Abstract

Examining stock options traded during the IPO period of the underlying security, this senior thesis shows that options are inefficiently priced on a predictable basis. In Phase I, intraday price volatility for stocks during the IPO period in different industries is predicted using a quasi-hyperbolic regression model first proposed by and used in Lewis (2011). In Phase II, the quasi-hyperbolic model is used to predict annualized volatility for IPO stocks. Forecasted annualized volatility is then used with the Black-Scholes model to value options and a trading simulation tests the profitability of purchasing undervalued securities; the results show positive median and mean returns associated with the purchase of undervalued options. In Phase III, a portfolio-based trading simulation is used to show that transaction fees do not fully explain option underpricing during the underlying stock IPO period. Phase IV includes an out-of-sample test that further evidences inefficient option pricing during the IPO period. In addition, a simple VIX-based option valuation method and trading strategy is tested; results evidence the relative accuracy of the quasi-hyperbolic model in forecasting stock price volatility and valuing options. Finally, applications of the study's results for investors, regulators, brokers, exchange managers, and scholars are proposed and the possibility of predictable options pricing inefficiency outside of the IPO period is discussed.

[1] To my parents, especially, who provided most of the coffee I drank while working.

To my mother, who tried so hard to keep me away from the markets

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Chapter 1

Introduction

The period immediately following the initial public offering (IPO) of common stock remains one of the most researched phases of a common stock's life cycle. Recent studies have investigated IPO phenomena ranging from the role of venture capitalists in IPO underpricing (Belghitar and Dixon (2012)) to the effects of various corporate board structures on IPO stocks (Chancharat et al. (2012)).

Rare, however, are academic investigations of the option contracts written during the heavily-studied stock IPO period. This gap in the literature is likely due in part to the fact that stock options do not start trading concurrently with a stock IPO; of the stocks examined in this study from 1996–2010, less than 25% had options listed within 90 days of IPO. Various requirements imposed by regulatory bodies and exchanges require certain benchmarks for trading volume and other metrics to be met in the underlying security before a market for its options can be established. Furthermore, options listing elibility does not guarantee actual listing; exchange management has complete autonomy to select on which securities to list options. Even so, no studies have firmly established efficiency in the options market immediately following an "option IPO," or the day that options start trading on a recently-issued stock.

Examining option prices and their relationship with overall market conditions, Jackwerth (2000) finds what appears to be a structural shift in options investor risk aversion following the 1987 stock market crash. The success of the Jackwerth (2000) trading strategy in exploiting overpriced options establishes option market mispricing as a known problem grounded in the market's inconsistent forecasts of underlying stock volatility. Inability to estimate volatility accurately can contribute both to underpricing and overpricing in the options market depending on assumptions and market conditions.

Under the hypothesis that pricing inefficiency exists, the goal of this study is to determine whether the equity options market is price-efficient during a 90-day stock IPO period. The skeptical hypothesis is based on two key expectations. First is the prospect that market inattention to the effects of IPOs on underlying stock volatility stems from the delay between stock IPO and option IPO. As shown in Lewis (2011), expected intraday stock volatility during the IPO period can be modeled with some consistency; using such a model to better forecast stock volatility during the IPO period may lead to more accurate options valuation using the Black-Scholes model. Second is the possible absence of "value" investors[1] in the options marketplace. According to Hull (2009), two primary types of options market participants exist: hedgers and information-motivated speculators. Neither investor type is focused primarily on the fair value of options. If, as Lee and Yi (2001) find, the options marketplace is dominated by information-motivated investors and the participation of value investors is substantially limited, market options prices may reflect short-term supply and demand equilibria more than fundamental valuations based on expected payouts.

Chapter 2 includes reviews of financial concepts important to understanding this study, the Lewis (2011) study, options exchanges and the "option IPO" process, and the benefits of active options markets for underlying securities. Chapter 3 details

[1]Value investors buy securities that they believe to be priced in the market below fair value with the expectation that their prices will eventually rise to fair value.

the stock and options trading data used throughout the experimental portion of the study.

To test the hypothesis that the options market is inefficient during the 90-day stock IPO period, this study includes four phases. Following Lewis (2011), Phase I (Chapter 4) used a quasi-hyperbolic least squares regression to construct models forecasting intraday stock price volatility during the IPO period for stocks in different industries. Applying the results of Phase I, the Black-Scholes options pricing model was used in Phase II (Chapter 5) to calculate the "fair values" of options available during IPO periods over a 1996–2010 observation period. Phase II also included an options trading simulation to test an investment strategy that purchases apparently undervalued options in the marketplace and sells them when their market values appreciate to their calculated fair values. To test the investment strategy in the presence of transaction fees and expenses, Phase III (Chapter 6) included a portfolio-based trading simulation to project expected returns for the investment strategy under different fee conditions. Phase IV (Chapter 7) included two "stress tests" to evaluate the credibility of the Phase II and III findings. First, out-of-sample simulations in the styles of Phases II and III were completed for options trading on stocks with 2011 IPOs. In addition, a simple trading strategy that calculates fair values for options using the VIX volatility index instead of the Lewis (2011) model was tested both with the 1996–2010 data and out-of-sample 2011 data.

Phase II results show options underpricing in a frictionless market and Phase III demonstrates positive expected portfolio returns with fees up to 10%. In Phase IV, portfolios using the strategy for out-of-sample 2011 options showed positive expected returns with fees up to 5%. The simple VIX trading strategy consistently underperformed the original strategy based on the Lewis (2011) model. On the whole, results suggest that options price discovery is inefficient during the stock IPO period.

Chapter 8 offers applications of the results for market participants, regulators, brokers, and options exchange managers to improve options pricing efficiency during the IPO period. In addition, Chapter 8 proposes a number of possible modifications to this study for further analysis of the price discovery problem as well as an investigation of the relationship between variety of listed options for a given security and the health of its underlying market. Finally, Chapter 9 explains why the inefficient options pricing problem may extend beyond the 90-day stock IPO period — a phenomenon suggested in Jackwerth (2000) — and discusses the implications of such a scenario.

Chapter 2

Background

2.1 Review of important concepts

This study examines phenemona in the stock and options markets during a 90-day stock IPO period; while stocks, options, and IPOs are frequently investigated in academic finance, little has been written about stock options during the IPO period. To understand this study's methodology, results, and conclusions, a basic understanding of financial concepts including IPOs, option contracts, security volatility, and the Black-Scholes option pricing model is crucial.

2.1.1 Initial public offerings

In an initial public offering (IPO), a company sells shares of its stock to the public for the first time. IPOs grant more liquidity to company owners (private company owners sometimes wish to "cash out" and sell some of their shares publicly) and raise capital for the company from new investors. By taking a company public, however, owners fundamentally cede control to gain liquidity. Day-to-day public company operations are overseen by corporate officers who, in turn, are monitored by the company's shareholder-appointed board of directors; when ordinary shareholders are unhappy with the way their company is being run, their only option is usually to “vote with their feet” and sell their shares.[1]

To launch an IPO, companies partner with investment banking firms that act as advisors and “underwriters.” In an advisory capacity, banks help companies to decide how to structure their equity offering and determine how much equity to sell at what price. As underwriters, investment banks agree to purchase the IPO shares directly from the company and handle the distribution of the new shares in the secondary market. Since the demand for shares of new public equity can never be predicted with absolute certainty, underwriting banks expose themselves to the risk of financial losses when weak demand leads the market to price shares below their offering price; to compensate for this risk, banks charge an “underwriting spread” (typically 7%) that is taken directly out of the company’s offering proceeds.

Various dimensions of the IPO process and period are common subjects of examination in financial academia: published in the first few months of 2012, Green and Hwang (2012) analyze the relationship between expected distributional skewness and first-day IPO returns, Belghitar and Dixon (2012) examine the role of venture capitalists in reducing IPO underpricing, and Chancharat et al. (2012) explore the effects of different corporate board structures on IPO firms across industries. Investigations of the options market during the IPO period are notably absent.

The underpricing of IPO shares — a regular subject in the literature — is commonplace and often produces large gains in share price on a stock’s first day of public trading. Berk and DeMarzo (2011) dismiss the explanation that private companies have no choice but to put up with underpricing in an oligopolic underwriters’ market; evidence abounds of adequate competition in the financial services industry and cheaper alternatives (such as the auction IPO system employed by WR Hambrecht + Co. designed to reduce underpricing) have failed to take significant market share

[1] While shareholders can influence corporate governance in a number of ways, discussion of these methods exceeds the scope of this study.

from traditional underwriters. Instead, efficiency in the traditional IPO model is confirmed by the reality of adverse selection and the "winner's curse": investors only receive all requested shares in an IPO when it is undersubscribed, demand is weak, and good performance is least likely. While IPO underpricing is common, it is possible that immediate IPO returns are left-skewed and common underpricing is not an inefficient phenomenon. In any case, the uncertainty associated with the IPO process leads to high volatility during the IPO period; this provides the foundation for the quasi-hyperbolic model of IPO period volatility described in Subchapters 4.1 and 4.2.

2.1.2 Options

Options are derivative securities grant the holder the *option* to buy or sell an underlying asset at a predetermined price. All options contracts have a number of defining terms listed below.

- All options are written on an **underlying asset** from which the value of the option is derived. This study examines only stock options but options can be written on a variety of other assets including bonds, currencies, and futures contracts.

- Two basic **types** of options exist: call options and put options. Call options allow the holder to purchase a security for a predetermined price ("call it in") while put options permit an owner to sell at a preset price ("put it away").

- **Strike price** is the price at which the underlying security can be purchased or sold. The value of call options decreases with strike price while the value of put options increases with strike prices. Options that would generate profits if exercised are called "in-the-money" while those that would not are "out-of-the-money." Call options are in-the-money when the "spot" (or market) price of the underlying asset is higher than the strike price while put options are in-the-money when strike price exceeds spot price. Options are called "at-the-money" when strike price equals underlying spot price. Using this nomenclature, options are described in degrees of "moneyness."

- An option's **expiration date** is the last day on which the option can be exercised. If an option is not exercised on or before this date, it expires worthless and the holder loses the right to buy or sell the underlying asset.

- **Option style** defines the dates on which an option may be exercised. Traded options are typically one of two styles: "European" or "American." European options can only be exercised on their expiration dates while American options can be exercised at any time leading up to and including expiration. Other types of "exotic" options are available with more complex exercise rules but are not examined in this study. Options of each style are valued differently; for a complete review of option valuation, see Subchapter 2.1.4

In addition to these contract terms and the spot price of the underlying asset, three other factors affect option values. First is the available risk-free interest rate (the rate at which money can be earned without assuming any risk); for this study, United States Treasury 10-year bond yields are used to approximate the risk-free rate. Second is the annualized volatility of the underlying asset. Asset volatility is not directly observable in the marketplace and must be calculated on an expected basis; refer to Subchapter 2.1.3 for a complete discussion of volatility and its relevance in this study. Finally, expected dividends reduce call values and increase put values because the payment of dividends reduces stock prices.

Investors typically participate in the options market for one of two reasons: to hedge or to speculate. Hedging investors buy options as insurance to reduce or eliminate risks associated with the price of an asset. For example, an investor owning stock in Company I trading at \$31/share may purchase put options on the stock with a \$30/share strike price; in the event that Company I stock trades below \$30, the investor will be protected from extreme losses and can sell the Company I shares for \$30 regardless of the prevailing market price. On the other hand, speculators participate in the options market by taking on risk for financial gain. As a result of their structural leverage,[2] options are popular investment vehicles for information-motivated speculators who believe that they can forecast price movements in underlying securities.

Due in part to fixed per-contract transaction fees imposed by exchange owners, options market participants usually incur brokerage fees on a per-contract basis. Different per-contract fees are incurred depending on broker, order size, and client type (retail or institutional). As a result, fees as a percentage of transaction value vary and are sometimes correlated with moneyness.[3] Instead of attempting to estimate fees on a per-contract basis, a variety of fixed-percentage fees are used throughout this study's simulations.

2.1.3 Volatility

Volatility is a measure of the uncertainty associated with future returns on a security; for a stock, volatility is measured as the standard deviation of its expected one-year return. Since volatility is the only factor affecting the value of options that is not directly observable in the market, its accurate estimation is critical to options traders and is a common subject of exploration in academic finance.

Sinclair (2008) provides the generic definition of volatility found in Equation 2.1; volatility v is measured over a period of N days using observed values x_i and mean value $\bar{x}$.

[2] A trader can control more shares with the same amount of capital commitment when investing in options than in the security outright.

[3] Out-of-the-money options tend to be nominally cheaper than other options; as a result, a flat per-contract fee usually represents a relatively higher percentage of transaction value for out-of-the-money options.

$$v = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{2.1}$$

Hull (2009) reaffirms the Sinclair (2008) definition and describes a method for estimating volatility using historical figures that is adopted in this study. For a complete description of stock volatility estimation methodology, refer to Subchapter 4.1.

The volatility of an underlying asset implied by market option prices typically increases with the distance between strike price and underlying spot price; because of its shape, the underlying security's implied volatility as a function of strike price is called its "volatility smile." It is important to note that the existence of volatility smiles means that similar options with different strike prices can (and frequently do) imply multiple levels of volatility for the same underlying security. The trough of a volatility smile is typically near the market price of the underlying security; that is to say that prices of at-the-money options usually imply the lowest underlying asset volatility.

