderately associated with *margin* and *risk_size* at significant correlations of .54 and .435, respectively. That was not reflected by the explanatory correlations for 1999 which yielded insignificant and negligible relationships between those combinations of variables.

V. Empirical Specification and Results

Regressions were run using OLS with heteroskedastic-consistent (Huber-White) standard errors. This is where the geometric abnormal returns dependent variable, *gar*, is first employed. An interaction term between most recent total revenues and adjusted age was included. The model for 1999 is:

$$\begin{aligned} GAR_{i,t+l} = {} & \beta_0 + \beta_1 Revenue2 + \beta_2 + \beta_3 NetIncome + \beta_3 NetIncome \\ & + \beta_4 Margin_{i,t} + \beta_5 Risk\_Size_{i,t} + \beta_6 ROA_{i,t} + \beta_7 ROE_{i,t} \\ & + \beta_8 Adj\_Age_{i,t} + \beta_9 OutputG_{i,t} + \beta_{10} Freq_{i,t} + \beta_{11} IPO\_Ratio_{i,t} \\ & + \beta_{12} Uses_{i,t} + \beta_{13} Invest_{i,t} + \beta_{14} Debt_{i,t} + \beta_{15} Promo_{i,t} \\ & + \beta_{16} General_{i,t} + \beta_{17} Tech_i + \beta_{18} Under\_Rank_{i,t} \\ & + \beta_{18} Revenue2_{i,t} * Adj\_Age_{i,t} + u_{i,t} \end{aligned} \tag{4}$$

Results are displayed in Table 15. The *general* variable was omitted due to collinearity with *uses*. The number of observations was 360 because of the missing ROE value. The model yielded a low R-squared of .168; however, the F-test yields a p-value of .0000 which provides evidence that the coefficients within the model are not zero by chance. Individual coefficients carried significant and meaningful results.

Revenue growth was extremely significant, but the coefficient itself was negligible. While it was initially expected that revenue growth would carry a positive coefficient, revenue growth may also proxy for inexperience. For every 100 percent increase in revenue growth, year-long buy-and-hold geometric abnormal returns are expected to drop around .02 percent holding all other variables constant. Net operating profit margin carried a significant negative relationship with geometric abnormal returns, opposing predictions and could be specific to the sample selected. Even accounting for significance, each of these provided negligible impacts to returns.

ROE yielded a significant, negative relationship with returns. While this may conflict with initial predictions, most firms carried positive ROE and negative returns, potentially indicating that this result is a sample issue. The natural logarithm of age was significant to an α of .1 and provided evidence that older companies drove higher returns one year after an IPO. This corroborates with why total revenues and net income are positive and revenue growth is negative[1]. Intuitively, this may make sense; in an era of so many IPOs, especially small ones, company experience may have been a differentiator. Surprisingly, monthly real GDP growth and quarterly frequency of IPOs carry significantly negative coefficients with returns. This is evidence that it is difficult to "time" an offering on the market and it may not be in a firm's best interest to try.

Interestingly, only disclosed uses of proceeds for promotional purposes, or *promo,* was significantly impactful on returns. This was the only variable between *uses*, *invest*, *debt*, and

[1] Total revenues, *revenue2,* and net income, *netincome*, were insignificant but positive, providing some evidence that larger and more profitable firms yield higher returns after an IPO. The direction of the coefficients corroborates with expectations, but outliers from being a scale variable may cause insignificance. Outliers could be mitigated by taking the natural logarithms of these scale variables similar to what was undertaken with age. Unfortunately, this analysis could not include this adjustment because net income carries negative values, and the presence of an adjusted revenue and scale profit decreases the integrity of the model.

promo, that was negative, providing evidence that using the IPO proceeds for a promotional strategy is counteractive to returns. The variable for *invest* being positive and insignificant aligns with Amor and Kooli (2017). The average predicted yearlong buy-and-hold abnormal returns of an IPO in 1999 would be -6.9 percent, significant to an α of .05, holding all of the explanatory variables constant, and the mean dependent variable was -66.6 percent.

