Initial Public Offerings Across Business Cycles

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Abstract

A vast literature exists pertaining to the prediction of stock performance, though a consistent pattern has yet to be found. The efficient market hypothesis provides one possible explanation. IPOs are different, however, as they are more regulated than typical stocks. This means there is a potential the IPO market may contain inefficiencies. My work combines ideas from earlier research on the effects that business cycles and IPO cycles have on IPO success. This study aims to predict short-term IPO success, measured both from an investor's and a firm's point of view. My results suggest IPO returns are predictable to some extent up to 90 days following an issue. Though the results are encouraging, making investment decisions on this knowledge is currently impractical because both the business cycle and the IPO cycle cannot be acknowledged in real-time.

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I. Introduction

Initial Public Offerings (IPOs) are important because they not only allow a company to raise capital for investment in a business initiative, but they also allow venture capitalists to stage a profitable exit. Both firms and investors are highly interested in an IPO's success. If IPO success follows an identifiable pattern, these groups should make optimal decisions based on that pattern. A firm makes an optimal decision by minimizing the money left on the table, a phrase which means minimizing an increase in the value of the stock in the secondary market. On the other hand, an investor looks for a stock that will provide extraordinary returns in the secondary market. One of the most common places to look for a pattern in IPO and stock returns is among macroeconomic variables, namely the IPO and business cycles.

Hot and *cold* IPO markets are popular topics of economic research. A hot IPO market is traditionally characterized by a relatively large number of initial stock offerings, and a cold IPO market is the opposite. Liang and Helwege (2004) identify a hot IPO market by a time period in which investors are more likely to buy IPO stock—this abstract idea is difficult to quantify. Their research concludes that there are not many significant differences between hot and cold market IPOs except for the volume, or total number of IPOs in a period, and capital expenditures in the long term.[1] Thus, researchers often use the number of IPOs to measure hot and cold IPO markets.

Interestingly, hot and cold IPO markets are generally unrelated with the business cycle. In fact, the business cycle is much slower-moving than the IPO market. There exists little published research that compares IPO success in a particular type of IPO market environment during an expansion to success during a recession. Understanding any potential link is important

[1] Defined here as years after an IPO. For the rest of the paper, the long run will be defined as greater than 180 days.

for firms. For example, Binder et. al (2002) estimated that companies having an IPO in 1999 and 2000 left $60 billion on the table because of underpricing.

Research finds that the general stock market can be a good proxy for the macro economy. Chauvet (1999) reports that business cycles can effectively be predicted by a stock market factor (a vector of variables). Fama and French (1989) find that default spread, dividend yield, and term spread are good indicators of both stock and bond returns. These broad market effects may have an effect on the success of individual IPOs, which become part of the secondary market after their issue.

It is important to identify empirically the characteristics that make an IPO successful. From a company's point of view, Binder et. al (2002) propose that IPO *success* be measured in one of two ways, either by market competitiveness ("relative company value equal to or higher than industry peers") or by market pricing ("less than 20 percent change between offering price and 30-day post-IPO market capitalization"). On the other hand, from an investor's point of view, it is important for the share price to rise in order to compensate him/her for the risk of their investment. Investment bankers work to set an IPO price that they hope will satisfy both the company's and the investors' wishes.

Does the success of an IPO vary by business cycle and IPO cycle? As implied by the theory of efficient markets, I propose a null hypothesis that no systematic relationship exists between IPO success and the IPO and business cycles. I test the hypothesis using a regression model adapted from Morton (1998) and others. I measure IPO success in two ways, concentrating on the more conventional method of success as IPO returns but also experimenting with Binder's et. al (2002) suggestion of firm-based market pricing as success. If there is in fact a relationship between IPO success and IPO or business cycles, firms and investors should make decisions that are financially beneficial. If my empirical work finds differences in hot or cold market success across the business cycle, there may be an unknown market imperfection at work. On the other hand, if I am unable to find a relationship, firm-specific variables may offer a better prediction of IPO success. These would be areas for further research.

My research will be different than previous research in a couple of ways. First, I increase the time period and hence the number of IPOs under investigation; I will be looking at IPOs from 1985 to the most recent National Bureau of Economic Research (NBER) business cycle dates (currently a trough in November of 2001). Second, I use different variables to represent the macro economy. Third, I incorporate new suggestions of IPO success into my analysis. Finally, I investigate whether the interaction of the various IPO and business cycles has an effect on IPO success.

II. The IPO Process[2]

Understanding the IPO process is important when studying IPO success because the former can have a significant effect upon the latter. As explained before, a company can have many reasons for raising money through an IPO. For example, a company may not have capacity for additional debt or venture capitalists may be looking for a profitable exit. No matter the motivation for having an IPO, the basic process is the same.

The first action a firm must take is to select an investment bank that will act as an advisor and lead underwriter. The firm usually chooses an investment bank that has some expertise in IPOs in the firm's industry and that deals with the type of clients to which the firm wishes to sell the majority of its shares (institutions versus individuals). The investment bank agrees if they feel the company is of a high enough quality to merit its attention and will market well to its client base. This chosen bank will be the lead underwriter, and it may decide to add other co-managers or syndicates to help in the distribution as necessary. The lead bank then drafts a letter of intent that indicates if an IPO is withdrawn anytime during the due diligence,[3] registration, or marketing stage, the aspiring IPO-company must cover the bank's financial losses. The letter also specifies the gross spread, or the percentage of the proceeds that the investment bank will receive from the offering. One important factor left out of the letter is the final offering price. The bank is then charged with actually performing the due diligence. Once it is satisfied with its due diligence efforts, the bank must register the IPO with the Security and Exchange Commission (SEC). This registration includes the initial prospectus, sometimes called the "Red Herring."

[2] This section is based heavily on Ellis, Michaely and O'Hara (1999).

[3] "Due diligence" refers to the investment bank's investigation of the firm, its assets and operations. This is done to assure investors that the firm actually exists and does what it claims to do.

After SEC approval, the bank sends out the now-finalized prospectus and goes on a road show to promote the company to mainly institutional investors. At the end of the presentation, each investor will furnish the bank with a price and the number of shares that they are interested in buying. After gathering this information over the period of usually a few months, the bank and the firm will sit down to determine the price and the number of shares for the offering. The price needs to be high enough so that the company does not leave too much money on the table, but also needs to be low enough to generate quick returns to compensate investors for the risk. A company may have to sacrifice some funding and take a lower price to ensure the offering is completed. The stock is then distributed to investors, and it is the investment bank's responsibility to maintain liquidity in the aftermarket. Twenty-five days following the offering, the firm makes its financial information completely public and the investment bank is allowed to comment on the firm's valuation and earnings estimates. The basic IPO process is over, but the investment bank continues to provide analyst coverage of the firm.