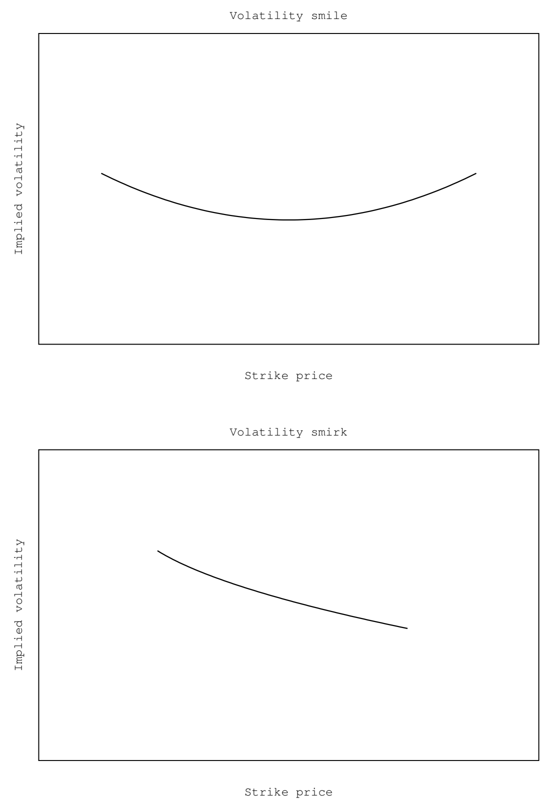


Figure 2.1: While many options markets demonstrate volatility symmetry around the underlying asset spot price, equity options typically have volatility smirks that are declining functions of strike price.

Equity options in particular, however, typically show decreasing implied volatility as strike increases; as a result, their volatility profiles are sometimes referred to as "volatility smirks," instead. The volatility smirk's implication is that higher volatilities are used in the market to price out-of-the-money call options and in-the-money put options; Hull (2009) explains that this phenomenon may be explained by the increased leverage associated with decreasing equity value as debt constitutes a larger relative portion of the underlying firm's capital structure. The volatility smirk suggests that option purchases made in this study's trading simulation are more likely to involve higher-strike options; the simulation makes no explicit adjustments for the volatility smirk and ignores firm capital structure altogether.

The Chicago Board Options Exchange Volatility Index (known colloquially by its ticker symbol as the "VIX") measures investor expectations of near-term market volatility as an annualized percentage. Although understanding the actual VIX calculation is unncessary for this study,[4] it is important to recognize that VIX values are derived from options written on the S&P 500 Index and, consequently, are frequently considered by options market participants when determining option values. In Subchapter 7.2, a trading strategy using the VIX to determine fair option valuations is tested against the strategy described in Subchapter 5.1.

2.1.4 Option valuation and the Black-Scholes model

The Black-Scholes model for valuing European options was developed in the early 1970s and remains the gold standard for European option valuation. The Black-Scholes model assumes that the distribution of future returns on the underlying asset is normal with a standard deviation equal to the underlying asset price volatility. Using iterative processes, the Black-Scholes model can be used to back out an "implied volatility" for the underlying asset using the market option price and the observable model inputs; implied volatilities typically follow the volatility smile patterns

[4] See "The New Look of VIX" (published by CBOE) for a complete description of VIX calculation methodology.

described in Subchapter 2.1.3.

The Black-Scholes model parameters include strike price K, underlying asset spot price S, risk-free rate r, time to maturity $(T - t)$, and underlying volatility σ. Preliminary calculations for the valuation of both call and put options include d_1 and d_2 in Equations 2.2 and 2.3. Call option value is calculated using Equation 2.4 while put options are valued with Equation 2.5. The function $\Phi()$ represents the standard normal cumulative distribution function.

$$d_1 = \frac{ln\left(\frac{S}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}} \tag{2.2}$$

$$d_2 = \frac{ln\left(\frac{S}{K}\right) + \left(r - \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}} \tag{2.3}$$

$$C(S,t) = \Phi(d_1)S - \Phi(d_2)Ke^{-r(T-t)} \tag{2.4}$$

$$P(S,t) = \Phi(-d_2)Ke^{-r(T-t)} - \Phi(-d_1)S \tag{2.5}$$

While failing to universally adopt a single pricing model, researchers have devised a variety of methods to value American options which, unlike European options, sometimes generate higher returns through early exercise than sale in the case of dividend-paying stocks. Although an uncommon practice, the basic Black-Scholes formula is used to calculate fair values for American options in this study, as well. The first motivation for this choice is the fact that, while the values of American options may be equal to or greater than those of comparable European options, American options are never less valuable than their European counterparts. In addition, few stocks pay dividends during their first 90 days of trading. As a result, the study makes use of the Black-Scholes model to estimate what amounts to a lower bound for American option fair values instead of selecting an inconsistent American option valuation technique. Subchapter 5.1 provides a complete description of valuation methodology used in the trading simulation. Throughout this study, the Black-Scholes model is critical for applying forecasted IPO-period volatility to option valuation.

2.2 Lewis (2011) and the quasi-hyperbolic model of IPO period volatility

The goals of Lewis (2011) were to examine trends in common stock volatility throughout a 30-day IPO period in different business sectors and to create a model to predict expected intraday stock volatility throughout the IPO period. A stock's price tends to be relatively volatile on its first day of trading. With the hypothesis that the increased volatility associated with a stock IPO persisted to some degree for many days after IPO, Lewis (2011) devised a model reflecting the daily stock price volatility levels for each trading day following an IPO; to this end, a series of quasi-hyperbolic regressions were run on various industry-based data sets to approximate price volatility on each of a stock's first thirty trading days. The results of these regressions showed that the quasi-hyperbolic model can predict industry volatility averages with high accuracy; for regressions run on 11 separate industry data sets, all R^2 values were above 0.8000 and seven of eleven were above 0.9500.

Defining P_{ijt}^H as intraday high price, P_{ijt}^L as intraday low price, and P_{ijt}^C as closing price, the Lewis (2011) method measured volatility v_{ijt} for each company i in industry j on each day from IPO t using Equation 2.6.

$$v_{ijt} = \frac{(P_{ijt}^H - P_{ijt}^L)^2}{P_{ijt}^C} \tag{2.6}$$

Instead of running regressions on the series of volatility ratings v_{ijt}, the Lewis (2011) method calculated an average industry volatility rating $\bar{v}_{jt}$ for each industry j

on each day t to use in regressions. For each industry j containing N_{jt} companies i_{jt} on day t from IPO, an industry volatility average $\bar{v}_{jt}$ was calculated using Equation 2.7.

$$\bar{v}_{jt} = \frac{1}{N_{jt}} \sum_{i=1}^{N_{jt}} v_{it} \tag{2.7}$$

For example, consider the first day after IPO ($t = 1$) in a 3-company data set for industry j in which company 1 has a volatility rating $v_{1,1}$ of 0.20, company 2 has a $v_{2,1}$ of 0.05, and company 3 has a $v_{3,1}$ of 0.08. In this case, the industry j volatility average $\bar{v}_{j1}$ would be 0.11, or the mean of 0.20, 0.05, and 0.08. Values for $\bar{v}_{jt}$ are calculated for industry j on each day t during the IPO period.

The industry volatility averages $\bar{v}_{jt}$ were used in a regression designed to predict the price volatility levels for a typical stock in the industry for each trading day following its IPO. Using calculated values $\bar{v}_{jt}$ and trading day relative to IPO t, the quasi-hyperbolic least squares regression in Equation 2.8 predicted the values of three unknown variables κ_j, λ_j, and μ_j.

$$\widehat{\bar{v}_{jt}} = \kappa_j + \frac{\lambda_j}{1 + \mu_j * (t-1)} + \varepsilon_{jt} \tag{2.8}$$

As shown in Equation 2.9, the denominator of the second term becomes equal to 1 on IPO day when $t = 1$. As a result, IPO day volatility can be represented without μ_j as written in Equation 2.10.

$$
\begin{aligned}
1 + \mu_j * (t-1) &= 1 + \mu_j * (1-1) && (2.9)\\
&= 1 + \mu_j * (0)\\
&= 1\\
\widehat{v_{j1}} &= \kappa_j + \lambda_j + \varepsilon_{jt} && (2.10)
\end{aligned}
$$

As time t grows, the second-term denominator $(1 + \mu * (t-1))$ grows with it and, as a result, the absolute value of the second term decreases. With this insight, each quasi-hyperbolic regression variable takes on individual significance. The first term of the regression contains only the κ variable and the t variable does not affect its value; consequently, the κ variable represents an industry's baseline level of daily volatility to which it steadily reverts over time as the IPO volatility effect decays. The λ variable effectively quantifies the excess volatility observed on IPO day ($t = 1$). The μ variable indicates the rate of the IPO effect's decay; as μ increases, so too does the rate at which the second term's denominator increases with t. Lewis (2011) results for each studied industry can be found in Table 2.1 with number of stocks used and regression t-scores in parentheses. Figure 2.2 illustrates the trends in intraday price volatility observed in Lewis (2011) in each industry examined and a market benchmark (S&P 500).

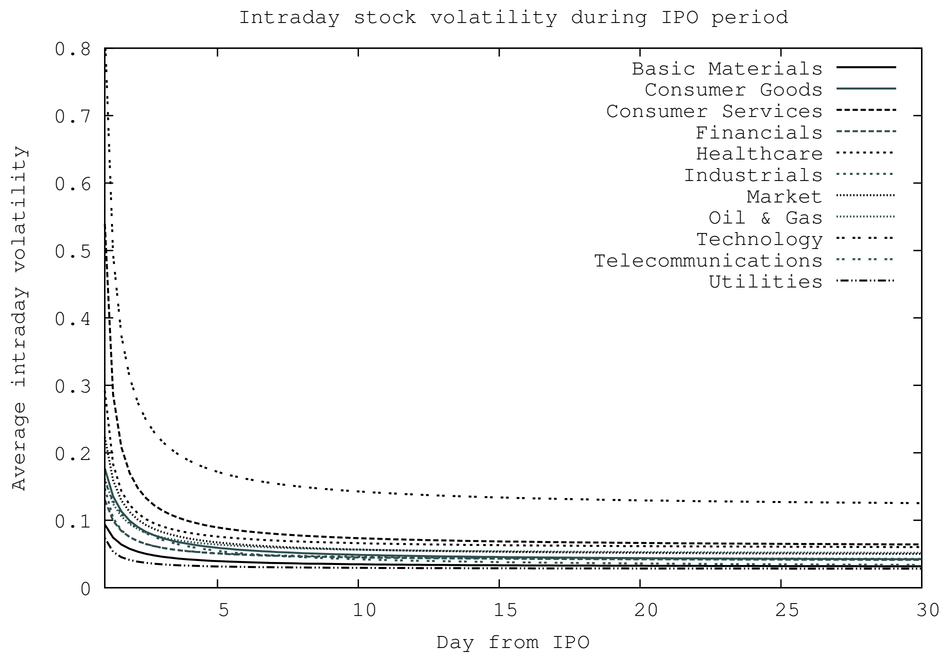
In its conclusion, Lewis (2011) describes a number of potential applications for its results; most significantly, the study suggests that the daily industry volatility levels it predicts during the IPO period can be used with the Black-Scholes options pricing model to better value stock options. This is the idea explored throughout this study.[5]

[5] In the context of this study, one problem with Lewis (2011) is that its initial calculation of volatility v_{ijt} in Equation 2.6 produces differing results for differently-priced stocks. This inconsistency is rooted in the fact that squaring the intraday trading range has the effect of increasing ranges greater than 1 and decreasing those smaller than 1. By squaring the dollar value of the intraday trading range $(P^H_{ijt} - P^L_{ijt})$, the calculated volatility level v_{ijt} understates volatility in lower-priced stocks. For example, a \$100 stock with an intraday trading range of \$5 has a calculated volatility

Table 2.1: Lewis (2011) quasi-hyperbolic regression results.

	κ (Baseline Volatility	λ (IPO-Driven Volatility)	μ (Stabilization Rate)	R^2
Basic Materials (548)	0.0303853 (47.53)	0.0632364 (27.65)	1.496436 (7.88)	0.9675
Consumer Goods (653)	0.0390784 (31.01)	0.1378587 (30.74)	1.463953 (8.81)	0.9929
Consumer Services (798)	0.0598604 (24.60)	0.4793099 (47.82)	3.806189 (8.87)	0.9884
Financials (2058)	0.0395426 (69.25)	0.0907731 (42.87)	1.769266 (11.59)	0.9860
Healthcare (821)	0.0575546 (25.57)	0.2345721 (25.97)	2.959527 (5.58)	0.9619
Industrials (1141)	0.0412802 (47.95)	0.1061883 (31.54)	2.424831 (7.50)	0.9740
Market (S&P 500)	*0.0470464 (20.04)*	*0.1760342 (19.88)*	*1.936521 (5.20)*	*0.9379*
Oil & Gas (578)	0.0494870 (17.32)	0.1118282 (10.66)	1.686358 (2.93)	0.8142
Technology (890)	0.1173751 (26.78)	0.7072644 (40.15)	2.997637 (8.57)	0.9837
Telecommunications (143)	0.0297135 (12.20)	0.1283577 (16.27)	1.045903 (4.98)	0.9137
Utilities (206)	0.0276752 (33.32)	0.0460092 (13.93)	2.732502 (3.12)	0.8794

Figure 2.2: Lewis (2011) regression results.



2.3 Institutional background

Mayhew and Mihov (2004) investigate which stocks are selected for options listing and detail the history of the options market. Listed options were first traded in 1973 and were SEC-approved only on an experimental basis while the benefits and risks of maintaining an organized options exchange were evaluated. Options were listed for large firms wth high trading volume until a listing moratorium was enacted in 1977; during the moratorium, the SEC reviewed the new options market and, in 1980, ended the listing freeze to establish the options exchanges as permanent fixtures in

rating $\frac{(5)^2}{100} = .25$ while a comparably volatile \$1 stock with an intraday trading range of \$0.05 has a calculated volatility rating of $\frac{(0.05)^2}{1} = .0025$. The volatility calculations made in this study differ from those in Lewis (2011) to avoid this inconsistency.

Another problem with Lewis (2011) is its use of industry average volatility values in its regressions. The study's quasi-hyperbolic regression uses a least squares regression method. In any form of least squares regression, outliers have an outsized impact on regression results. The Lewis (2011) calculation of $\bar{v}_{jt}$ minimizes the impact of outliers because it is a simple average. While the choice to regress using the averages $\bar{v}_{jt}$ instead of all observations v_{ijt} may have had no significant impact on the study's ordinal results, even small chances of outsized stock price volatility are important to recognize in order to efficiently calculate the fair value of underlying stock options. This study uses a modified method of measuring daily volatility to ensure that the impact of outliers is fully captured.

the financial markets. Since then, the rate of new options listings has continued to grow.