Finally, technology firms were significantly associated with nearly 46 percent higher geometric abnormal returns one year after the offering than non-technology firms in our 1999 sample, holding all other variables constant. Primary underwriter ranking was surprisingly negative but insignificant. Variables mostly corroborated with predicted effects whether they were significant, impactful, or both. Proportional revenue growth, ROE, net operating profit margin, and the primary underwriter reputation rank were the only that directly contradicted initial predictions, but those have been addressed whether the culprit was a discovery (revenue growth, monthly real GDP growth, and quarterly IPO frequency), a sample error (ROE or net operating profit margin), or insignificant (underwriter rank). Firms in the 1999 sample succeeded when aligning with traditional methods of company success.

The regression technique was replicated for the IPO sample of 2019 and results are in Table 16. The only differences were the conversion of *promo* from a continuous to a dummy variable and inclusion SOX and JOBS regulatory dummies. The *general* variable was again omitted due to collinearity with *uses*. There were 58 total observations in the regression. The model's R-squared was significantly higher than the previous regression at .484 along with another F-test p-value of approximately .000. While the fit of the model is higher than the last, the individual coefficients do not yield as many significant results.

Contradictory to 1999's regression, the coefficient for total revenues was negative and

Table 15: Linear regression with interactions for the IPO sample of 1999

gar	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
revenue2	1.82e-07	0	0.45	.656	0	0	
revenueg	-.000231	0	-8.85	0	0	0	***
netincome	3.35e-07	0	0.22	.824	0	0	
margin	-.0001358	0	-1.96	.051	0	0	*
risk_size	279.448	266.586	1.05	.295	-244.912	803.809	
roa	.031	.032	0.99	.323	-.031	.093	
roe	-.027	.012	-2.31	.021	-.05	-.004	**
adj_age	.115	.067	1.71	.088	-.017	.247	*
outputg	-50.198	20.582	-2.44	.015	-90.682	-9.715	**
freq	-.006	.002	-3.22	.001	-.009	-.002	***
ipo_ratio	-.141	.544	-0.26	.796	-1.212	.93	
uses	.008	.093	0.09	.932	-.175	.191	
invest	.062	.109	0.57	.569	-.152	.276	
debt	.059	.097	0.60	.546	-.132	.25	
promo	-.323	.145	-2.23	.027	-.608	-.038	**
o.general	0	.	.	.	.	.	
tech	.457	.124	3.68	0	.213	.701	***
under_rank	-.017	.04	-0.43	.669	-.097	.062	
o.revenue2	0	.	.	.	.	.	
o.adj_age	0	.	.	.	.	.	
c.revenue2#c.adj_age	0	0	-0.43	.666	0	0	
Constant	-.069	.517	-0.13	.894	-1.085	.948	

Mean dependent var	-0.666	SD dependent var	1.154
R-squared	0.168	Number of obs	360.000
F-test	50.227	Prob > F	0.000
Akaike crit. (AIC)	1095.439	Bayesian crit. (BIC)	1169.275

*** *p*<.01, ** *p*<.05, * *p*<.1

Recall the dependent variable is *gar*, the proportional geometric abnormal returns for a security a year after IPO

significant, which contradicts initial predictions. In the same vein, *adj_age* was significant and negative. These alone are the only company characteristics that were statistically significantly impactful on geometric abnormal returns in the 2019 sample. Rather than favoring larger firms, seen in 1999, the market seems to favor smaller, efficient companies. This might provide external evidence that regulation has changed the composition of companies going public and how they perform on the equity market post-IPO. The environment was different in 1999; due to different listing requirements and a plethora of IPOs, investors seemed more risk averse. Similarly, because many companies going public recently are pre-revenue, investors may be less committed to revenues or company financials as a proxy for firm success. These distinctions in the IPO market are paramount when understanding the differences between the two years.