Looking at the process from an investor's point of view, the change in the price of a stock in the aftermarket should compensate him/her for the risk taken from investing in an IPO. They want compensation in the form of quick positive returns. Institutions and individual investors are generally encouraged to invest in a company for the long run and therefore not to sell their shares immediately after receiving them. This helps provide some stability in the stock price of IPOs. Insiders of the company are actually bound by law not to sell shares until at least 90 days following an IPO. Another fact to keep in mind is that investors who sell their shares less than a year after investing in the IPO face higher taxes on their gains than if they had held on to them for a year, so they should be inclined to hold shares if the IPO is successful. This should drive the price of shares up as no one wants to sell their shares. On the other hand, if an IPO goes sour, investors may try to dump their shares as quickly as possible, thus driving the share price lower still.

Why is understanding the IPO process important for an investigation into the success of an IPO after it is issued? The IPO process is important because it influences the pricing of an IPO. Furthermore, it is the change in price of an IPO determines the success of an IPO. It is valuable to recognize that I am not taking into consideration the effect of the IPO process on IPO success. This could be an extension of my research in the future.

III. Literature Review

Academic research has thus far addressed this issue from two separate angles. First, are the stock market and the business cycle related? Research that focuses on the effect of the stock market on the business cycle attempts to forecast business cycles, while research that focuses on the effect of the business cycle on the stock market or IPOs aims at predicting stock prices. Second, are there differences in hot and cold markets that affect IPO success?

The Stock Market and the Business Cycle

Any relationship between IPOs and the business cycle may be part of a larger relationship between the stock market, in general, and the business cycle. Chauvet (1999) considers the effect of the stock market on the business cycle. She notes that using preliminary economic data to predict the future of the economy is extremely unreliable because the data are nearly always updated or changed. To determine if there is a relationship, Chauvet uses an empirical model that "allow[s] the underlying process for business cycles and stock market cycles to switch non-synchronously over time." Single financial or non-financial variables have not been found to predict shifts in the business cycle very successfully, so Chauvet considers a stock market factor. The stock market factor is made up of "the excess stock return, defined as the difference between continuously compounded returns on the CRSP valued-weighted index and the 3-month T-bill rate, the first difference in the log of the S&P 500 dividend yield, and changes in the S&P 500 price-earning ratio and in the 3-month T-bill rate" and other similar variables. She also does analysis using a Composite Index of Leading Indicators (CLI).

Chauvet finds that the stock market factor predicts changes in the business cycle very well. In general, the stock market factor goes down a few months before a recession and anticipates an expansion by increasing before the business cycle reaches a trough. Though changes in the stock market and the business cycle may be "driven by the same fundamentals," the stock market factor is able to increase in advance of the whole economy. It is important to note that stock market prices alone do not predict the business cycle well—it is the stock market factor that correctly predicts all of the recessions in the sample, missing none, and only giving four false peak signals. Results for the CLI are a bit more difficult to interpret because the data in the CLI are revised and not the originally reported numbers. By performing an out-of-sample analysis, Chauvet shows that the CLI is not as successful as the stock market factor in predicting changes in the business cycle. This finding is important because it helps identify the predictability of business cycles.

Chauvet and Piger (2008) revisit Chauvet's (1999) earlier findings. They compare the effectiveness of the Dynamic Factor Markov-Switching Model (DFMS) that Chauvet used and of the Harding and Pagan (2006) algorithm in predicting NBER cycle dates in real-time. They conclude that neither model is able to consistently predict an NBER business cycle peak before it is reported. The DFMS model, for example, is behind the NBER in predicting business cycle peaks by nearly two months. On the other hand, their results suggest that both models are in fact able to predict business trough dates significantly before the NBER. Surprisingly, the DFMS and Harding and Pagan (2006) algorithm models are able to declare a trough has been reached on average 200 days before it is announced by the NBER. Even with this lead, however, the two models typically date a trough that happened at least six months earlier. The amount of time between the detection of a trough and the actual trough itself may be too long to allow investors to make investments in IPOs based on business cycles in real time.

Looking at the relationship in the opposite direction, Morton (1998) investigates the effect that macroeconomic factors—namely monthly changes in the yield curve, monthly changes in the default premium, and monthly changes in the consumer price index—have on IPO returns. He studies IPOs in the years 1984 through 1990 using a regression model with IPO returns as the dependent variable. He observes that "IPO returns decline following increases in the yield curve since investors use a higher opportunity cost to discount cash flows," and that "IPO returns are positively related to changes in the default premium." Morton's model works well for hot markets (defined using Forbe's annual survey of IPOs) but does not explain much during cold markets. He hypothesizes that firm-specific variables may be better predictors for cold-market IPO success than macroeconomic variables. These findings imply that macroeconomic variables have an effect on IPOs and that an investigation of IPOs and the more broadly defined business cycle is warranted. In addition I will be adding significantly more IPO observations to this study.

Fama and French (1989) also look at the effect of the broad economy on the stock market. They report that "there is mounting evidence that stock…returns are predictable." Their study finds that the dividend yield and default spread on bonds forecast high returns during consistently weak economic periods and conversely forecast low returns during strong economic periods. Fama and French's research supports the idea that stock market returns—and therefore IPO returns, too—can be partially predicted by business cycle-like variables.

Hot and Cold IPO Markets

There is also a large empirical literature on the characteristics of hot and cold IPO markets. The research focuses on the characteristics of firms and of the equity markets in hot and cold markets. The three major theories of hot and cold markets are (following Helwege and Liang (2004)) signaling models; decision theories of the choice between an IPO or staying private; and behavioral finance models.

The first of these, the signaling model, follows the premise that as the outlook for businesses improves more firms will have IPOs. For instance, Allen and Faulhaber (1989) created a model that "predicts a hot market when firms' expected profits increase." Unfortunately, this theory is not fully supported by empirical tests, as Jegadeesh, Weinstein, and Welch (1993), Michaely and Shaw (1994), and Spiess and Pettway (1997) find.