Mayhew and Mihov (2004) highlight the historical gap between the number of optioned stocks and the number of stocks meeting options listing eligibility criteria. From the establishment of the market in 1973 to 1996, the growth in number of stocks meeting options eligibility criteria has generally outpaced the rate of new options listings; this has created a growing pool of unlisted but option-eligible stocks. If the options exchanges always prefer that more options be listed to maximize profits, this illustrates that the rate at which options exchanges can list new options is restricted by some external factor. As a result, IPO stocks compete with other traded stocks to become optioned and are not always listed once eligible. While the Mayhew and Mihov (2004) figures illustrating this point only reflect market conditions before 1997, no evidence exists today to suggest that all option-eligible stocks have been listed and that options listing saturation has been achieved.

The day a stock has its IPO never coincides with that stock's "option IPO," or the day that options on the stock begin trading. On its public website, The Options Industry Council — an organization sponsored by the major American options exchanges[6] — claims that there generally exists a minimum of five days following a stock IPO before options can be listed on that stock. It also notes, however, that this five-day delay may be (and frequently is) extended for various reasons. The OIC's defined requirements for permission to list on any options exchange are itemized below; while some IPO stocks may meet the criteria, many stocks do not after only five days of active trading.

- The underlying equity must be listed on the NYSE, AMEX, any national stock

[6] As of April 2012, OIC sponsors include BATS Options, the Boston Options Exchange, C2 Options Exchange, Inc., the Chicago Board Options Exchange, the International Securities Exchange, NASDAQ OMX PHLX, NASDAQ Options Market, NYSE Amex, NYSE Arca and OCC. OIC's stated goal is "to provide a financially sound and efficient marketplace where investors can hedge investment risk and find new opportunities for profiting from market participation." OIC claims to provide free education about investing in options to achieve this goal.

exchange or Nasdaq National Market.

- The closing stock price must have a minimum price of $3.00 per share for a majority of the trading days during at least five trading days.

- There must be at least seven million publicly-held shares outstanding excluding shares held by directors or holders of 10% or more of the underlying equity shares. (e.g. the public "float" must be seven million or more.)

- There must be at least 2,000 shareholders.

In their more detailed rulebooks, the individual options exchanges do not explicitly define the relationship between stock IPO and option IPO. Underlying security criteria rules at the major American exchanges show little variation; Chicago Board Options Exchange (CBOE) Rule 5.3, BATS BZX Exchange Rule 19.3, and NYSE Amex Rule 915 each outline underlying security criteria for options listing eligibility and are virtually identical. Review of all American options exchange rulebooks show that, in fact, each does follow the general OIC guidelines listed above.

As private entities, however, each options exchange endows its own management with the ability to decide which options to list at what time. Although published option listing eligibility rules are consistently followed, it is clear that not all IPO stocks are optioned immediately upon fulfillment of the OIC criteria. Since exchanges decide which options to list and when to list them in a closed process and IPO stocks compete with other non-optioned stocks to be listed, forecasting when options will be listed on any given IPO stock is difficult. The possible consideration of known and unknown external factors further complicates option IPO decisions; for example, Mayhew and Mihov (2004) find evidence suggesting that exchanges prefer to list stocks already expected to undergo price volatility increases in the future.

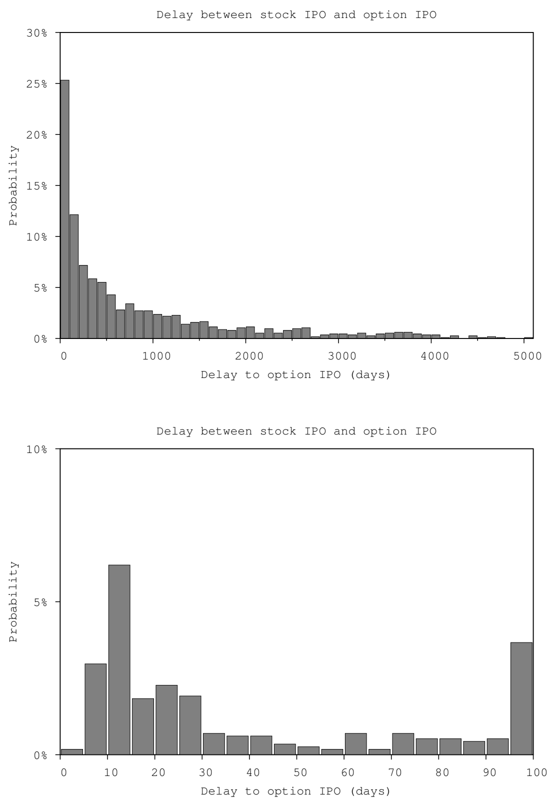


Figure 2.3: While the delay between stock IPO and option IPOs can vary, nearly 75% of option IPOs occur more than 100 days after stock IPO.

The SEC identifies the member-owned options exchanges as “self-regulatory organizations” and does not directly involve itself in the option IPO decision. Instead, it requires exchanges to officially register as “national securities exchanges” that establish their own rules to meet the goals outlined in Securities Exchange Act of 1934 Rule 6(b)(5).[7] The self-regulating exchanges submit any proposed rule changes to the SEC for approval; at this point, the SEC can veto a proposed change. The SEC does not independently require that options be listed once listing standards are met. In order to ensure that options be listed once their listing criteria are met, a new rule would have to be written; this could be achieved only if the options exchanges proposed such a rule in an unlikely and voluntary forfeiture of flexibility or if the SEC otherwise required that such a rule be established.

The options and stock data used in this study show that, for stocks with IPOs between 1996 and 2010, 21.1% of option IPOs occur during the 90-day stock IPO period and 11.6% of option IPOs launch within 3 weeks of stock IPO. The 78.9% of stocks with option IPO delay greater than 90 days are not examined in this study.

[7]Securities Exchange Act of 1934 Rule 6(b)(5): “The rules of the exchange are designed to prevent fraudulent and manipulative acts and practices, to promote just and equitable principles of trade, to foster cooperation and coordination with persons engaged in regulating, clearing, settling, processing information with respect to, and facilitating transactions in securities, to remove impediments to and perfect the mechanism of a free and open market and a national market system, and, in general, to protect investors and the public interest; and are not designed to permit unfair discrimination between customers, issuers, brokers, or dealers, or to regulate by virtue of any authority conferred by this title matters not related to the purposes of this title or the administration of the exchange.”

In general, examined stocks that have larger IPO day market capitalizations tend to have shorter delays between stock IPO and option IPO.[8] The market capitalizations of all IPO stocks examined between 1996–2010 totalled \$10.7 trillion. The market capitalization of those stocks with option IPOs occuring within the 90-day stock IPO period totalled \$4.0 trillion (37.7% of total); these are the stocks examined in this study.

In future studies, scholars may consider investigating the extent to which liberties are taken by options exchange managers in deciding to list options later than their rulebook guidelines necessitate. Current options listing criteria, exchange managers' ability to delay option IPOs, and listing competition amongst non-optioned stocks may have unexpected effects on the markets for both options and their underlying securities. In addition, a fresh look at the number of unlisted but option-eligible stocks may provide new insight into the state of the options market and indicate whether options exchanges will ever reach listing saturation.

2.4 Options and underlying stocks

While uncertainties about the effects of options on underlying securities remain, previous studies generally find that listing an option has positive effects for the market on its underlying security. Boehmer et al. (2011) find that optioned stocks have more liquid equity and superior price discovery. Jubinski and Tomljanovich (2006) find that the introduction of options does not affect the underlying stock for the majority of firms but that listed options do improve price discovery for underlying stocks with the highest trading volume and volatility levels. Kumar et al. (1998) conclude that, after options listings, stocks are characterized by decreased variance in pricing er-

[8]An ordinary least squares regression estimating the effect of IPO day market capitalization on the number of "spread" days between stock IPO and option IPO shows a 0.0466-day expected decrease in spread time for each additional million dollars of IPO day market capitalization. A t-score of -4.72 implies significant correlation.

ror, reduced bid-ask spreads, and increases in quoted depth, trading volume, trading frequency, and transaction size.

de Jong et al. (2006) show that the markets for stocks with traded options benefit both from improved informational efficiency and lower price volatility than markets for stocks with no traded options. The positive effect from option trading on the underlying security's market quality becomes more significant as the intrinsic values of underlying options increase; this is explained by the increased trading activity associated with options as their intrinsic values rise and their moneyness increases. As options trading volume increases, price discovery in the options market improves. A vibrant options market creates a feedback loop between the prices of an option and its underlying security; option price changes cause price revisions in the underlying stock and, in turn, price shifts in the underlying stock affect option values. This multi-security mechanism for efficient price discovery is least effective when options are out-of-the-money since these options have lower delta (Δ) values[9] and are least reactive to changes in underlying prices.

Contrary to most studies, Danielsen et al. (2007) claim that option IPO candidacy is endogenous to characteristics of the underlying securities; specifically, market improvements for underlying stocks develop *before* they are optioned and a low bid-ask spread is the single most important criterion in the option IPO decision. The study concludes that the option IPO actually has no effect on the underlying security's market quality. However, Danielsen et al. (2007) do not address the possibility that, under the rational expectations theory, market participants accurately forecast option IPOs and consequently increase their activity in underlying stocks during the period preceding an option IPO; in this scenario, the option IPO is, in fact, the catalyst that drives the liquidity increase in the underlying security (albeit before the listing decision is announced).

[9]Option delta (Δ) measures the rate at which an option price moves relative to changes in the price of its underlying security.

Studies examining foreign markets provide mixed conclusions about the relationship between options and their underlying securities. In Japan, Liu (2010) finds that the introduction of stock options has a positive effect on the price of the underlying security but also *increases* price volatility relative to a group of control stocks. Lepone and Yang (2006) find that the introduction of stock options in Australian markets does not materially affect the observed volatility of their underlying securities; however, the study does find that the impact of large trades on underlying stock prices decreased when FLEX options[10] were listed on a stock. Inconsistent conclusions between studies investigating American and international markets might be explained by differences in regulatory environments. In addition, younger financial markets have typically introduced index options before single-stock options whereas American markets introduced single-stock options first; this important difference in market development may have created significantly varied market dynamics since market participants typically develop long-lasting hedging strategies with the first derivative securities available to them.

If a healthy options market benefits the market for underlying stocks, improving efficiency in the options market during the IPO period may boost stock market quality, as well. In this case, the benefits of correcting inefficiencies in the options markets are multidimensional. Minimizing option market inefficiencies may lead to improvements in liquidity and price efficiency for both the options and stock markets while contributing to financial market completeness.

Lee and Yi (2001) claim that the options market is a theater primarily for "information-motivated" traders. Information-motivated trades are based on information that a trader believes is valuable but will rapidly lose value over time as other market partic-

[10]Whereas regular options are listed directly by exchange operators, FLEX options are listed by registered brokers on behalf of their clients. These options allow market participants to craft options with nonstandard contract terms such as strike price or expiration date. According to Hull (2009), FLEX options were introduced in an attempt to compete with decentralized over-the-counter (OTC) options markets.

ipants take advantage of the information; as a result, information-motivated traders favor quick trade execution over optimal transaction cost in order to maximize the value of the information. An apparent underrepresentation of value-motivated investors — those who buy securities at prices they perceive to be below intrinsic value — may cause pricing inefficiencies and increased price volatility in the options market. The trading simulation in this study adopts a value-oriented strategy that attempts to detect and exploit possible profit opportunities created by the disproportionate amount of information-motivated participants in the options market.

Chapter 3

Data

Securities selected for both the stock and options data sets constructed in this study were based on securities chosen by MarketWatch as components of its sector and subsector indices. Stock data is used in both the quasi-hyperbolic intraday stock volatility regression and trading simulation phases of this study while options data is relevant only during the latter. Both stock and options data sets are classified by business type and divided into one of ten sector groups and one of twenty-three subsector groups based on MarketWatch classification.[1] The MarketWatch index components were reviewed and modified to eliminate any securities that were not primary common stock shares; as a result, bonds, funds, b-shares, and other securities were removed from the lists before proceeding. The MarketWatch indices were chosen for their preclassification of securities by sector and subsector in addition to their size and diversity. Additional out-of-sample stock and options data sets for 2011 IPOs were used only in Phase IV.

[1] In general, each subsector group comprises a portion of its corresponding primary sector group and every stock in a sector group is assigned to one subsector. In a few cases, however, stocks in a given sector are assigned to multiple subsector groups. The "Utilities" sector group is too small and homogenous to break down into subsector groups. As a result, Utiltiies is considered both a sector and a subsector group for the purposes of this study.

3.1 Stock data

Stock data sets were constructed to contain the MarketWatch industry-based index components. Ticker symbols are relatively inconsistent identifiers of securities because they sometimes change and the "retirement" of any given ticker symbol is not always permanent (a previously-used but inactive ticker symbol can be adopted by another unrelated company in the future). To ensure that trading data for specific stocks were properly identified, the ticker symbols retrieved from MarketWatch for each sector and subsector industry group were matched with security PERMNOs to better identify the securities.

Oil & Gas	308
Oil & Gas Producers	193
Oil & Gas Equipment & Distribution	115
Basic Materials	285
Basic Resources	188
Chemicals	97
Industrials	782
Construction & Materials	91
Industrial Goods & Services	694
Consumer Goods	401
Automobiles & Parts	48
Food & Beverage	130
Personal & Household Goods	224
Healthcare	550
Healthcare Equipment & Services	259
Pharmaceuticals & Biotechnology	292
Consumer Services	544
Media	135
Retail	253
Travel & Leisure	157
Telecommunications	83
Fixed Line Telecommunications	45
Mobile Telecommunications	38
Utilities	106
Financials	930
Banks	451
Financial Services	151
Insurance	124
Real Estate	205
Technology	590
Software & Computer Services	260
Technology Hardware & Equipment	330

Table 3.1: Number of stocks in sector and subsector data sets

Using the PERMNO lists for each sector and subsector group, stock data sets were constructed containing PERMNO, trading date, ticker symbol (used later to merge stock data with options data), dividend payments, intraday low bid price, intraday high asking price, closing price, and cumulative stock price adjustment factors from January 1, 1996 to December 31, 2010. All data points were retrieved from the Center for Research in Security Prices (CRSP) database available through Wharton Research Data Services (WRDS). Entries representing inactive trading days were removed and price data were adjusted to reflect the real effects of dividend payments and stock splits on shareholder value. An event day variable was created to reflect the number of days a stock had been trading since its IPO; event day is equal to 1 on IPO day and each subsequent trading day is represented by incrementing the variable. Stata scripts used to prepare and organize stock data for regression are included in Appendix A.