Table 16: Linear regression with interactions for the IPO sample of 2019

gar	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
revenue2	-2.68e-07	0	-2.47	.018	0	0	**
revenueg	.023	.02	1.18	.246	-.017	.063	
netincome	8.76e-07	0	1.11	.274	0	0	
margin	.013	.038	0.34	.738	-.064	.09	
risk_size	-80.418	225.627	-0.36	.724	-537.582	376.746	
roa	-.897	.577	-1.56	.128	-2.066	.271	
roe	-.119	.1	-1.20	.238	-.321	.082	
adj_age	-.446	.147	-3.04	.004	-.744	-.148	***
outputg	44.901	50.129	0.90	.376	-56.67	146.471	
freq	.005	.007	0.72	.478	-.01	.021	
ipo_ratio	.093	.663	0.14	.889	-1.249	1.436	
uses	-.066	.092	-0.72	.476	-.252	.12	
invest	-.003	.097	-0.03	.973	-.2	.194	
debt	-.082	.186	-0.44	.661	-.459	.294	
promo	-.207	.366	-0.57	.574	-.948	.534	
o.general	0	.	.	.	.	.	
sox	.408	.47	0.87	.391	-.544	1.361	
jobs	.262	.289	0.91	.369	-.322	.847	
tech	-.038	.357	-0.11	.916	-.762	.686	
under_rank	.25	.092	2.72	.01	.064	.436	***
o.revenue2	0	.	.	.	.	.	
o.adj_age	0	.	.	.	.	.	
c.revenue2#c.adj_age	0	0	1.48	.148	0	0	
Constant	-1.199	1.314	-0.91	.367	-3.861	1.462	

Mean dependent var	-0.031	SD dependent var	0.785
R-squared	0.484	Number of obs	58.000
F-test	5.090	Prob > F	0.000
Akaike crit. (AIC)	139.166	Bayesian crit. (BIC)	182.435

*** *p<.01, ** p<.05, * p<.1*

Interestingly, almost every direction contradicted the results of 1999, with the exception of net income, ROE, and disclosed promotional uses of proceeds. Net income being positive in both years and ROE being negative is puzzling. On one hand, there is evidence that balancing operational efficiency with size (maximizing profits) is beneficial for returns, although insignificantly in both samples. On the other, ROE as a proxy for management of ownership in generating profits are detrimental to returns, although insignificantly in 2019.

The coefficients of 2019's monthly real GDP growth and quarterly frequency of IPOs being positive directly contradicts 1999's results. However, they are both insignificant, so there is not ample evidence to assume it became possible to "time" the market with IPOs in 2019.

Book-to-market ratio, *risk_size*, yielding the highest magnitude for a coefficient is surprising, shared by both regressions, and the fact that it is negative in 2019 can be explained by Jensen's FCF hypothesis (Jensen, 1986). As shareholder's equity as a percent of the company increases, which occurs more so after an offering, extra cash on hand could have facilitated overzealous and ineffective business activities in IPO companies of 1999, especially with smaller and less seasoned companies. However, the result was insignificant, providing an avenue for future research.

Disclosed total uses of proceeds and the specifics of uses were all negatively associated with returns holding all other variables constant, but each were insignificant. The only one consistent with results from 1999 was *promo*. Even though the coefficient for *promo* was insignificant, it was of larger magnitude, and these differences could be because it is a dummy variable in this model. Furthermore, the coefficient for disclosed uses of proceeds for investment was lower in magnitude than the others, confirming the results of Amor and Kooli (2017) that disclosed uses for investment purposes are most beneficial (or, rather, least detrimental) to returns.

Whether a firm was constrained to the Sarbanes-Oxley Act carried a positive coefficient, consistent with expectations and in favor of regulation. Because it is a dummy variable, it can be interpreted as: holding all other variables constant, a firm that abides by the SOX regulations have expected returns of 40.8 percent higher than those who do not, but insignificant to an α of .1. Companies that were classified as EGCs under the JOBS Act but chose to abide by further reporting regulation saw 26.2 percent boost to returns on average in the same direction, holding all other variables constant, but this was also insignificant. Insignificance may be because the firms in the sample are already impacted by the regulations, decreasing the variability of each effect on returns.

Finally, the reputation for the underwriters in 2019 carried a significant positive coefficient and was consistent with expectations, but contradictory to the negative, insignificant result of *under_rank* in 1999. This is evidence that the use of a highly regarded underwriter was a signal to investors and lowered uncertainty about the IPO process in 2019. On average, IPOs in the 2019 sample carried slightly negative year-long buy-and-hold abnormal returns of -3.1 percent. Because the constant is so high in magnitude and the individual coefficients are mostly negative, it seems that the IPO market of 2019 was more strong-form efficient than 1999.