The second set of theories, about the decision between an IPO and remaining private, is more multifaceted. One reason a firm could claim for deciding to go public is that it is in a high-growth business. Pagano, Panetta, and Zingales (1998) and Fischer (2000) find evidence of this from firms in Italy and Germany. The IPO funds will help it grow without having to add more debt. Another reason a firm might go public is productivity shocks, which in turn increase a firm's forecasted profitability and investor interest, raising the cost of staying private. Chemmanur and Fulghieri (1999) suggest that positive productivity shocks increase firm values, and Hoffman-Burchardi (2001) predict that as an industry's prospects rise, the costs of staying private rise, too. Helwege and Packer (2003) add that IPOs are many times exit strategies for venture capitalists, yet another reason a firm could decide to go public.

Finally, behavioral finance models look at potential irrationality of hot market IPOs. This theory claims that investors can become overly optimistic about IPOs, initiate a hot IPO market, and experience long-term underperformance. As supported by Ljungqvist, Nanda, and Singh (2006), the theory also "predicts that hot market IPOs have higher market valuations and worse stock price performance."

Helwege and Liang (2004) evaluate these theories that attempt to explain differences between hot and cold IPO markets using IPO data from 1975 to 2000 from the Securities Data Company (SDC). After removing from the dataset financial companies, reversed leveraged buyouts, and other potentially troublesome data, they are left with a sample of 3700 IPOs. They define hot and cold markets by using a "three-month centered moving average of the number of IPOs scaled by new business formations for each month in the sample." For tracking long-term stock performance, Helwege and Liang use returns starting two weeks after the IPO so as to replicate returns for a typical investor.

The results end up not supporting much of the previous theory. Helwege and Liang find that IPOs as a group are underperformers in the long run and that hot issues (defined by volume) usually underperform cold issues in the long run. In addition, hot market IPOs have less industry clustering than their cold market counterparts. As a result, a hot market in one industry is likely at the same time as a hot market in another industry. They further find that hot market IPOs raise more money than cold markets. "The median firm age is seven years for both hot and cold market IPOs, and both capital expenditures and R&D are lower for hot market IPOs." Helwege and Liang also deduce that hot market IPO firms can not be generalized as young and having a higher growth potential. Using a multivariate logit of the decision to issue in a hot or cold market they challenge the "idea that hot market firms are a special type of IPO firm in special types of businesses." To check the robustness of their results, the authors also define a hot IPO market as one with severe underpricing and come to the same conclusions. In the end, Helwege and Liang believe that there "is always a market for high-growth firms, and in some periods only a small fraction of them are palatable to investors."

Malkiel (2003) provides an alternative perspective on stock research. He declares that the stock market is more unpredictable than some research suggests. He believes that most research into stock prices does not provide enough predictive power to guarantee returns for investors. To make matters worse, patterns seem to disappear after they are discovered. He argues that the dividend yield and risk spreads are no longer good predictors for the stock market. Finally, using evidence from Fama and French (1993), Malkiel indicates that size may be a good predictor for company stock performance. Malkiel's work suggests that it is impossible to predict the performance of stocks, at least with current methods.

My research will mainly build upon the work in Helwege and Liang (2004) and Morton (1998). Not only will I be adding additional data, but I will also be looking for differences in hot and cold markets during different phases of the business cycle. My work will also take into account Malkiel's idea about the size of a company. Finally, I will measure IPO returns from the first day of trading because it is just as important for institutional investors who have taken on much of the risk of the IPO to have good returns as it is for a typical investor who might get his/her shares two weeks after the IPO.

IV. Theory & Model

Economic theory related to risk and return leads to finance theory on stock market prices. The major model is the Capital Asset Pricing Model (CAPM). It is expressed as an equation:

$$\hat{R}_e = R_f + \beta(\hat{R}_m - R_f),$$

where $\hat{R}_e$ is the expected return on a stock, R_f is the risk-free rate of return (typically the return on a T-Bill or a similar investment), $\hat{R}_m$ is the expected stock market return, and β is a measure of the level of market risk in the stock. According to the model, β is calculated as follows:

$$\beta = \frac{\mathrm{Cov}(R_e, R_m)}{\mathrm{Var}(R_m)}.$$

A positive β means that the stock moves in the same direction as the market, while a negative β denotes stock that moves opposite to the market. Stocks with a β greater than one, according to Hoover (2006), are those that "tend to swing up and down along with the market, but tend to have wider swings than the market." Those stocks with a β less than one (but greater than zero) "tend to swing up and down along with the market, but they tend to not swing as much as the market itself." Thus, the CAPM predicts that the return on a stock is directly related to the amount of risk investors are willing to take. With the CAPM, higher risk equals higher return.

A related theory is known as the Arbitrage Pricing Theory (APT), developed by Ross (1976). It concludes that a stock's price depends on several unknown factors. This is in contrast to the CAPM which concludes that a stock's price only depends on a stock's β. The factors of the APT are not only unknown but can also change over time (Wang 2003). The APT uses a concept called "factor loading." Factor loading assigns a weight to each of the factors in the APT according to the amount a stock's return is affected by unexpected news about the factor. The APT also assumes investors perform "arbitrage in expectations" (Goetzmann 1993).

Arbitrage in expectations is different from standard arbitrage in that the return is not guaranteed, it is *expected.* Investors buy assets with higher expected returns (and the same amount of risk) until the price rises enough to equalize the expected returns. The theory further suggests that mispricings exist and that investors are able to exploit these mispricings.

The CAPM leads to what is commonly known as the efficient market hypothesis. Assuming rational expectations on the part of financial investors, the efficient market hypothesis predicts that stock prices incorporate all known information. Therefore investors should not be able to predict stock returns, and returns should not vary systematically with economic variables such as the business cycle.

As stated above, the theory of efficient markets assumes rational expectations on the part of financial investors. I use this theory for IPO pricing, too. This simplification implies that IPOs are priced appropriately at their issue. If this is the case, then we should not be able to predict IPO returns (and hence, success) either. In theory, then, I expect IPO success to be largely unexplained from the variables included in the model. Sargent (2002) adds that "investors' forecasts become built into or reflected in the price of stocks." Investors' forecasts should therefore already include expectations about IPO success coming from a particular IPO market and business cycle.