A total of 4,448 unique securities were included in the industry-based stock data sets. MarketWatch included some companies in multiple sector groups; for this reason, 128 securities are included in 2 sectors and 3 other securities in 3 sectors. Table 3.1 shows the number of stocks included in each sector and subsector data set.

The stock data are subject to some level of selection bias. The stocks comprising each sector and subsector data set were all trading as of January 2, 2012 when the MarketWatch index component tickers were recorded. As a result, companies that failed, were taken private, acquired, or delisted for other reasons may be underrepresented. For example, companies that were purchased in 2011 (after the 1996–2010 observation range) are not included in the stock data set.

In addition, intraday trading volatility of the underlying stocks cannot be measured perfectly because of the data's daily observation frequency; low data granularity may account for imperfect estimations of underlying stock volatility. A method for approximating intraday volatility using only daily high, low, and closing price is detailed in Subchapter 4.1.

A separate, smaller stock data set was constructed for the Phase IV out-of-sample test that included daily price data throughout 2011 for 151 stocks with IPO dates in that year. This data set was only used in Phase IV.

3.2 Options data

As were the stock data sets, this study's options data sets were constructed on an industry-by-industry basis. Data for every exchange-listed option written on the stocks with tickers in each MarketWatch subsector[2] were retrieved for trading days from January 1, 1996 to December 31, 2010 using the Ivy DB OptionMetrics database available through WRDS. Initial data set variables included ticker symbol, trading date, exercise style (European or American), option type (call or put), expiration date, option ID, strike price, option contract closing price, and the lowest closing bid and highest closing ask prices for the option across the exchanges on which it trades. As appropriate for the date and underlying stock in each observation, underlying stock closing price, event time (days from stock IPO as described in Subchapter 3.1), and risk-free rate[3] were appended to the options data. Options data were finally sorted by option ID and date (from earliest to latest) for analysis with the trading simulation program. Further

Oil & Gas	
Oil & Gas Producers	1,110
Oil & Gas Equipment & Distribution	1,054
Basic Materials	
Basic Resources	1,234
Chemicals	564
Industrials	
Construction & Materials	294
Industrial Goods & Services	3,404
Consumer Goods	
Automobiles & Parts	1,068
Food & Beverage	1,218
Personal & Household Goods	2,522
Healthcare	
Healthcare Equipment & Services	995
Pharmaceuticals & Biotechnology	637
Consumer Services	
Media	2,579
Retail	1,891
Travel & Leisure	2,072
Telecommunications	
Fixed Line Telecommunications	646
Mobile Telecommunications	1,974
Utilities	522
Financials	
Banks	245
Financial Services	2,592
Insurance	784
Real Estate	1,082
Technology	
Software & Computer Services	2,606
Technology Hardware & Equipment	1,232

Table 3.2: Number of option contracts in subsector data sets

[2]Except for the "Utilities" sector, primary sectors were not used to assemble options data sets.

[3]Commonly used as such in the literature, 10-year United States Treasury bond yields act as a proxy for the risk-free rate in this study. Historical yields were retrieved from the Federal Reserve Bank of St. Louis Economic Research website.

explanation of data preparation mechanics and relevant Stata scripts can be found in Appendix A.

Since the OptionMetrics database does not recognize the CRSP PERMNO security identifier, ticker symbol was used to query the OptionMetrics database. As mentioned in Subchapter 3.1, ticker symbol is a relatively poor identifier of securities. As a result, it is possible that some subsector assignments or appended underlying stock data are inaccurate because of ticker mismatching; however, this is not expected to materially affect trading simulation performance. In addition, the options contracts selected may be subject to selection biases similar to those described in Subchapter 3.1 since the stock data sets act as foundations for the options data: delisted companies may be underrepresented.

Trading opportunities actually available to options market participants are difficult to capture with daily data points that do not reflect all fluctuations in option prices throughout the trading day. This is expected to limit trade frequency in the trading simulation by only allowing one transaction per day for each security. In addition, observed returns may underestimate potential returns because of limited opportunities to sell options in offsetting orders during simulation. Daily trading volume and open interest may lend added insight into daily market opportunities but were ignored because contracts with low historical trading activity do not always indicate a frozen market; for example, even if no contracts were outstanding for an out-of-the-money option, investors still may have been willing to write the option for a very low premium.

A separate, smaller options data set was constructed for the Phase IV out-of-sample test. Based on the Phase IV stock data set mentioned in Subchapter 3.1, this data set included daily price data throughout 2011 for options listed on 151 stocks with IPO dates in that year. This data set was only used during Phase IV.

Chapter 4

Phase I: Modeling IPO period stock volatility

The first phase of this study investigates the intraday price volatility of stocks during a 90-day IPO period. Adapting the Lewis (2011) quasi-hyperbolic model of IPO period volatility, regressions are run using each of the sector and subsector stock data sets described in Subchapter 3.1 that, in turn, can be used to forecast daily stock volatility during the IPO period. A 90-day IPO period was selected to fully capture the impact of the IPO event while excluding the effects of shareholder lockup expirations (which typically occur 180 days after IPO). Despite modifications to the way volatility is measured, an extended IPO period, and more restricted observation period, the results of this study's quasi-hyperbolic regression are expected to be ordinally similar to those observed in Lewis (2011).

4.1 Methodology

The first step in modeling IPO period volatility is to accurately calculate historical volatility for the stock data; the low data granularity calls for an approximation method. Since only intraday low, high, and closing prices are available, intraday volatility is assumed to fluctuate at a constant rate around the intraday mean price between high price P_{ijt}^{H} and low price P_{ijt}^{L} as illustrated in Figure 4.1. Volatility must also be normalized for stocks trading at different prices; to adjust accordingly, volatility is represented as a percentage of closing price P_{ijt}^{C}. Following the Sinclair (2008) defintiion of volatility in Equation 2.1, intraday percentage volatility for stock i in industry j on event day t was calculated using Equation 4.1. Although uncommon in the literature due to the growing availability of intraday secruity trading data, this sort of approximation should not significantly reduce the accuracy of results.

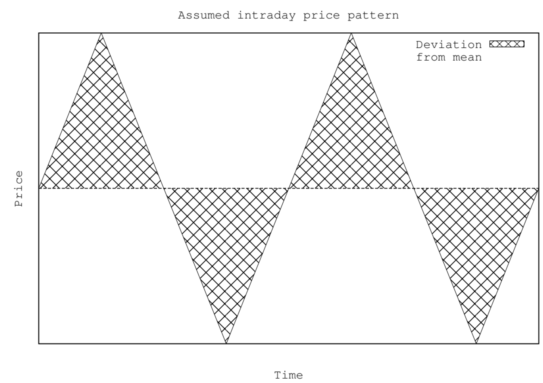


Figure 4.1: Under the assumption of constant-rate intraday price fluctuation around the mean, daily volatility is equal to one half the intraday trading range squared.

$$v_{ijt} = \left(\frac{P_{ijt}^{H} - P_{ijt}^{L}}{2 * P_{ijt}^{C}} \right)^2 \tag{4.1}$$

$$\widehat{v_{jt}} = \kappa_j + \frac{\lambda_j}{1 + \mu_j * (t-1)} + \varepsilon_{jt} \tag{4.2}$$

After intraday volatility v_{ijt} was calculated for each stock-day observation in all industry data sets, the Lewis (2011) quasi-hyperbolic model was used to predict average intraday stock volatility for each sector and subsector group during regression over a 90-day IPO period. Using Equation 4.2, the Lewis 2011 irregular regression model was applied to each data set using the observed volatility levels v_{ijt} for each company i in sector or subsector j on day relative to IPO t to approximate the values for three unknown variables κ_j, λ_j, and μ_j. Appendix A includes details on regression analysis procedure and relevant Stata scripts.

4.2 Regression results

Table 4.1: Quasi-hyperbolic regression results (part 1) with t-scores in parentheses.

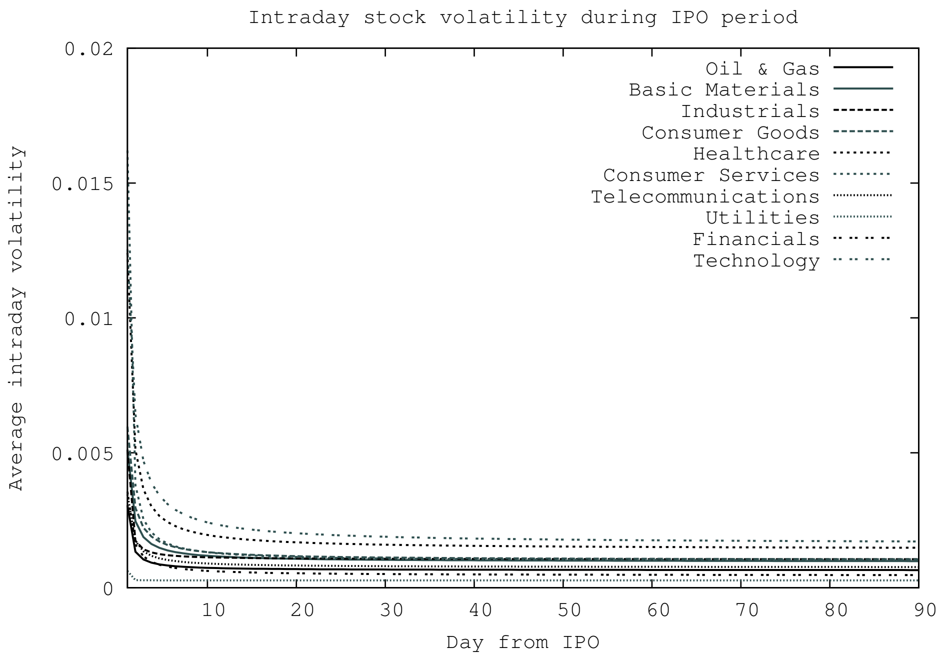
	$\boldsymbol{\kappa}$		$\boldsymbol{\lambda}$		$\boldsymbol{\mu}$	
Oil & Gas	0.0645%	(30.17)	0.2408%	(14.03)	2.7832	(3.53)
Producers	0.0738%	(25.01)	0.3267%	(13.64)	3.4875	(3.00)
Equipment & Distribution	0.0483%	(15.13)	0.0967%	(4.42)	0.8641	(1.66)
Basic Materials	0.0962%	(27.03)	0.4170%	(15.16)	1.9708	(4.50)
Basic Resources	0.0934%	(22.25)	0.4599%	(13.96)	2.2233	(3.93)
Chemicals	0.1048%	(15.77)	0.2873%	(6.02)	1.2270	(2.10)
Industrials	0.1047%	(33.09)	0.4052%	(15.43)	5.4011	(2.52)
Construction & Materials	0.0927%	(16.04)	0.4416%	(8.83)	30.9622	(0.32)
Industrial Goods & Services	0.1063%	(30.26)	0.4005%	(13.83)	4.7476	(2.48)
Consumer Goods	0.1023%	(20.00)	0.4946%	(12.54)	1.7301	(3.94)
Automobiles & Parts	0.0943%	(8.11)	0.3286%	(4.40)	0.7122	(1.69)
Food & Beverage	0.1029%	(10.22)	0.4968%	(6.49)	1.5479	(2.12)
Personal & Household Goods	0.1039%	(16.85)	0.5409%	(10.95)	2.4850	(2.92)
Healthcare	0.1426%	(23.26)	1.0986%	(22.57)	2.1972	(6.41)
Equipment & Services	0.1062%	(20.52)	0.5891%	(15.55)	1.1323	(5.55)
Pharmaceuticals & Biotechnology	0.1666%	(17.37)	1.4439%	(18.67)	2.7892	(4.70)
Consumer Services	0.0976%	(9.04)	1.5230%	(17.20)	4.8812	(3.02)
Media	0.0984%	(2.67)	4.0558%	(13.51)	6.1344	(2.00)
Retail	0.1165%	(14.74)	0.5254%	(8.24)	3.5634	(1.79)
Travel & Leisure	0.0692%	(21.28)	0.5343%	(20.82)	2.0726	(6.06)
Telecommunications	0.0752%	(12.05)	0.2705%	(5.50)	1.9565	(1.64)
Fixed Line Telecommunications	0.0695%	(11.42)	0.2754%	(6.25)	1.0472	(2.27)
Mobile Telecommunications	0.0800%	(7.56)	0.2689%	(3.04)	5.7088	(0.48)
Utilities	0.0270%	(21.57)	0.0354%	(3.24)	29.1849	(0.12)
Financials	0.0451%	(22.91)	0.3113%	(20.37)	1.8799	(6.18)
Banks	0.0258%	(8.65)	0.2485%	(11.69)	1.0345	(4.25)
Financial Services	0.1006%	(20.00)	0.3183%	(7.80)	2.8616	(1.97)
Insurance	0.0488%	(17.74)	0.2496%	(10.73)	4.8246	(1.91)
Real Estate	0.0444%	(9.96)	0.5364%	(14.51)	5.8677	(2.23)
Technology	0.1630%	(25.01)	1.0913%	(22.13)	1.4226	(7.43)
Software & Computer Services	0.1665%	(14.54)	1.1617%	(14.10)	1.1001	(5.06)
Hardware & Equipment	0.1581%	(25.32)	1.0140%	(20.42)	2.0357	(6.00)

Regression results are detailed in Table 4.1 with applicable t-scores in parenthesized. As hypothesized, the regression results are ordinaly similar to those in Lewis (2011). In general, regression t-scores were higher for sector groups than for subsector groups but t-scores were consistently high across all group data sets. In Table 4.2, the

Table 4.2: Quasi-hyperbolic regression results (part 2).