VI. Discussion

Both samples of 1999 and 2019 yielded varying and conflicting results. Over the past twenty years, it seems there have been differences in the companies going public and what information drives returns after the offering. Firms in 1999 performed better when they were larger, older, and growing at a slower pace, seemingly risk-averse investments. Conversely, comparatively younger, riskier firms performed better in 2019. Due to the new environment of regulation and going public, investors favored best opportunities for fast returns by taking risks, especially because many firms going public recently are pre-revenue.

Firms that went public in 1999 provided evidence that more disclosed uses for investment purposes positively affects abnormal returns, confirming results of Amor and Kooli (2019). The subcategory *promo* consistently carried negative coefficients in both tests, providing evidence that a disclosed promotional strategy for the proceeds of the IPO is harmful to stock performance. Finally, evidence in favor of Jensen's FCF hypothesis, especially in 2019, that an IPO may lead to ineffective allocation of funds and lower the value of the firm.

This paper has successfully confirmed or uncovered a number of interesting phenomena. First, certain information and factors before an IPO that correlate with or signal stock performance can change across time. Second, there is now novel evidence that abiding to more regulation pre-IPO leads to better stock performance. While the direction of the link is unknown, there is now a clear and quantified relationship between IPO regulation requirements and stock performance. More research is required to deduce the strength and causality of this trend. Third, in the same vein, there is evidence that the IPO market of 2019 is more strong-form efficient than 1999. Regulations, faster information exchange through media, changing business environments, and the democratization of investing though innovations like Robinhood may be responsible for making the market more efficient, providing evidence to corroborate with James and Valenzuela (2019). Further research regarding just how IPO markets can change levels of efficiency could build off the research of this paper. We could be in a trend toward more strong-form efficient IPO markets.

An important component of research that was not discussed in this paper was the effect of public perception regarding IPOs on stock performance, especially through media and discourse. Furthermore, the topic of how information flows from social media affect returns and efficiency of markets is relatively unexplored in research and could complement the work in this paper.

Finally, the frequency of SPAC IPOs has risen dramatically over the past two decades. While the process of these IPOs is different and could not be included in this research, identifying the most successful course of action for going public through SPACs could offer important information to both investors and companies.

VII. References

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Appendix A: Descriptive Statistics of 1999

Table 6: Description of IPO statistics for the sample of 1999 (number of issues = 361)

Variable	Mean	Min	25%	Median	75%	Max	SD
Revenue in thousands of $ (*revenue2*)	151,504	.327	3,795	10,337	30,296	19,606,000	1,158,760
Revenue growth (*revenueg)*	34.202	-.996	0.45	0.971	2.652	10,179.13	536.518
Net income in thousands of $ (*netincome)*	-5,288.28	-199,765	-9,765	-3,722	170	366,000	31,567.86
Net operating profit margin (*margin*)	-12.372	-3,712.2	-1.322	-0.427	0.03	1.538	195.386
Book-to-market ratio (*risk_size*)	0.000017	-0.000643	-0.000045	0.000007	0.000058	0.002157	0.000184
Return on assets (*roa*)	-0.332	-25.423	-0.413	-0.166	0.019	6.696	1.479
Return on equity (*roe*)*	-0.167	-48.0	-0.358	0.053	0.366	58.796	4.645
Firm age in years (*age*)	10.596	1	3	5	10	104	16.215
Natural logarithm of *age* (*adj_age*)	1.825	0	1.099	1.609	2.303	4.644	0.915
Monthly GDP growth (*outputg*)	0.0037	-0.0016	0	0.00395	0.00564	0.0088	0.0029
Quarterly frequency of IPOs (*freq*)	131.654	41	98	140	156	187	36.218
IPO size ratio (*ipo_ratio*)	0.235	0.022	0.159	0.213	0.289	1	0.112
Total number of disclosed uses (*uses*)	4.643	0	4	5	6	16	4.643
Number of investment uses (*invest*)	2.374	0	2	2	3	6	1.148
Number of debt repayment uses (*debt*)	0.778	0	0	0	1	6	1.16
Number of promotional uses (*promo*)	0.471	0	0	0	1	5	0.619
Number of general uses (*general*)	1.019	0	1	1	1	4	0.634
Underwriter reputation rank (*under_rank*)	8.086	1	8	9	9	9	1.539