The model in this research is based on Liang and Helwege (2004) and Morton (1998). Using both micro and macroeconomic variables, the model aims to predict the success of an IPO by looking at the timing in the IPO cycle and the business cycle. It measures the business and IPO cycles with dummy variables accounting for hot, neutral, or cold IPO markets and for economic expansion or recession. The microeconomic variables include firm-specific variables that describe the firm's financial condition, such as assets and long-term debt/assets. Finally, I use interaction variables to account for the relationship of the IPO cycle and the business cycle. Formally, my model can be expressed as follows:

(1) $S_i = f(H_i, C_i, R_i, CE_i, HE_i, AMT_i, CAPX2A_i, D2A_i, FA2A_i, ASST_i)$

Where the variables are defined as:

S_i = IPO success

H = dummy variable for a hot IPO market

C = dummy variable for a cold IPO market

R = dummy variable for an economic recession

CE = interaction variable for a cold IPO market and an expansion

AMT_i = the initial market capitalization of the firm

$CAPX2A_i$ = ratio of capital expenditures to assets

$D2A_i$ = ratio of long-term debt to assets

$FA2A_i$ = ratio of property, plant, and equipment to assets

$ASST_i$ = total assets of the firm

This model also attempts to address the problem that Morton (1998) had with cold markets in his research. Recall that Morton found cold markets insignificant and suggested that the success of cold market firms may be better predicted using firm-specific variables. By changing the macroeconomic factors into a broader economic indicator variable, it may be possible to replicate similar results in hot markets and determine whether there is a difference in cold markets. The model, therefore, purposely focuses on general, not specific, business cycle variables.

The focal variables for this study include H, C, R, and CE. These variables allow the model to directly measure the effect of each on the success of an IPO. The model also includes control variables, namely AMT, CAPX2A, D2A, FA2A, and ASST. These variables are used to control for the effect of firm-specific variables on IPO success. The control variables account for the size (AMT and ASST), the capital structure (D2A), and the industry (CAPX2A and FA2A) of the firm.

I expect the following signs to be associated with the variables:

Variable	Short Run Expected Sign	Long Run Expected Sign
H	+	-
C	-	+
R	-	+
CE	+	+
AMT	+	+
ASST	+	+
CAPX2A	unclear	Unclear
D2A	+	+
FA2A	unclear	Unclear

I will first explain my reasoning for the focal variables H, C, R, and CE. H (a hot market) should have a positive sign in the short run and a negative sign in the longer run. Hot markets are typically characterized as markets with significant initial underpricing, but the evidence points to underperformance in the long run. On the other hand, for C, or a cold market, I expect a negative sign in the short run and a positive sign in the longer run. A cold market firm is willing to issue into an otherwise depressed market, likely believing its long-term prospects are good. For R, the recession variable, I expect to have a negative sign in the short run but a positive sign in the longer run. This comes from the fact that recessions in the U.S. since World War II have been short-term, so most IPOs issued during a recession will actually be in an expansion market in less than one year. In my research the longest time horizon is one year. I expect a positive sign for CE, the interaction variable between a cold market and an expansion. The expansion part of the variable will overcome the initial negative returns I expect from a cold IPO. This is because the economy is growing, and yet there may be just a few firms that choose to have an IPO in a particular three-month period. Those that issue should perform well in the economic expansion.

The signs for the control variables, AMT, ASST, CAPX2A, D2A, and FA2A are more difficult to predict. I expect AMT, or the initial market capitalization of a firm, to have a positive sign, as larger firms should be more stable in the after-market. For assets (ASST), I expect a positive sign. Assets are a difficult measure as small start-up or tech firms will not likely have many assets but could still perform as well as a company with more assets. The expected sign for CAPX2A, or the ratio between capital expenditures and assets, is unclear. If a firm is in a capital intensive industry, such as a manufacturing firm, then a higher ratio may lead to higher success. On the other hand, if a firm is in a more intellectually intensive industry, such as a research firm, then a higher CAPX2A ratio could have a negative effect on success. The story is similar for the FA2A ratio. The effect of these two ratios really depends on the industry a company is in, so the associated sign should not be easily predicted. Finally, for D2A, or the ratio of debt to assets for a company, I expect a positive sign. The more debt a young company has, the more likely it is growing so fast that it cannot take on any additional debt and needs equity financing. This idea comes from the fact that a company can actually grow itself into bankruptcy.[4] Equity financing brings with it an infusion of cash that fast-growing companies usually require.

[4] As sales grow some companies do not realize the necessary growth in net working capital, causing them to go bankrupt.

V. Data

The data used in this analysis comes from multiple sources, including Standard & Poor's Compustat, the Center for Research in Security Prices (CRSP), and the National Bureau of Economic Research (NBER). Each observation incorporates data from the three sources. From Compustat, I gathered a list of IPOs between 1985 and November 2001, as well as the firm-specific financial variables of assets, capital expenditures, long-term debt, and property, plant, and equipment as reported in the year of the IPO. From CRSP, I gathered daily stock prices as well as the number of shares outstanding. Finally, from the NBER I generated a dummy variable to identify an expansion and a recession. After merging the datasets, I took out all financial companies, all companies with an IPO for less than $1 per share, all companies listed as American Depository Receipts (ADRs), and all companies with missing data. Dropping companies with missing prices data means that I may have dropped companies that did not survive one year after their IPO. The company may have been sold or CRSP may just not have reliable data for it. This left me with a sample of 5,529 IPOs.

This basic data was used to form additional variables. From the data, I calculated the quartiles of the three-month moving average of the number of IPOs. Following Helwege and Liang (2004), I classified months in which there were a greater number of IPOs than the third quartile as "hot" (in my work, this number equals 51.75) , months in which there were less IPOs than the first quartile as "cold" (measured at 13.67), and the remaining as "neutral." The following table shows the number of IPOs during various economic periods:

	Recession	Expansion	Total
Hot	0	2615	2615
Cold	54	161	215
Neutral	42	2657	2699
Total	96	5433	5529

Using the IPO market and business cycle dummy variables, I created an interaction variable for a cold market IPO during an expansion. Because there are no recorded hot market IPOs during an expansion, I can only create one interaction variable from this dataset. The market capitalization was calculated by multiplying the price on the first day of trading by the number of shares outstanding on that day. I then calculated the three ratios using the Compustat variables (assets divided by: long-term debt, capital expenditures, and property, plant, and equipment). Finally, I created the returns to investors by finding the percent change in price since the first day of trading for five different holding periods (30 days, 60 days, 90 days, 180 days, and one year).

The dependent variable, IPO success, will be measured in a few different ways. In order to determine IPO success for investors, I will use IPO returns after various time periods. Additionally, as suggested by Binder (2002), I will measure IPO success for the firm by looking to see if its price increased more than 20% in the first 30 days of trading. To do this, I create a dummy variable equaling "1" if a stock has returned zero to twenty percent during the first 30 days of trading, and "0" if the returns were either less than zero or greater than twenty.