	R^2	Observations	Implied first-year annual volatility σ_{j1}	Added IPO effect σ^*_{j1}
Oil & Gas	0.0133	15,527	41.45%	0.89%
Producers	0.0199	9,588	44.36%	0.98%
Equipment & Distribution	0.0044	5,939	36.03%	0.93%
Basic Materials	0.0174	14,555	51.10%	1.57%
Basic Resources	0.0191	11,031	50.43%	1.62%
Chemicals	0.0125	3,524	53.14%	1.45%
Industrials	0.0076	31,447	52.48%	0.81%
Construction & Materials	0.0208	3,679	49.15%	0.54%
Industrial Goods & Services	0.0070	27,768	52.90%	0.85%
Consumer Goods	0.0113	15,853	53.03%	1.97%
Automobiles & Parts	0.0144	1,880	51.60%	2.57%
Food & Beverage	0.0080	6,015	53.36%	2.12%
Personal & Household Goods	0.0162	7,868	53.16%	1.68%
Healthcare	0.0179	30,882	63.44%	3.13%
Equipment & Services	0.0239	12,513	55.11%	3.07%
Pharmaceuticals & Biotechnology	0.0199	18,369	68.45%	3.27%
Consumer Services	0.0110	27,182	53.13%	3.24%
Media	0.0242	7,455	57.46%	7.38%
Retail	0.0061	11,498	55.75%	1.24%
Travel & Leisure	0.0553	8,229	44.28%	2.27%
Telecommunications	0.0069	4,920	44.94%	1.16%
Fixed Line Telecommunications	0.0198	2,490	43.99%	1.89%
Mobile Telecommunications	0.0039	2,430	45.76%	0.60%
Utilities	0.0051	2,060	26.30%	0.08%
Financials	0.0098	47,403	35.65%	1.75%
Banks	0.0071	24,703	28.41%	2.74%
Financial Services	0.0080	8,433	51.58%	0.93%
Insurance	0.0214	5,490	36.06%	0.77%
Real Estate	0.0235	8,877	35.21%	1.56%
Technology	0.0169	34,145	68.37%	3.90%
Software & Computer Services	0.0141	17,650	70.06%	4.91%
Hardware & Equipment	0.0274	16,495	66.39%	2.90%

Figure 4.2: Primary sector quasi-hyperbolic regression results.



standard deviation value σ_{j1} for industry j represents projected first-year annualized volatility on IPO day ($t = 1$) for a stock in industry j. Calculated using Equation 4.3, these values σ_{j1} are equal to the square root of the sum of each day's projected volatility $\widehat{v_{jt}}$ during the first 255-day year of trading using the appropriate values κ_j, λ_j, and μ_j for industry j. This calculation extrapolates the predicted daily intraday volatility levels to approximate volatility on an annualized basis for use in Phase II of this study.

$$\sigma_{j1} = \sqrt{\sum_{t=1}^{255} \left(\kappa_j + \frac{\lambda_j}{1 + \mu_j * (t-1)} \right)} \tag{4.3}$$

In the long run, daily volatility in industry j should approach κ_j as t increases. "IPO effect" volatility σ_j^* is calculated in Equation 4.4 as the value of σ_{j1} attributable solely to the IPO event; it is the difference between predicted volatility σ_{j1} and annualized volatility if only baseline volatility κ_j is expected. Figure 4.2 shows the

the difference between projected volatility attributable to the IPO event σ^*_{j1} and normal baseline volatility.

$$\sigma^*_{j1} = \sigma_{j1} - (255 * \kappa_j) \tag{4.4}$$

As the percentage values for σ_{j1} and σ^*_{j1} detailed in Table 4.2 illustrate, IPOs have a relatively small impact on volatility on an annualized basis; the Media subsector had the largest IPO-driven volatility effect σ^*_{j1} with 7.38% but most sector and subsector groups were characterized by IPO volatility effects σ^*_{j1} smaller than 2%. The apparent insignificance of IPO event-driven volatility relative to total annualized volatility may cause market participants to underestimate its importance; this would contribute to the tendency for relevant stock options to be underpriced in the market during the IPO period.

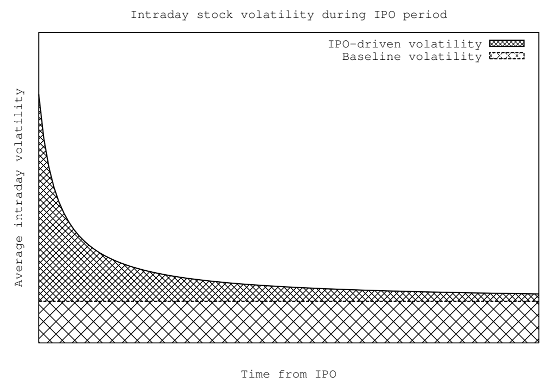


Figure 4.3: IPO-driven volatility declines with time while baseline volatility remains constant.

Chapter 5

Phase II: Fair value analysis and options trading simulation

The second phase of this study extrapolates the results of the Phase I quasi-hyperbolic regressions. Taking the form of an options trading simulation, the fair value analysis process includes calculating implied fair values for options in each subsector group using the volatility estimations made in Phase I as inputs to the Black-Scholes model, buying options when their calculated fair values are higher than their trading values, and selling them when market prices rise above fair values. Although the trading simulation does not perfectly reflect real market opportunities, the high returns on simulated trades indeed suggest that options tend to be undervalued during the IPO period.

5.1 Methodology

Since component stocks in umbrella sectors are wholly composed of stocks from relevant subsectors, the fair value analysis was only run using subsector regression results (except for the Utilities sector which has no subsectors). When analyzing an option, the added specificity of the subsector classifications makes the use of umbrella sector regression results unnecessary for projecting volatility and valuing options; for example, Ford Motors options are better valued as "Automobiles & Parts" securities than "Consumer Goods" securities.

Following Sinclair (2008) (Equation 2.1 in Subchapter 2.1.3), this study calculates annualized volatility $\widehat{\sigma_{jt}}$ for a company in industry j on event day t using Equation 5.1 with the three values κ_j, λ_j, and μ_j taken from the appropriate industry's Phase I regression results found in Subchapter 4.2. The calculation assumes a 255-day trading year.

$$\widehat{\sigma_{jt}} = \sqrt{\sum_{t}^{254+t} \left(\kappa_j + \frac{\lambda_j}{1 + \mu_j * (t-1)} \right)} \tag{5.1}$$

Using the combined stock-option data sets described in Subchapter 3.2, daily fair values were predicted for each examined option k using the option's defined strike price K_k, underlying stock spot price S_{ijt}, risk-free rate r_t, time to maturity $(T_k - t)$, projected annualized volatility $\widehat{\sigma_{jt}}$, and the standard normal cumulative distribution function $\Phi()$. Preliminary calculations for fair valuations of both put and call options included the calculations of d_1 and d_2 in Equations 5.2 and 5.3. The fair values of both put and call options were then calculated using the Black-Scholes model detailed in Equations 5.4 and 5.5.[1]

[1] Refer to Subchapter 2.1.4 for a description of calculations using the Black-Scholes model.

$$d_1 = \frac{ln\left(\frac{S_{ijt}}{K_k}\right) + \left(r_t + \frac{\widehat{\sigma_{jt}}^2}{2}\right)(T_k - t)}{\widehat{\sigma_{jt}}\sqrt{(T_k - t)}} \tag{5.2}$$

$$d_2 = \frac{ln\left(\frac{S_{ijt}}{K_k}\right) + \left(r_t - \frac{\widehat{\sigma_{jt}}^2}{2}\right)(T_k - t)}{\widehat{\sigma_{jt}}\sqrt{(T_k - t)}} \tag{5.3}$$

$$C(S_{ijt}, t) = \Phi(d_1)S_{ijt} - \Phi(d_2)K_k e^{-r_t(T_k - t)} \tag{5.4}$$

$$P(S_{ijt}, t) = \Phi(-d_2)K_k e^{-r_t(T_k - t)} - \Phi(-d_1)S_{ijt} \tag{5.5}$$

After calculating fair values for each option on each day it was actively traded, a simulation mimicked the purchase of undervalued and the sale of overvalued options in the market. Assuming an available option price equal to the midpoint between daily high and low option prices, an option was purchased whenever its available price was below its predicted fair value and sold whenever its available price was above its predicted fair value, the option expired, or the 90-day IPO period ended. The midpoint method ignores the fact that the Options Industry Council allows standard options with prices above $3.00 to trade only in $0.05 increments but this should not materially affect the accuracy of calculated returns.

The exercise styles of all options examined were either American or European.[2] Although the Black-Scholes model is an accepted method for valuing European options, it is not recognized as an appropriate method for valuing American options. Nevertheless, the Black-Scholes model is used to value American options in the trading simulation for reasons described in Subchapter 2.1.4: the Black-Scholes model still provides a firm lower bound on the fair values of American options and few stocks pay dividends within their first 90 days of active trading. The decision to use the Black-Scholes model to value American options maintains simplicity while ensuring that only undervalued options are purchased in the simulation.

[2]See Subchapter 2.1.2 for a complete description of option style.

The simulation process does not reflect the cumulative effects of trades on a portfolio; option contracts are analyzed individually during their respective 90-day IPO periods and trades are evaluated by percentage returns from purchase to sale. Consequently, the results of the analysis do not reflect the cumulative returns attributable to a portfolio and, instead, are presented as an array of hypothetical percentage returns for individual transactions.

The simulation does not perfectly represent real market opportunities. Since the simulation assumes purchase at minimum and sale at maximum prices, it may overestimate returns made in an open market setting by ignoring imperfect market timing. In addition, no transaction costs or taxes are taken into account in this simulation.

A primary limitation of this study is the low granularity of both option and stock data used; for all securities, relevant price and trading information is only observed daily. One implication of this limitation is an inability to fully incorporate intraday trading fluctuations into analysis. While daily high and low quotes were used to approximate daily stock volatility and available price points for options, the study does not account for increased volatility from multiple intraday price swings or increased trading volumes. This may lead to imprecise calculations of volatility in Equation 5.1.

In addition, the low granularity of options data makes determining both the liquidity and realistically available market price of relevant options difficult. The midpoint method used to approximate the available prices at which options can be purchased or sold does not reflect opportunities with certainty. Furthermore, this study ignores open interest and volume data in favor of simplicity; instead, it assumes that options are always available at the intraday range midpoint regardless of how frequently or infrequently the options were actually traded. As a result, some options that were listed but untraded in the market were included in this simulation. Potential overoptimism about trading opportunities may have inflated observed returns.

On the whole, the various limitations of this study may contribute to either over- or underestimation of realistic returns. On the one hand, the simulation may overestimate liquidity for and, consequently, realistic returns on many options contracts. On the other hand, the low data granularity may contribute to return underestimation if profitable trade opportunities pass undetected in the trading simulation. Assuming that the opposite effects of these recognized limitations are roughly comparable in magnitude, the available data should still provide reasonably credible evidence of option market efficiency or inefficiency during the 90-day IPO period.

5.2 Fair value analysis results

Tables 5.1, 5.2, and 5.3 show the results of fair values analysis for each subsector. Table 5.1 shows the number of trades executed in the trading simulation, observed return averages, and return ranges. Tables 5.2 and 5.3 respectively show number of trades and percentage of trades with positive, neutral, or negative returns. The final "Cumulative" line items in each table capture the averages, ranges, and statistics for all trades executed across the 23 subsector groups.

On the whole, the fair value analysis took on over thirty thousand trading positions; each position constituted a purchase triggered by suspected option undervaluation and a subsequent offsetting sale order. When simulating purchase of these options, more than half of all trades executed produced positive returns. No trade return median in any industry was negative and all industry means were positive; the lowest mean of 1.11% return per trade was observed in the "Automobiles & Parts" data set while the highest mean return was 133.41% per trade for "Chemicals" options.

The subsector maximum trade returns observed throughout the analysis — peaking with a 12,150% return on the purchase and sale of an option written on Google

Table 5.1: Fair value analysis results (part 1).

	Trades	Mean	Median	Max	Min
Oil & Gas					
Producers	1,445	23.78%	2.48%	3233.33%	-99.12%
Equipment & Distribution	1,052	59.47%	4.98%	9500.00%	-92.86%
Basic Materials					
Basic Resources	1,639	18.52%	0.00%	3540.00%	-98.00%
Chemicals	665	133.41%	8.82%	4700.00%	-98.64%
Industrials					
Construction & Materials	391	17.07%	0.00%	2380.00%	-95.83%
Industrial Goods & Services	3,846	25.42%	1.42%	5100.00%	-98.40%
Consumer Goods					
Automobiles & Parts	1,436	1.11%	1.24%	466.67%	-98.08%
Food & Beverage	1,365	42.79%	2.86%	9700.00%	-99.37%
Personal & Household Goods	1,730	12.96%	3.20%	1075.00%	-99.31%
Healthcare					
Equipment & Services	559	23.59%	0.00%	1125.00%	-99.35%
Pharmaceuticals & Biotechnology	656	14.13%	1.68%	1500.00%	-90.00%
Consumer Services					
Media	714	48.52%	0.00%	4900.00%	-99.13%
Retail	2,684	57.80%	3.17%	7900.00%	-97.96%
Travel & Leisure	2,197	11.07%	0.85%	1028.57%	-98.41%
Telecommunications					
Fixed Line Telecommunications	195	17.83%	0.00%	411.11%	-94.23%
Mobile Telecommunications	1,026	16.83%	2.56%	1900.00%	-97.56%
Utilities	236	3.99%	0.00%	400.00%	-93.33%
Financials					
Banks	105	2.91%	2.53%	106.67%	-77.78%
Financial Services	3,770	14.19%	0.64%	1884.62%	-99.69%
Insurance	787	12.50%	0.00%	1271.43%	-97.06%
Real Estate	1,399	21.11%	2.17%	1300.00%	-96.67%
Technology					
Software & Computer Services	3,727	57.87%	0.00%	12150.00%	-99.93%
Hardware & Equipment	2,094	7.79%	0.00%	783.33%	-98.67%
Cumulative	33,718	29.25%	1.14%	12150.00%	-99.93%

Table 5.2: Fair value analysis results (part 2).