*Sample for this variable is 360

Appendix B: Descriptive Statistics of 2019

Table 9: Description of IPO statistics for the sample of 2019 (number of issues = 58)

Variable	Mean	Min	25%	Median	75%	Max	SD
Revenue in thousands of $ (*revenue2*)	617,047.7	430.97	19,467	71,909	330,517	11,270,000	1,741,595
Revenue growth (*revenueg)*	1.175	-0.279	0.212	0.487	1.103	26.14	3.516
Net income in thousands of $ (*netincome)*	-23,906.94	-911,335	-29,886	-6,967.5	1277	285,244	139,412.70
Net operating profit margin (*margin*)	-0.572	-11.66	-0.451	-0.169	0.04	3.54	1.909
Book-to-market ratio (*risk_size*)	-0.000011	0.00107	-0.000108	-0.000049	0.000065	0.00143	0.0003588
Return on assets (*roa*)	-0.108	-1.669	-0.209	-0.064	0.017	.808	0.294
Return on equity (*roe*)	0.057	-2.668	0.0003	0.065	0.249	5.611	0.975
Firm age in years (*age*)	20.293	2	8	11	17	166	28.704
Natural logarithm of *age* (*adj_age*)	2.562	0.693	2.079	2.398	2.833	5.112	0.823
Monthly GDP growth (*outputg*)	0.00171	-0.002	-0.00053	0.00211	0.00316	0.008	0.00233
Quarterly frequency of IPOs (*freq*)	54.91479	23	44	58	65	83	16.784
IPO size ratio (*ipo_ratio*)	0.196	0.007	0.12	0.167	0.251	1	0.137
Total number of disclosed uses (*uses*)	4.724	1	4	4	6	12	2.093
Number of investment uses (*invest*)	2.672	0	2	3	3	8	1.711
Number of debt repayment uses (*debt*)	0.431	0	0	0	1	3	0.704
Number of promotional uses (*promo*)*	0.190						
Number of general uses (*general*)	1.431	0	1	1	1	8	1.286
Application of Sarbanes-Oxley (*sox*)	0.138						
Application of JOBS (*jobs*)	0.362						
Underwriter reputation rank (*under_rank*)	8.483	0	9	9	9	9	1.600
Technology dummy (*tech*)	0.138						

*Adjusted to dummy

Appendix C: Correlation Matrix for 1999

Table 8: Pairwise correlation matrix with significance for explanatory variables of 1999 distributions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) revenue2	1																	
(2) revenueg	-0.01	1																
(3) netincome	**0.44*** **	-0.01	1															
(4) margin	0.008	-0.001	-0.003	1														
(5) risk_size	**0.11*** **	0.032	**0.094***	0.006	1													
(6) roa	0.036	-0.003	**0.14**** **	0.03	0.037	1												
(7) roe	0.003	-0.002	0.045	**0.13*** **	-0.021	**0.47**** **	1											
(8) adj_age	**0.29**** **	-0.074	**0.18**** **	0.017	**0.16**** **	**0.09***	-0.032	1										
(9) outputg	0.054	0.045	-0.006	-0.03	0.08	-0.01	-0.001	0.03	1									
(10) freq	-0.047	0.044	-0.018	-0.03	0.083	-0.04	0.035	**-0.14**** **	**0.3**** **	1								
(11) ipo_ratio	-0.002	0.064	0.03	0.036	0.058	0.057	0.04	**0.29**** **	-0.003	**-0.12*** **	1							
(12) uses	**-0.19**** **	**0.12*** **	**-0.1***	-0.04	**-0.09***	-0.01	-0.033	**-0.14**** **	-0.021	0.06	**0.09***	1						
(13) invest	**-0.22**** **	**0.12*** **	**-0.14**** **	-0.03	**-0.115*** **	-0.07	-0.035	**-0.32**** **	-0.032	**0.12*** **	**-0.11*** **	**0.63**** **	1					
(14) debt	0.013	0.05	0.012	-0.01	0.03	**0.104*** **	0.01	**0.283**** **	0.000	**-0.15**** **	**0.23**** **	**0.43**** **	**-0.25**** **	1				
(15) promo	**-0.09***	0.046	-0.07	-0.05	**-0.103***	**-0.11*** **	-0.045	**-0.2**** **	-0.001	**0.105*** **	-0.01	**0.59**** **	**0.35**** **	-0.02	1			
(16) general	-0.067	-0.002	0.007	0.003	-0.01	0.022	-0.005	**-0.15**** **	0.001	**0.14**** **	0.02	**0.37**** **	**0.1*** **	**-0.13*** **	**0.11*** **	1		
(17) tech	-0.08	-0.05	0.02	-0.06	**-0.13*** **	-0.02	-0.06	**-0.12*** **	0.025	**0.112*** **	**-0.24**** **	0.05	**0.15**** **	**-0.13*** **	**0.1***	0.02	1	
(18) under_rank	0.07	0.033	-0.026	**0.18**** **	-0.006	**0.13*** **	**0.16**** **	-0.04	0.016	0.006	**-0.26**** **	**-0.25**** **	-0.08	**-0.15**** **	**-0.2**** **	**-0.1***	**0.1***	1