So that my research could potentially be recreated by another researcher, I will explain in greater detail how I gathered this dataset. In order to gather all IPOs between 1985 and 2001 using the Compustat Fundamentals Annual database, I selected the date range as 1985 to 2001, and the "Entire Database" as the method of search. I eliminated all companies without an IPO date in the database. Next, I selected the following variables: CUSIP (company identifier), IPODATE (date of IPO), NAICS (industry code), FYEAR (the fiscal year), AT (assets), CAPX (capital expenditures), DLTT (total long-term debt), PPENT (property plant and equipment gross total). Then, I used Stata to sort the data so that each company only lists variables for the year of its IPO.

Next, I screened the dataset. First, following Helwege and Liang (2004), I removed all financial companies. I used NAICS codes, i.e. those beginning with 52, to identify the financial firms. Second, I took out all firms with initial prices of under $1. I then took out firms with ADRs because they are not American companies. Next I removed companies that have missing data from Compustat or if their value of assets equals 0. I was left with 6830 observations.

Stock prices are necessary for measuring IPO success. To obtain this data, I used the CRSP database. I searched the CRSP using the CUSIPs from the dataset created earlier. Unfortunately, opening prices for stocks in the CRSP database are only available after June 15, 1992, so I had to use closing prices for the first day. This could alter results because I am unable to account for typically large shifts in price on the day of an IPO. I selected appropriate dates so that the CRSP search will return at least one year of stock prices for each IPO. Some stocks do not actually show up in the CRSP database on the date of its IPO as reported in the Compustat database. The variables used from the CRSP are: CUSIP, Price[5], and the Number of Shares Outstanding. Using the various daily stock prices I created a single observation for each company that includes the price on the first day of trading as well as 30 days, 60 days, 90 days, 180 days, and 1 year later.

Next, I merged the two files and dropped the observations that do not have data from the CRSP. After this was done, I needed to calculate returns over the various periods, create an interaction variable, and finalize the control variables. Returns are calculated by subtracting the IPO price from the price some period after the IPO and then dividing by the IPO price. This

[5] In the CRSP database the price will have a negative sign in front of it if the quote is the average of the bid-ask spread instead of the closing price. To fix this problem take the absolute value of all of the prices. We will assume that the average spread is the price for this exercise.

gives the return a holder of the stock would receive over the specified period of time. To calculate the market capitalization of a company, I multiplied the number of shares outstanding by the price of the stock on its first day of trading. I also needed to create the ratio variables by dividing capital expenditures, long-term debt, and property, plant, and equipment by assets, respectively. This dataset includes 5529 observations and is what I used for analysis. I also used a sample of 500 IPOs including the 96 recession IPOs and a random sample of 404 expansion IPOs.

Table 1 and 2 shows simple descriptive statistics, and Figure 1 shows the mean IPO returns. The mean IPO returns are rather low, suggesting that investing in many IPOs may be unwise in general. On the other hand, the range in returns is very large, and some IPOs return sevenfold in one year. It is therefore possible that, taken as a whole, returns compensate investors for the risk. Recession's mean of .017 shows that there are very few recession IPOs, and hence it may be worth taking a stratified sample including all recession IPOs. The large variation in the AMT and ASST variables may cause problems with the regressions. Future research may decide to create dummy variables for different ranges.

Figure 2 shows the number of IPOs over time. The rectangular shapes mark the years of recession, while the other data shows the number of IPOs. The sharp peaks show that the IPO cycle can move very quickly as compared to the business cycle. The chart also suggests that the 1990s may contain the largest number of IPOs in any decade before. An explanation for this could be that the financial markets have deemed IPOs a better method of raising capital than before or just that the 1990s was the dot-com age.

VI. Results

I first explain the regressions and compare and contrast them. Next, I describe the significance of each of the four focal variables. Then, I go on to discuss some other aspects of the results and present the results from using an alternative measure of IPO success, which involves a probit regression.

The regression results for success measured as 30-day returns are found in Table 3. Two focal variables, R and H, are significant in the population regression, while only R is significant in the sample regression. The recession coefficients are both negative and less than -.08, which indicates that a recession initially has a large, economically significant negative effect on IPO returns. Though the hot market variable is statistically significant in the population regression, its coefficient of .025 is not very economically significant. In addition, as we observe with the other regressions, some of the control variables show significance, too. This factor suggests that IPO returns might be better explained with more company-specific variables, some of which are not necessarily quantitatively measurable. Both the population and the sample regressions have low R-squared values. This is not surprising, however, since the regressions attempt to explain stock prices, a nearly impossible task.

Table 4 shows the regression results for success measured as 60-day IPO returns. With these regressions we notice that three focal variables (R, C, and CE) are significant in both, and that H is significant in the regression of the population. The coefficients themselves are large, too. R and CE show negative coefficients around -.14, while C shows a positive coefficient around .14. It is interesting to note that a cold market adds 14% to the returns of an IPO, ceteris paribus, while a cold market expansion IPO detracts 14%. Once again we see the effect of the hot market variable (H) to be less than 5%.

The results for the regressions using success measured as 90-day returns are found in Table 5. As in the last regressions, the R, C, and CE variables are significant in both the sample and population, and H is significant in the population regression. The signs of the coefficients remain the same but the magnitudes of R, C, and CE increase. R and C change by approximately .09, while CE changes by .055. These numbers suggest that the effects of the factors become more pronounced in the third month following an IPO. The hot market coefficient does not change and holds steady at .048.

Table 6 summarizes the regressions for success measured as 180-day returns. The only focal variable significant here is the CE variable in the sample regression. Even then, it is only statistically significant at the 10-percent level. The coefficient is rather large, though, coming in at -.261. That 26% effect, which is similar to the regression using 90-day returns, is one of the largest in all of the regressions. R^2 drops to its lowest level in the regressions for both the population and the sample. These results clearly show that 180-day IPO returns are very difficult to predict using these variables.

Finally, Table 7 reports the regressions using 1-year returns as a measure of IPO success. Once again, there is a lack of significant focal variables. The only significant focal variable is H from the population regression, and it has a coefficient of -.125. This negative coefficient implies that hot market IPOs typically underperform the market in the longer-term. A lot of changes can occur in a company during a year's time, so it is not surprising to see many insignificant variables measured a year before.