	Trade balance		
	Positive returns	**Neutral returns**	**Negative returns**
Oil & Gas			
Producers	786	143	516
Equipment & Distribution	618	100	334
Basic Materials			
Basic Resources	795	171	673
Chemicals	302	71	191
Industrials			
Construction & Materials	174	58	159
Industrial Goods & Services	2,040	365	1,441
Consumer Goods			
Automobiles & Parts	774	130	532
Food & Beverage	831	125	409
Personal & Household Goods	973	155	602
Healthcare			
Equipment & Services	273	69	217
Pharmaceuticals & Biotechnology	347	66	243
Consumer Services			
Media	337	52	325
Retail	1,466	288	930
Travel & Leisure	1,117	250	830
Telecommunications			
Fixed Line Telecommunications	53	96	46
Mobile Telecommunications	582	68	376
Utilities	95	40	101
Financials			
Banks	63	10	32
Financial Services	1,922	264	1,584
Insurance	375	109	303
Real Estate	749	162	488
Technology			
Software & Computer Services	1,709	267	1,751
Hardware & Equipment	989	235	870
Cumulative	17,370	3,294	12,953

Table 5.3: Fair value analysis results (part 3).

	Trade balance (percentage)		
	Positive returns	**Neutral returns**	**Negative returns**
Oil & Gas			
Producers	54%	10%	36%
Equipment & Distribution	59%	10%	32%
Basic Materials			
Basic Resources	49%	10%	41%
Chemicals	54%	13%	34%
Industrials			
Construction & Materials	45%	15%	41%
Industrial Goods & Services	53%	9%	37%
Consumer Goods			
Automobiles & Parts	54%	9%	37%
Food & Beverage	61%	9%	30%
Personal & Household Goods	56%	9%	35%
Healthcare			
Equipment & Services	49%	12%	39%
Pharmaceuticals & Biotechnology	53%	10%	37%
Consumer Services			
Media	47%	7%	46%
Retail	55%	11%	35%
Travel & Leisure	51%	11%	38%
Telecommunications			
Fixed Line Telecommunications	27%	49%	24%
Mobile Telecommunications	57%	7%	37%
Utilities	40%	17%	43%
Financials			
Banks	60%	10%	30%
Financial Services	51%	7%	42%
Insurance	48%	14%	39%
Real Estate	54%	12%	35%
Technology			
Software & Computer Services	46%	7%	47%
Hardware & Equipment	47%	11%	42%
Cumulative	52%	10%	39%

stock in the Software & Computer Services subsector — show that the trading return results are right-tailed and characterized by some significant high-return outliers. The right-tailed nature of the data is further highlighted by the fact that means are higher than medians for all industries except Automobiles & Parts. While a trade's upside is theoretically unlimited, the lowest possible return for any one trade is limited to -100% in the event that purchased options become worthless. While no simulated purchases actually led to a total loss of value, the lowest returns were below -99%. In a real market setting, it is unlikely that buyers would exist for these options and, in practice, a trader owning these options would likely lose all value. About 7.8% of all observed trade returns were 100% or greater while 1.7% of returns were "catastrophic" and led to losses of 90% or more.

The trade balance numbers in Tables 5.2 and 5.3 show that, in general, trades executed in the fair value analysis generated positive returns more frequently than negative returns. This further suggests that options are inefficiently priced during the IPO period. Only two subsectors — Utilities and Software & Computer Services — were characterized by slightly more negative than positive returns.

The cumulative results show a median trade return of 1.14% and mean return of 29.25%; the outsized mean indicates a right-tailed distribution of returns which is highlighted in Figure 5.1. If 255 trading positions are taken during a year (one for each trading day) and each returns 1.14% (equal to the cumulative median return), an overall return of 1,703% is realized. Furthermore, 52% of all trades executed resulted in positive returns while only 39% led to losses. Evidence

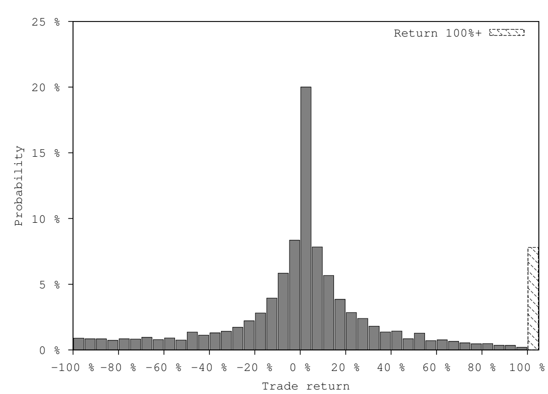


Figure 5.1: The distribution of returns observed in the simulation was right-tailed. More than 7% of observed returns were equal to or greater than 100%.

from both individual subsector simulation and cumulative trading results strongly suggest that stock options are inefficiently priced during the 90-day stock IPO period.

The results also highlight the uncertainty associated with options prices. The lowest standard deviation of trade returns for an industry was 17% in the Banks subsector while the highest was 481% in the Chemicals subsector. This significant standard deviation shows the high-risk, "hit-or-miss" nature of applying the quasi-hyperbolic model to a trading strategy — many seemingly undervalued options turned out to be practically worthless as evidenced by the minimum returns observed in most subsectors. The high uncertainty and risk associated with stock options during the IPO period, however, do not mean that options are efficiently priced in today's market; the universally positive median and mean returns in addition to the imbalance of positive and negative returns generated in the simulation imply that options are regularly undervalued. This is likely due to a lack of demand tied to some market participants' risk aversion, the speculative nature of trading significantly out-of-the-money securities, and the relative absence of "value" investors in the options marketplace.

Chapter 6

Phase III: Portfolio strategy evaluation

In Phase III, an additional simulation was run to determine the relationship between trading fees and the options underpricing problem; fees and other expenses associated with the purchase and sale of options may deter investors from investing in undervalued options and contribute to the mispricing found in Phase II. Using the observed distribution of returns described in Subchapter 5.2, a fixed-ratio portfolio investment strategy simulation shows positive expected returns with fees and expenses of up to 10% per transaction. Results were expected to illustrate decreasing portfolio returns associated with increased trading fees. Also expected was confirmation that trading fees do not fully explain the underpricing. Consistent with this hypothesis, simulation results indeed show that trading fees are unlikely to be the cause of option underpricing during the IPO period.

6.1 Methodology

The portfolio simulation was run to test the effects of increasing trading fees on portfolio returns. For consistency, all trials were run using a total of 255 positions (to reflect one security purchased and sold per trading day in a 255-day trading year) and only one security was held at a time.

Each trial begins with a $1,000,000 endowment. For each of 255 iterations, a fixed percentage of the portfolio (called the "investment ratio") is invested in a security with a payout distribution equal to the distribution of returns observed in Subchapter 5.2. In each trial, the 255 pre-fee investment returns constitute a simple random sample (without replacement during the trial) of the the 33,718 returns observed in Phase II (detailed in Subchapter 5.2). The selection of random security returns from the Phase II distribution minimizes distortions that may come from examining options during a fixed observation period and ensures a market-neutral test. Although options trading fees are typically structured on a per-contract basis, simulation fees were set as a fixed percentage of trade value charged at the time of both purchase and sale transactions (twice for each position held).[1] Following the fixed ratio investment strategy, larger amounts of capital were risked following gains while decreased investment followed losses.

A total of 500 trials were run for each of 560 ratio-fee profiles with investment ratio ranging from one to thirty-five percent and fees ranging from zero to fifteen percent of transaction value. Refer to Appendix B for relevant simulation code.

This simulation is limited by the same factors affecting the Phase II simulation — most importantly that real market opportunities are imperfectly reflected in the low-granularity options data — and does not account for holding limits imposed by options exchanges. Even with these considerations, the results indicate that transaction fees are unlikely to cause the option underpricing observed during the IPO period.

Table 6.1: Median portfolio returns for fixed-ratio investment strategy after 255 positions (part 1).

Portfolio investment ratio	Trading fees & expenses 0%	1%	2%	3%	4%	5%	6%	7%
1%	89%	77%	64%	56%	48%	35%	32%	23%
2%	233%	182%	155%	137%	108%	84%	63%	48%
3%	538%	366%	278%	241%	196%	142%	104%	57%
4%	883%	654%	490%	387%	265%	193%	131%	87%
5%	1593%	1102%	738%	544%	371%	255%	171%	118%
6%	2470%	1393%	1080%	745%	549%	373%	244%	121%
7%	3707%	2123%	1442%	1038%	641%	416%	231%	117%
8%	6288%	4031%	2229%	1304%	907%	506%	281%	138%
9%	8347%	5490%	2918%	1662%	1071%	514%	235%	162%
10%	13978%	9297%	3297%	2055%	1148%	670%	292%	175%
11%	18227%	9103%	5463%	2664%	1363%	743%	335%	148%
12%	27731%	10757%	6030%	2891%	1627%	940%	335%	121%
13%	40152%	14871%	6654%	4268%	1759%	948%	420%	121%
14%	58959%	27423%	7764%	4439%	2124%	889%	438%	73%
15%	68417%	24067%	11694%	5993%	2742%	1030%	428%	95%
16%	90520%	28345%	14209%	6007%	3110%	1164%	333%	111%
17%	115588%	48577%	15444%	5651%	3001%	950%	477%	84%
18%	124938%	48694%	22510%	7524%	3207%	1201%	347%	42%
19%	234383%	68684%	23909%	8472%	4148%	1146%	363%	6%
20%	250618%	80001%	24148%	7153%	2539%	1046%	388%	38%
21%	243624%	128245%	21858%	9254%	3037%	1030%	289%	-7%
22%	271064%	122597%	30664%	8697%	2957%	893%	340%	13%
23%	498730%	125125%	61860%	11987%	2114%	567%	230%	2%
24%	503700%	238524%	50406%	10759%	3349%	785%	170%	-15%
25%	653195%	196726%	34724%	12136%	3873%	602%	192%	-38%
26%	766892%	216774%	45847%	14703%	3319%	653%	118%	-46%
27%	1050484%	320365%	54668%	17462%	3049%	875%	102%	-57%
28%	1632512%	404892%	72750%	11221%	2969%	508%	65%	-57%
29%	945047%	262772%	69772%	13627%	2287%	407%	35%	-59%
30%	1446156%	427744%	61423%	16465%	3133%	330%	58%	-72%
31%	2745377%	343196%	83512%	20569%	2428%	452%	-15%	-81%
32%	1817857%	473721%	63156%	17418%	2308%	351%	31%	-84%
33%	2481286%	503447%	119094%	12057%	2190%	503%	-6%	-78%
34%	2412893%	503945%	102669%	15587%	4064%	400%	-5%	-83%
35%	3884544%	710587%	99524%	10202%	1957%	201%	-56%	-90%

Table 6.2: Median portfolio returns for fixed-ratio investment strategy after 255 positions (part 2).

Portfolio investment ratio	Trading fees & expenses 8%	9%	10%	11%	12%	13%	14%	15%
1%	16%	10%	4%	-3%	-6%	-12%	-18%	-21%
2%	35%	11%	2%	-10%	-15%	-26%	-31%	-38%
3%	40%	35%	0%	-15%	-24%	-38%	-45%	-53%
4%	60%	27%	-1%	-18%	-40%	-48%	-61%	-68%
5%	42%	14%	-15%	-30%	-40%	-61%	-70%	-77%
6%	56%	16%	-12%	-39%	-59%	-68%	-77%	-84%
7%	52%	17%	-28%	-47%	-67%	-77%	-82%	-88%
8%	56%	16%	-36%	-59%	-68%	-82%	-88%	-92%
9%	44%	-3%	-47%	-65%	-75%	-87%	-91%	-94%
10%	49%	-28%	-53%	-68%	-81%	-91%	-94%	-97%
11%	31%	-31%	-58%	-76%	-88%	-92%	-95%	-98%
12%	29%	-40%	-65%	-84%	-89%	-95%	-97%	-99%
13%	6%	-45%	-71%	-86%	-93%	-96%	-98%	-99%
14%	-3%	-45%	-77%	-88%	-94%	-97%	-99%	-99%
15%	-14%	-62%	-82%	-91%	-96%	-98%	-99%	-100%
16%	-23%	-66%	-84%	-94%	-98%	-99%	-99%	-100%
17%	-3%	-63%	-88%	-95%	-98%	-99%	-100%	-100%
18%	-37%	-77%	-91%	-97%	-98%	-99%	-100%	-100%
19%	-40%	-78%	-92%	-97%	-99%	-100%	-100%	-100%
20%	-59%	-83%	-92%	-98%	-99%	-100%	-100%	-100%
21%	-72%	-83%	-96%	-99%	-99%	-100%	-100%	-100%
22%	-65%	-88%	-95%	-99%	-100%	-100%	-100%	-100%
23%	-69%	-90%	-97%	-99%	-100%	-100%	-100%	-100%
24%	-79%	-94%	-98%	-100%	-100%	-100%	-100%	-100%
25%	-84%	-93%	-99%	-100%	-100%	-100%	-100%	-100%
26%	-81%	-94%	-99%	-100%	-100%	-100%	-100%	-100%
27%	-91%	-97%	-99%	-100%	-100%	-100%	-100%	-100%
28%	-93%	-98%	-100%	-100%	-100%	-100%	-100%	-100%
29%	-91%	-99%	-100%	-100%	-100%	-100%	-100%	-100%
30%	-94%	-99%	-100%	-100%	-100%	-100%	-100%	-100%
31%	-96%	-99%	-100%	-100%	-100%	-100%	-100%	-100%
32%	-96%	-99%	-100%	-100%	-100%	-100%	-100%	-100%
33%	-98%	-99%	-100%	-100%	-100%	-100%	-100%	-100%
34%	-98%	-100%	-100%	-100%	-100%	-100%	-100%	-100%
35%	-98%	-100%	-100%	-100%	-100%	-100%	-100%	-100%

6.2 Portfolio evaluation results

In a fee-free environment, expected returns are an increasing function of investment ratio. As fees are added and introduce friction into the investing strategy, however, expected returns show an optimal investment ratio; if investment ratio exceeds this optimum, expected returns for a given fee rate decline. For example, with a 5% fee, an optimal investment ratio range arises in Table 6.1 between 15 and 20%. While an aggressive 35% investment ratio produces higher returns in the fee-free environment, that same investment ratio reduces returns by about three quarters from those expected using a 15–20% ratio with a 5% trading fee. Positive expected returns are achievable with fees up to 10% per transaction when using the most conservative one-percent investment ratio. When fees exceed 10%, expected returns become negative regardless of investment ratio.