**** p<0.01, ** p<0.05, * p<0.1*

Appendix D: Correlation Matrix for 2019

Table 14: Pairwise correlation matrix with significance for explanatory variables of 2019 distributions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) revenue2	1																			
(2) revenueg	-0.08	1																		
(3) netincome	0.02	-0.04	1																	
(4) margin	0.11	-0.11	0.1	1																
(5) risk_size	0.05	-0.06	0.152	**0.26****	1															
(6) roa	0.07	-0.06	**0.27****	**0.54*****	**0.44*****	1														
(7) roe	0.04	0.08	-0.06	0.147	-0.03	**0.23***	1													
(8) adj_age	**0.24***	0.07	**0.29****	0.104	0.16	-0.01	-0.2	1												
(9) outputg	-0.11	**0.42*****	0.14	-0.1	-0.09	0.01	**0.2***	0.05	1											
(10) freq	-0.09	**-0.29****	0.11	0.2	0.005	**0.26****	0.03	-0.18	0.09	1										
(11) ipo_ratio	-0.11	**-0.22***	0.19	0.21	**0.27****	0.19	0.01	0.18	0.16	0.15	1									
(12) uses	-0.18	**0.37*****	-0.11	-0.19	**-0.33****	**-0.25***	0.05	-0.12	**0.22***	**-0.4*****	-0.14	1								
(13) invest	-0.12	**0.4*****	-0.13	**-0.27****	**-0.4*****	**-0.24***	0.01	**-0.3***	0.08	**-0.4*****	**-0.3****	**0.75*****	1							
(14) debt	-0.05	-0.14	0.14	0.1	**0.24***	0.08	-0.1	**0.4*****	0.1	**0.26***	**0.29****	-0.16	**-0.4*****	1						
(15) promo	-0.14	-0.02	-0.06	-0.14	**-0.35*****	**-0.4*****	-0.1	0.004	0.05	0.01	0.04	**0.3****	0.17	-0.17	1					
(16) general	-0.07	0.146	-0.07	0.04	-0.01	-0.01	0.13	-0.05	0.19	-0.2	0.05	**0.62*****	0.07	-0.19	0.04	1				
(17) sox	**0.71*****	-0.1	-0.14	0.2	**0.24***	0.18	0.05	**0.5*****	-0.14	-0.07	-0.07	**-0.33****	**-0.3****	0.18	-0.19	-0.14	1			
(18) jobs	**0.37*****	0.15	0.17	**0.23***	**0.31****	**0.25***	-0.1	**0.3****	-0.001	-0.05	0.16	-0.125	-0.17	0.1	-0.09	-.002	**0.4*****	1		
(19) tech	-0.08	-0.07	0.05	0.06	-0.03	0.001	-0.1	0.19	0.057	0.05	0.116	0.03	-0.04	0.11	0.06	0.02	-0.02	0.11	1	
(20) under_rank	0.09	-0.1	-0.03	**0.29****	0.05	**0.56*****	-0.1	-0.19	-0.15	0.18	0.08	**-0.24***	0.01	-0.04	**-0.2***	**-0.3****	0.1	0.14	0.04	1

**** p<0.01, ** p<0.05, * p<0.1*