The four focal variables did not all behave as the theory predicts. Take the cold-expansion interaction variable, CE, for example. When statistically significant (and mostly even when it was not), the CE variable had a large negative coefficient. CE was found to be significant in the 60-day, 90-day, and 180-day return regressions. When it was significant, the coefficient ranged from -.143 to -.267. If correct, this effect is detrimental to cold market expansion IPO investors. What is unclear from the data, however, is if these companies typically turn around after a few bad months. If so, it might seem opportune to wait until the prices have fallen and then buy up these firms.

The cold IPO market variable, C, did not behave as expected either. In all of the regressions, C's coefficient was positive, while I had predicted that it would be first negative and then positive. An explanation for the persistent positive sign could be that cold market firms have good business prospects and this is why they are willing to issue during a cold market. It is interesting to note that in the first few regressions the coefficient of C closely followed the magnitude of R, and when both variables turned out to be significant (60 and 90-day regressions) the absolute values of their coefficients differ at most by only .006. Also, it is worth noting that C's coefficients are always greater that H's coefficients. This contradicts the idea that hot market IPOs are more underpriced than cold IPOs.

Two of the variables did actually follow some of the theory and model, however. The recession variable, R, returned a negative coefficient in the first four regressions and a positive coefficient in the final 1-year regression. R becomes insignificant after the 90-day regression, but it shows a steady progression in magnitude up to that time (from -.085 to -.236). It seems logical that the variable would have less predictive power the longer time goes on because it becomes more unlikely that the economy is still in a recession. This is one point where it would be good to know the returns of the IPO relative to the market because currently recession IPOs are considered recession IPOs no matter how long they actually trading during a recession.

Assuming IPO stocks have some correlation with the overall market, the negative coefficient makes sense because the overall stock market usually drops during recessions, too.

Lastly, the hot variable H turned out as expected with its sign but not in its magnitude. It also turned out to only be significant in the population regressions. H's coefficient climbed from .025 in the 30-day regression to .048 in both the 60 and 90-day regression. The effect of a hot market is definitely smaller than expected. In the 180-day regression H was insignificant and had an even smaller coefficient (.016), but in the 1-year regression H's coefficient had a statistically significant negative coefficient of -.125. This value confirms the idea that hot market IPOs underperform in the long run.

Another fact worth reviewing is that the fixed assets to assets variable, FA2A, is significant in the first three population regressions. It is the only non-focal variable that is consistently significant in three regressions. This suggests that firms with a higher FA2A ratio perform worse in the short run than firms with lower FA2A ratios. Assets (ASST) and initial IPO capitalization (AMT) are both significant in the final two regressions, though it is difficult to consider the actual effect of each as the size of their observations differs greatly. A final review of the first regressions reveals that the R^2 value is always higher for the sample regression than the population regression.

Recall that I also was interested in measuring IPO success using the method suggested by Binder et. al. (2002). I used a probit regression model to investigate this idea because the dependent variable is now binary (1 if the stock returned 0 to 20 percent 30 days following the IPO and 0 otherwise). The results from this investigation provide little insight. None of the focal variables turn out to be statistically significant, and the pseudo R^2 values for the population and sample are .0043 and .0115, respectively. In addition, take note that for the population model, prob > chi2 is .0006 and for the sample is prob > .6468. These results suggest that this measure of success may not be empirically useful. The measure may work better in other tests, however.

VII. Conclusion

The efficient market hypothesis predicts that there should be no relation between the stock market and economic variables, but I find a statistical relationship with a pattern in the short run and not in the long run. This suggests that the IPO market is not efficient immediately following an issue, but eventually becomes efficient in the longer-term. A possible contributor to this inefficiency could be the restriction of trading immediately following an IPO.

Research has shown that we are currently unable to predict the business cycle in real time. In addition, it is nearly impossible to measure a hot or cold IPO period in real time, at least when measuring with moving averages like Helwege and Liang (2004). The combination of these problems with the fact that the regression does not do a good overall job of explaining IPO success suggests that it is extremely difficult to predict IPO success using micro or macroeconomic variables. The results echo the modern view that in order to pick good stocks an investor should use both quantitative and qualitative data.

Future research into this topic should utilize returns relative to the stock market rather than absolute returns. This would take out much of the market effect on the return of a particular IPO. Other researchers may also want to change the measurement of IPO success. I would suggest looking at the market capitalizations of the IPO firm versus its competitors a month after the IPO. This will prove to be a tedious task because it is difficult to always find a close competitor in the public market. In addition, a close competitor may not be of the same size, which would cause the results to be skewed. For now, though, companies and investors alike should focus on the underlying business a company is involved in rather than timing the business or IPO cycle. It seems that a more firm-specific investigation should provide a better prediction of IPO success.

Appendix

Tables:

Table 1 - Full Dataset				
	Mean	**Std. Dev.**	**Min**	**Max**
Return (30 days)	0.026	0.263	-0.763	3.507
Return (60 days)	0.036	0.367	-0.905	3.995
Return (90 days)	0.059	0.483	-0.915	6.196
Return (180 days)	0.050	0.622	-0.964	7.600
Return (one year)	0.009	0.753	-0.995	7.909
CAPX2A	0.090	0.113	-0.003	1.367
D2A	0.129	0.200	0	3.537
FA2A	0.330	0.221	0	0.996
AMT	3.73E8	1.63E9	139750	5.43E10
CE	0.029	0.168	0	1
R	0.017	0.131	0	1
H	0.473	0.499	0	1
C	0.039	0.193	0	1
ASST	441	2993	0.135	113294

Table 2 – Sample				
	Mean	**Std. Dev.**	**Min**	**Max**
Return (30 days)	0.009	0.265	-0.713	1.794
Return (60 days)	0.006	0.312	-0.814	1.865
Return (90 days)	0.034	0.472	-0.836	4.54
Return (180 days)	0.070	0.717	-0.944	7.51
Return (one year)	0.010	0.663	-0.984	5.57
CAPX2A	0.094	0.124	-0.003	1.367
D2A	0.146	0.197	0.000	1.158
FA2A	0.259	0.242	0.000	0.949
AMT	3.00E8	8.45E8	822250	1.23E10
CE	0.028	0.165	0	1
R	0.192	0.394	0	1
H	0.382	0.486	0	1
C	0.136	0.343	0	1
ASST	479	2850	0	44207