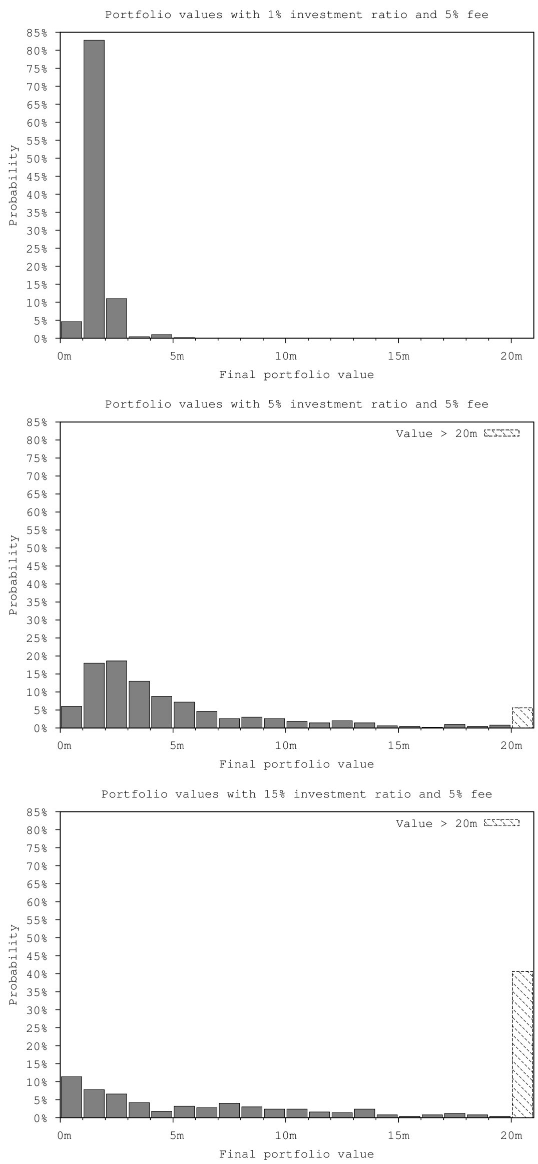


Figure 6.1: Holding fees fixed at 5% of transaction value, both standard deviation and median outcome increase as a function of investment ratio.

The high-return outlier trades in the Phase II results cause the distributions of outcomes associated with fixed-ratio portfolio investing to be right-tailed. Ex-

[1]Per-contract fees vary depending on broker, order size, and client type (institutional or retail). Fixed-percentage fees were used to test the trading strategy in order to maintain simplicity and minimize distortions caused by specific per-contract fee schedules.

ecuting 255 trades that each generate a return equal to the Phase II cumulative median trade return[2] (1.14%) generates an overall return of 1,703%; Phase III simulation results show that, in a fee-free environment when investment ratio is at least 6%, median expected portfolio return exceeds 1,703% because of the high-return outlier trades observed in Phase II. The outsized median portfolio returns associated with a 35% investment ratio in a fee-free environment underperform 255 trades returning the Phase II cumulative mean of 29.25%. As they increase, however, fees mitigate the ability of outliers to counteract the 1.7% chance of "catastrophic" losses exceeding 90%.

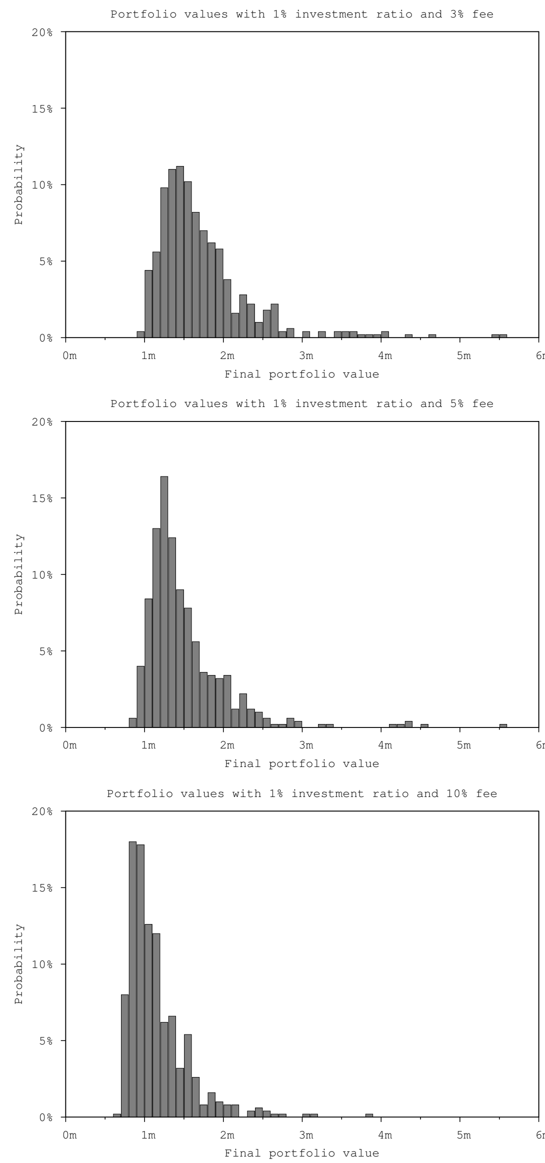


Figure 6.2: When investment ratio is held constant, increasing transaction fees has the effect of reducing both standard deviation and expected final portfolio value.

The distributions in Figure 6.1 illustrate the sensistivity of both expected value and the standard deviation of portfolio value to different levels of fee expense. Figure 6.2 shows that, when investment ratio is held constant, increases in fees decrease the probability of outsized final portfolio values and deflate overall outcome expectations.

When a conservative 1% investment ratio is used, median returns remain positive with trading fees up to 10% per transaction. Brokers typically charge clients on a

[2] See Table 5.1 in Subchapter 5.2.

per-contract basis for trades; while these fees may be relatively high when purchasing the cheapest options, fees associated with these securities are relatively lower during subsequent sale if contracts appreciate in value or expire (in which case no fees are paid). Although the simulation does not reflect a per-contract fee schedule, discounts for high-volume orders make it unlikely that realized options trading fees consistently reach 10% of transaction value for market participants with significant trading activity.

The observed returns generated by purchasing undervalued options are likely made possible by investors' simple oversight of the options market's pricing inefficiency. As mentioned in Subchapter 2.1.2, Hull (2009) describes two types of options market participants: hedgers and speculators. While hedgers buy options to mitigate risk and speculators typically enter the options market to profit from forecasted movements in underlying security prices, it is not clear that a substantial number of "value" investors buy apparently cheap options to sell them in offsetting orders when their market values match or exceed their inherent fair values.

Chapter 7

Phase IV: Stress tests

To test the methodology and results of Phases II and III against over-fitting, both per-trade and portfolio returns were calculated for options listed on stocks with IPOs during 2011. Following Phase II and III methodologies, this out-of-sample test shows that, although median portfolio returns turned negative when transaction fees reached 6%, option price discovery remains inefficient during the IPO period. Finally, fair value analyses and portfolio simulations were run with an alternative valuation method that derives volatility from daily VIX closing prices instead of the Phase I quasi-hyperbolic IPO period volatility forecasts; this method underperforms the original strategy but further evidences options pricing inefficiency during the stock IPO period. Consolidated results are provided in Table 7.1.

	Original strategy		**VIX strategy**	
	1996-2010	**2011**	**1996-2010**	**2011**
Trades	33,718	11,417	4,625	6,993
Mean	29.3%	12.9%	13.1%	3.9%
Median	1.1%	0.8%	2.1%	0.9%
Min	-99.9%	-97.7%	-99.2%	-85.5%
Max	12150%	3900%	2150%	485%
100%+	7.8%	3.4%	4.6%	0.8%

Table 7.1: Consolidated results show that, although the VIX strategy produces a higher median return, the original quasi-hyperbolic forecasting strategy has a higher mean return than the simple VIX-based strategy and outperforms it in portfolio investment simulation.

7.1 Out-of-sample test

A total of 151 stocks with IPOs in 2011 were chosen for the out-of-sample test. These stocks were not used in and make no impact on the results of Phase I, Phase II, or Phase III. As a result, possible over-fitting resulting from the use of 1996–2010 stock data to predict options prices during the same period should be absent in this out-of-sample test. Table 7.2 lists to which subsector groups the out-of-sample stocks belong.

First, trading data for options and stocks during 2011 were merged for use in a fair value analysis. Following Phase II methodology, each listed option was examined in isolation and a simulation was run to purchase or sell the option based on expected volatility as calculated using the quasi-hyperbolic regression results from Phase I. The observed trading returns were then applied to a portfolio evaluation following Phase III methodology using 500 trials with 255 trades each for 280 different ratio-fee profiles; returns on the 255 trades in each trial represent a simple random sample (without replacement) of returns from the out-of-sample 2011 IPO fair value analysis distribution.

Oil & Gas	
Oil & Gas Producers	14
Oil & Gas Equipment & Distribution	15
Basic Materials	
Basic Resources	6
Chemicals	3
Industrials	
Construction & Materials	0
Industrial Goods & Services	4
Consumer Goods	
Automobiles & Parts	3
Food & Beverage	3
Personal & Household Goods	3
Healthcare	
Healthcare Equipment & Services	7
Pharmaceuticals & Biotechnology	14
Consumer Services	
Media	6
Retail	4
Travel & Leisure	2
Telecommunications	
Fixed Line Telecommunications	0
Mobile Telecommunications	0
Utilities	1
Financials	
Banks	9
Financial Services	9
Insurance	0
Real Estate	10
Technology	
Software & Computer Services	27
Technology Hardware & Equipment	11

Table 7.2: Of the 2011 IPO stocks selected for the out-of-sample test, the Oil & Gas and Technology sectors were most heavily represented.

Table 7.3: Median portfolio returns for fixed-ratio quasi-hyperbolic forecast investment strategy after 255 positions for 2011 out-of-sample test.

Portfolio investment ratio	Trading fees & expenses							
	0%	**1%**	**2%**	**3%**	**4%**	**5%**	**6%**	**7%**
1%	34%	28%	21%	15%	8%	3%	-3%	-8%
2%	83%	60%	45%	26%	13%	4%	-9%	-15%
3%	142%	95%	68%	42%	20%	2%	-10%	-24%
4%	200%	141%	94%	62%	26%	-1%	-17%	-32%
5%	295%	213%	124%	79%	36%	-1%	-20%	-42%
6%	386%	268%	168%	85%	42%	-3%	-27%	-48%
7%	546%	323%	188%	110%	43%	-6%	-32%	-55%
8%	668%	413%	232%	135%	34%	-8%	-37%	-58%
9%	931%	472%	273%	138%	45%	-14%	-43%	-64%
10%	1203%	675%	384%	200%	47%	-23%	-49%	-69%
11%	1622%	838%	373%	153%	42%	-20%	-45%	-74%
12%	1938%	887%	444%	174%	50%	-19%	-59%	-77%
13%	2248%	1038%	410%	232%	36%	-25%	-63%	-81%
14%	2626%	1051%	591%	236%	42%	-38%	-69%	-84%
15%	3457%	1633%	547%	234%	40%	-30%	-69%	-87%
16%	4199%	1689%	630%	229%	31%	-40%	-73%	-88%
17%	4586%	1929%	708%	247%	40%	-50%	-78%	-89%
18%	6723%	2160%	822%	207%	30%	-48%	-80%	-93%
19%	6511%	2530%	866%	215%	37%	-58%	-84%	-94%
20%	7430%	2921%	957%	241%	31%	-49%	-86%	-95%
21%	10684%	2754%	1179%	251%	17%	-52%	-87%	-95%
22%	11982%	3253%	1137%	212%	27%	-59%	-88%	-96%
23%	16287%	4327%	1244%	217%	8%	-63%	-91%	-97%
24%	17427%	3902%	1191%	284%	-14%	-74%	-92%	-97%
25%	20030%	5435%	1350%	263%	-1%	-75%	-93%	-98%
26%	23883%	5850%	1249%	286%	1%	-73%	-94%	-98%
27%	26590%	5595%	1406%	233%	-6%	-78%	-94%	-99%
28%	33137%	6768%	1371%	306%	-22%	-84%	-96%	-99%
29%	42977%	6327%	1426%	232%	-30%	-82%	-96%	-99%
30%	37437%	8055%	1510%	256%	-39%	-82%	-97%	-99%
31%	35897%	8968%	1699%	274%	-32%	-85%	-98%	-99%
32%	46009%	9597%	1799%	166%	-24%	-88%	-98%	-100%
33%	55614%	9410%	1823%	221%	-39%	-89%	-98%	-100%
34%	72315%	10488%	1653%	197%	-49%	-90%	-98%	-100%
35%	68177%	13346%	1654%	209%	-37%	-93%	-99%	-100%

Simulating the execution of 11,417 trades, the 2011 out-of-sample fair value analysis produced returns ranging from -97.67% to 3,900.00% with mean return of 12.91% and median return of 0.82%. Standard deviation of trade return was 93.56% and, while return distribution was still right-tailed, only 3.4% of returns met or exceeded 100% compared to 7.8% of returns in the Phase II fair value analysis. Of the trades executed, 5,907 (52%) returns were positive, 1,172 (10%) were neutral, and 4,338 (38%) were negative. These results show general consistency with the Phase II fair value analysis results.