Table 3: Regression Results for Success Measured as 30-day Returns		
	OLS with Robust Standard Errors	
	Population	Sample
Constant	0.033*	.052*
	(0.006)	(.025)
R	-.085*	-.099*
	(.028)	(.033)
H	.025*	.002
	(.007)	(.029)
C	.045	.047
	(.040)	(.041)
ASST	-1.03E-08	2.31E-07
	(4.74E-07)	(1.09E-06)
CAPX2A	-.005	-.158°
	(.029)	(.093)
D2A	-.019	-.105*
	(.015)	(.053)
FA2A	-.069*	-.001
	(.016)	(.053)
AMT	1.35E-12	7.24E-12
	(3.10E-12)	(8.70E-12)
CE	-.054	-.102
	(.042)	(.064)
R^2	.0085	.0260
N	5529	500

* Significant at the 5-percent level. ° Significant at the 10-percent level

Table 4: Regression Results for Success Measured as 60-day Returns		
OLS with Robust Standard Errors		
	Population	Sample
Constant	0.031*	.023
	(.009)	(.027)
R	-.140*	-.147*
	(.038)	(.042)
H	.048*	-.002
	(.010)	(.033)
C	.145*	.140*
	(.060)	(.062)
ASST	6.77E-07	-8.89E-07
	(9.10E-07)	(1.94E-06)
CAPX2A	.008	-.181
	(.043)	(.126)
D2A	-.014	-.047
	(.020)	(.078)
FA2A	-.070*	.075
	(.023)	(.077)
AMT	-2.08E-12	1.01E-11
	(3.47E-12)	(9.24E-12)
CE	-.143*	-.184*
	(.063)	(.083)
R^2	.0080	.0205
N	5529	500
* Significant at the 5-percent level. ° Significant at the 10-percent level		

Table 5: Regression Results for Success Measured as 90-day Returns		
OLS with Robust Standard Errors		
	Population	Sample
Constant	.062*	.049
	(.011)	(.044)
R	-.229*	-.236*
	(.044)	(.053)
H	.048*	.030
	(.013)	(.051)
C	.233*	.233*
	(.075)	(.077)
ASST	9.72E-07	-1.09E-06
	(1.11E-06)	(2.44E-06)
CAPX2A	.041	.008
	(.057)	(.253)
D2A	-.014	-.090
	(.031)	(.107)
FA2A	-.114*	.015
	(.031)	(.098)
AMT	-2.95E-12	1.04E-11
	(3.86E-12)	(2.10E-11)
CE	-.199*	-.267*
	(.079)	(.105)
R^2	.0071	.0236
N	5529	500
* Significant at the 5-percent level. ° Significant at the 10-percent level		

Table 6: Regression Results for Success Measured as 180-day Returns		
OLS with Robust Standard Errors		
	Population	Sample
Constant	.063*	.126*
	(.014)	(.054)
R	-.071	-.102
	(.089)	(.096)
H	.016	.035
	(.017)	(.076)
C	.146	.173
	(.126)	(.129)
ASST	2.95E-06°	-2.62E-06
	(1.62E-06)	(2.82E-06)
CAPX2A	-.012	-.043
	(.072)	(.212)
D2A	-.015	-.287*
	(.044)	(.122)
FA2A	-.062	-.085
	(.041)	(.126)
AMT	-1.49E-11*	7.72E-12
	(3.87E-12)	(1.58E-11)
CE	-.150	-.261°
	(.131)	(.156)
R^2	.0025	.0126
N	5529	500

* Significant at the 5-percent level. ° Significant at the 10-percent level

Table 7: Regression Results for Success Measured as 1-year Returns		
OLS with Robust Standard Errors		
	Population	Sample
Constant	.071*	.036
	(.019)	(.058)
R	.049	.097
	(.108)	(.116)
H	-.125*	-.069
	(.021)	(.066)
C	.019	.041
	(.154)	(.157)
ASST	4.19E-06°	-8.15E-06
	(2.42E-06)	(5.65E-06)
CAPX2A	-.212*	-.244
	(.101)	(.259)
D2A	.115°	.009
	(.068)	(.168)
FA2A	.036	.027
	(.054)	(.148)
AMT	-2.37E-11*	-2.00E-12
	(5.57E-12)	(2.04E-11)
CE	-.047	-.150
	(.163)	(.198)
R^2	.0117	.0141
N	5529	500

* Significant at the 5-percent level. ° Significant at the 10-percent level

Table 8: Regression Results for Success Meaning 30-day Returns Between 0-20%

Probit Regression Model

	Population	Sample
Constant	-.524*	-.609*
	.032	(.120)
R	-.304	-.283
	(.219)	(.238)
H	-.024	-.105
	(.036)	(.135)
C	.164	.195
	(.283)	(.286)
ASST	8.50E-06	-1.29E-5
	(5.86E-06)	(2.64E-5)
CAPX2A	-.390*	-.167
	(.177)	(.572)
D2A	.151	-.174
	(.091)	(.331)
FA2A	.137*	.359°
	(.054)	(.214)
AMT	1.64E-11	7.93E-11
	(1.09E-11)	(6.88E-11)
CE	.059	-.118
	(.302)	(.463)
Pseudo R^2	.0043	.0115
LR chi2	29.27	6.91
Prob > chi2	.0006	.6468
N	5529	500

* Significant at the 5-percent level. ° Significant at the 10-percent level

Figure 1

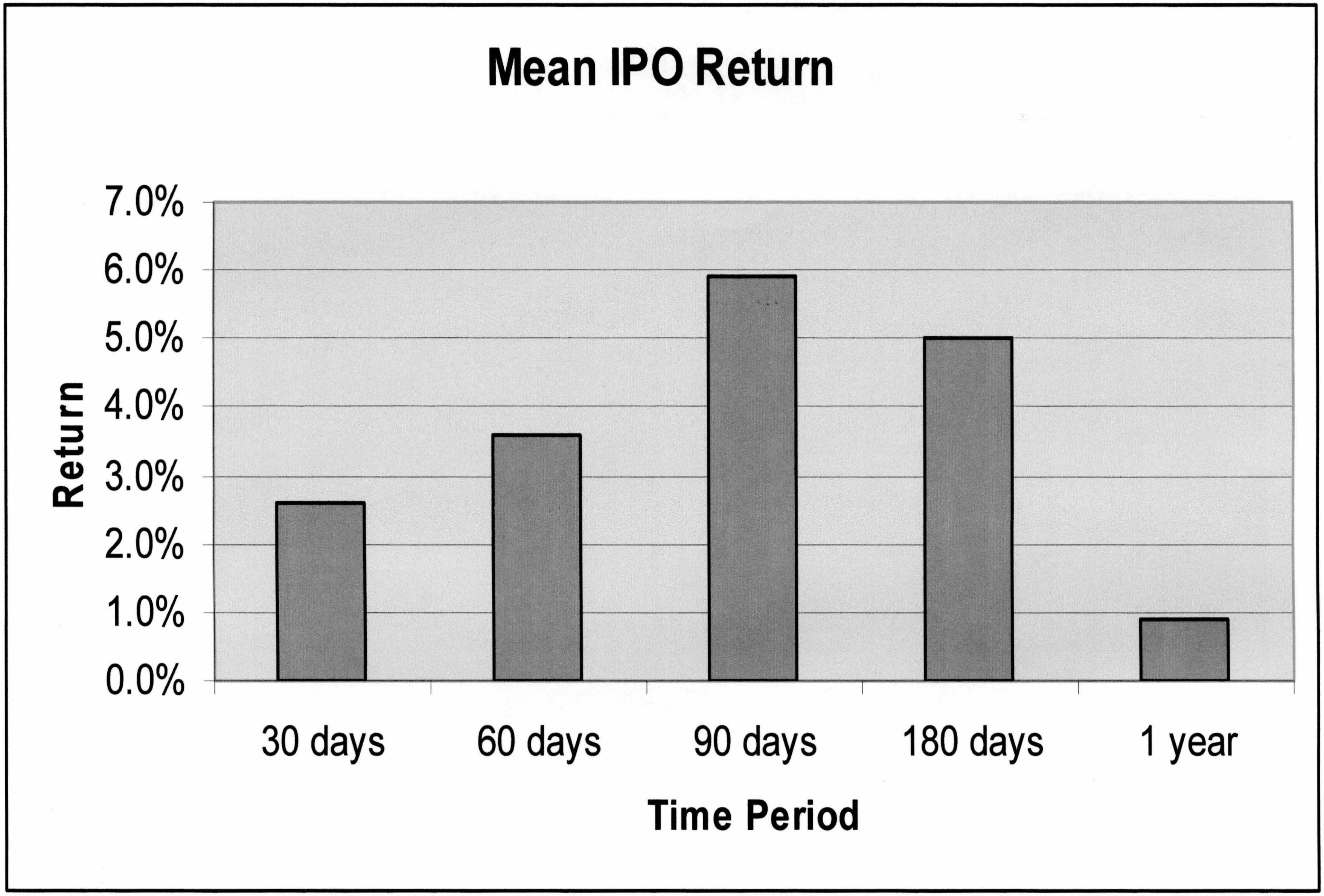
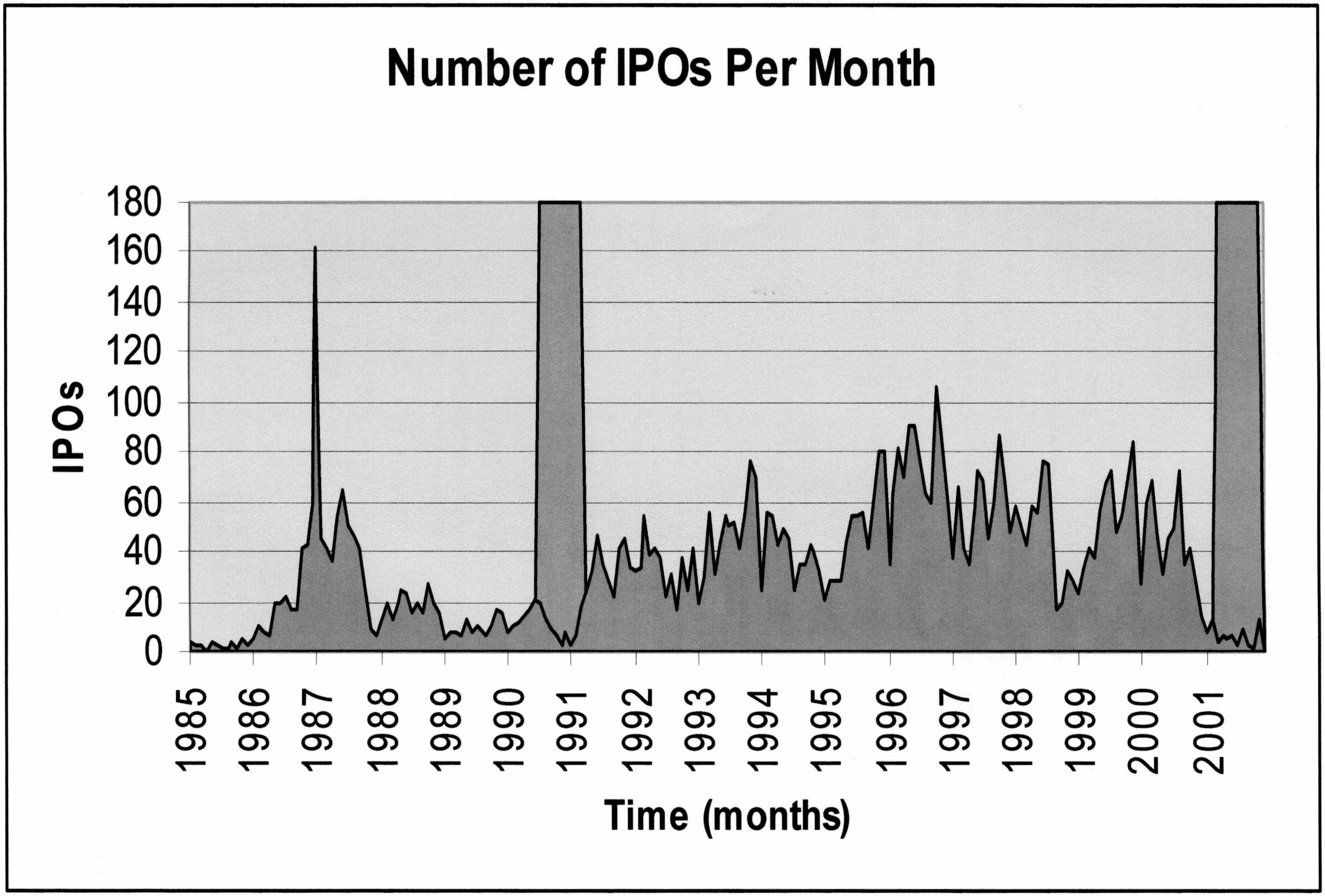

Mean IPO Return
7.0%
6.0%
5.0%
4.0%
3.0%
2.0%
1.0%
0.0%
Return
30 days
60 days
90 days
180 days
1 year
Time Period

Figure 2



Number of IPOs Per Month
IPOs
180
160
140
120
100
80
60
40
20
0
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
Time (months)

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