Using a 1% fixed investment ratio, median portfolio returns remained positive with fees up to 5%. This maximum fee level significantly differs from the 10% level found in Phase III and suggests that trading fees may have played a larger role in options mispricings during 2011 than during the 1996–2010 period. Alternatively, possible over-fitting between Phase I regression results and options price data from 1996–2010 relevant for Phases II and III may have contributed to outsized expected return results; since quasi-hyperbolic regression results from Phase I that do not include 2011 data are used to value options in Phase IV, out-of-sample results cannot be affected by such a bias.

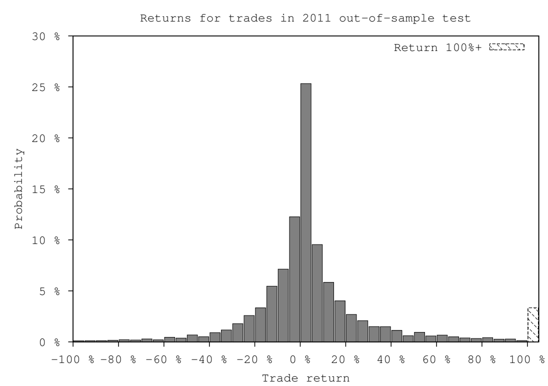


Figure 7.1: While still right-tailed, the distribution of of returns from 2011 IPO options trades was characterized by only 3.4% of returns meeting or exceeding 100% compared to 7.8% of returns in Phase II.

Decreased returns observed in the 2011 out-of-sample test indicate the possibility that market efficiency has partially improved; in this case, Phases II and III may highlight a problem that, if mispricing has become recognized by some market participants, has begun to correct itself. The outsized median portfolio returns observed when transaction fees are lower than 5%, however, suggest that fees still cannot completely explain the option mispricing problem during the underlying stock IPO period that persisted throughout 2011.

7.2 Control case: A VIX-based strategy

If the options underpricing problem is significant enough, a simpler trading strategy may be able to exploit it to generate returns equal to or greater than those observed using the original strategy in Phase II. To explore this possibility, fair value analysis and portfolio evaluation processes were repeated for IPO-period options in both the main 1996–2010 and 2011 out-of-sample data sets to test a strategy that measures annualized volatility using daily closing prices of the VIX index.[1] If the Lewis (2011) quasi-hyperbolic model does, in fact, predict volatility better than the market, the strategy that uses it should outperform a VIX-based strategy in simulation for both in- and out-of-sample data sets.

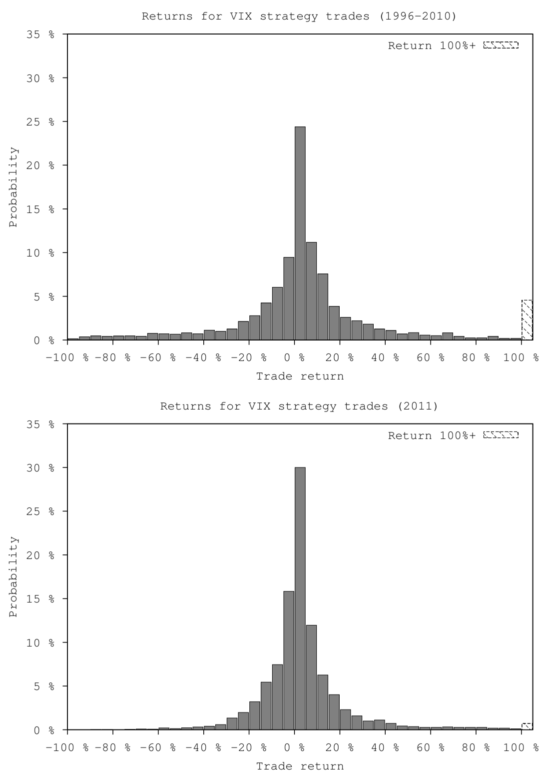


Figure 7.2: The VIX strategy produces higher median returns than the Phase II strategy but has fewer high-return outliers.

For options in the 1996–2010 sample, the simple VIX strategy generates returns ranging from -99.2% to 2,150.0% with median return of 2.1%, mean return

[1] The Chicago Board Options Exchange Volatility Index is introduced in Subchapter 2.1.3. Daily VIX closing prices were retrieved from the public CBOE website. In 2003, CBOE revised the VIX calculation method but provides historical VIX price equivalents dating back to 1990 for the new methodology. For consistency, these historical equivalents are used for dates prior to the 2003 revision instead of observed historical values that use old methodology.

of 13.1%, and standard deviation of 84.1%. Of 4,625 simulated trades, returns for 2,583 (56%) were positive, 449 (10%) were neutral, and 1,593 (34%) were negative. Although the VIX strategy generated a larger median return (2.1% versus 1.1% in Phase II) and a higher percentage of positive trade outcomes (56% versus 52% in Phase II), the VIX strategy simulation failed to buy many of the highest-yielding outlier options; only 4.6% of VIX strategy returns equalled or exceeded 100% compared to 7.8% of Phase II returns.

For 2011 options, the VIX strategy produced similar results relative to the quasi-hyperbolic forecast strategy. VIX strategy median return was 0.9% for 2011 IPOs and standard deviation was only 21.5%; mean return, however, was 3.9% and returns equalling or exceeding 100% composed merely 0.8% of the complete distribution. The VIX strategy produces few high-return outlying trades for options on 2011 IPO stocks.

In portfolio evaluation (detailed in Tables 7.4 and 7.5), the VIX-based strategy underperformed the original trading strategy for the 1996–2010 and 2011 observation periods; VIX strategy median portfolio returns were lower for all 280 ratio-fee profiles examined. A conservative 1% portfolio investment ratio generated positive returns with fees up to 5% for options from 1996–2010 but produced negative returns when fees reached only 2% using the out-of-sample 2011 IPO options.

Since both Phase III and VIX strategy portfolio simulation trials were run assuming 255 trades per year, the trial results only reflect differences in intensive trade margins. The Phase II strategy executed 33,718 trades during the 1996–2010 period while the VIX strategy executed only 4,625 (86% fewer) trades during the same period; the original trading strategy is more sensitive than a simple VIX strategy and detects more opportunities to purchase undervalued options. When portfolio simulations were modified to execute the average number of trades observed annually for each strategy (2,247 trades for the original strategy and 308 trades for the VIX

Table 7.4: Median portfolio returns for fixed-ratio VIX investment strategy after 255 positions for 1996–2010 options.

Portfolio investment ratio	Trading fees & expenses 0%	1%	2%	3%	4%	5%	6%	7%
1%	37%	29%	22%	15%	9%	3%	-2%	-7%
2%	86%	67%	50%	31%	17%	5%	-5%	-14%
3%	148%	105%	75%	49%	28%	6%	-9%	-22%
4%	221%	159%	105%	72%	36%	6%	-15%	-29%
5%	324%	200%	140%	86%	42%	6%	-20%	-35%
6%	486%	299%	187%	103%	43%	7%	-24%	-43%
7%	614%	362%	236%	126%	59%	10%	-27%	-48%
8%	790%	484%	271%	123%	52%	3%	-37%	-57%
9%	1018%	597%	326%	156%	70%	-5%	-42%	-61%
10%	1335%	780%	411%	171%	72%	-7%	-45%	-66%
11%	1649%	943%	441%	205%	81%	-14%	-46%	-71%
12%	1899%	956%	461%	224%	75%	-7%	-52%	-75%
13%	2580%	1371%	554%	320%	56%	0%	-62%	-78%
14%	3060%	1732%	561%	236%	80%	-14%	-63%	-81%
15%	3715%	1618%	790%	273%	68%	-29%	-68%	-84%
16%	4956%	2158%	861%	249%	52%	-24%	-67%	-85%
17%	5748%	2417%	902%	277%	41%	-26%	-72%	-90%
18%	7886%	2572%	911%	248%	55%	-45%	-76%	-92%
19%	8090%	2715%	1140%	361%	60%	-52%	-81%	-92%
20%	10466%	3639%	1134%	344%	52%	-50%	-82%	-94%
21%	12731%	4617%	1057%	264%	38%	-49%	-81%	-94%
22%	12814%	4173%	1375%	358%	28%	-56%	-85%	-96%
23%	16661%	5426%	1317%	265%	16%	-62%	-88%	-96%
24%	18778%	4796%	1526%	295%	44%	-59%	-91%	-97%
25%	21396%	5280%	1397%	349%	12%	-70%	-91%	-97%
26%	24977%	5622%	1818%	288%	-9%	-72%	-92%	-97%
27%	37171%	6311%	1433%	254%	-7%	-73%	-92%	-98%
28%	36187%	8010%	2092%	247%	-14%	-78%	-94%	-99%
29%	43180%	7545%	1677%	304%	-6%	-82%	-95%	-99%
30%	43982%	8732%	1647%	239%	-22%	-82%	-96%	-99%
31%	44253%	10361%	2143%	328%	-35%	-81%	-97%	-99%
32%	56134%	8910%	2001%	273%	-18%	-86%	-97%	-100%
33%	54213%	10625%	2204%	314%	-35%	-90%	-98%	-100%
34%	66052%	13536%	1631%	186%	-43%	-90%	-98%	-100%
35%	68625%	10505%	1813%	299%	-50%	-91%	-99%	-100%

Table 7.5: Median portfolio returns for fixed-ratio VIX investment strategy after 255 positions for 2011 out-of-sample test.

Portfolio investment ratio	Trading fees & expenses 0%	1%	2%	3%	4%	5%	6%	7%
1%	10%	5%	-1%	-6%	-10%	-15%	-19%	-23%
2%	22%	8%	-1%	-12%	-20%	-28%	-34%	-41%
3%	32%	13%	-3%	-16%	-28%	-39%	-47%	-54%
4%	46%	20%	-4%	-22%	-36%	-48%	-57%	-65%
5%	61%	24%	-4%	-26%	-43%	-56%	-65%	-73%
6%	75%	26%	-6%	-32%	-48%	-63%	-72%	-79%
7%	92%	31%	-8%	-35%	-55%	-68%	-78%	-84%
8%	107%	37%	-7%	-40%	-60%	-73%	-82%	-88%
9%	139%	40%	-9%	-45%	-64%	-77%	-86%	-91%
10%	156%	46%	-13%	-49%	-67%	-81%	-88%	-93%
11%	171%	55%	-12%	-50%	-72%	-84%	-91%	-95%
12%	190%	54%	-15%	-56%	-75%	-86%	-93%	-96%
13%	223%	62%	-15%	-58%	-77%	-89%	-94%	-97%
14%	246%	68%	-19%	-60%	-80%	-90%	-95%	-98%
15%	281%	81%	-23%	-63%	-83%	-92%	-96%	-98%
16%	314%	82%	-22%	-66%	-85%	-94%	-97%	-99%
17%	350%	78%	-22%	-69%	-87%	-94%	-98%	-99%
18%	398%	92%	-20%	-71%	-88%	-95%	-98%	-99%
19%	418%	86%	-25%	-72%	-89%	-96%	-99%	-99%
20%	470%	96%	-33%	-76%	-91%	-96%	-99%	-100%
21%	522%	109%	-29%	-76%	-92%	-97%	-99%	-100%
22%	569%	110%	-36%	-78%	-93%	-98%	-99%	-100%
23%	575%	111%	-34%	-79%	-94%	-98%	-99%	-100%
24%	628%	105%	-40%	-81%	-94%	-98%	-99%	-100%
25%	772%	120%	-34%	-83%	-95%	-99%	-100%	-100%
26%	774%	144%	-44%	-84%	-95%	-99%	-100%	-100%
27%	837%	118%	-41%	-86%	-96%	-99%	-100%	-100%
28%	977%	147%	-44%	-88%	-97%	-99%	-100%	-100%
29%	951%	122%	-47%	-89%	-97%	-99%	-100%	-100%
30%	1106%	144%	-50%	-89%	-98%	-99%	-100%	-100%
31%	1131%	141%	-44%	-89%	-98%	-100%	-100%	-100%
32%	1252%	155%	-53%	-90%	-98%	-100%	-100%	-100%
33%	1354%	149%	-51%	-92%	-98%	-100%	-100%	-100%
34%	1362%	147%	-57%	-92%	-99%	-100%	-100%	-100%
35%	1334%	148%	-57%	-93%	-99%	-100%	-100%	-100%

strategy) instead of assuming 255 trades per trial, the results demonstrated increased expected returns for portfolios using the original strategy relative to those using the VIX strategy for all profitable profiles.[2] In addition, positive expected portfolio returns were achievable with fees up to 11% using the original strategy when 2,247 positions were taken; this represents an increase from the 10% fee threshold observed with 255-trade trials.

For the 2011 out-of-sample test, the VIX strategy executed only 6,993 trades compared to 11,417 trades using quasi-hyperbolic forecasts. The increased trade volume associated with the original strategy leads to superior extensive margins for portfolio returns and further suggests that the quasi-hyperbolic model's forecasts of IPO period volatility (and subsequent fair value estimations for options) are more accurate than those made using a simple VIX-based indicator.

The 2011 reduction in VIX strategy profitability suggests that options pricing efficiency during the IPO period may have partially improved during that year. In addition, the erosion of positive returns at the 2% fee level suggests that using basic measures of market volatility to detect option undervaluation is unlikely to provide significant profit opportunities for options market participants. This may cause investors to unsoundly assume that fair pricing in the options market persists during the 90-day stock IPO period; consequently, use of the Phase I quasi-hyperbolic model to forecast volatility may continue to provide superior options valuations relative to the market.

[2] Median portfolio returns that were positive in Phase III results become more positive using an increased number of trades. Most median portfolio returns that were negative in Phase III results became more negative but some became more positive. In general, profitable ratio-fee profiles become more profitable as more trades are executed while unprofitable profiles incur greater losses over time. Larger gains were observed for the original strategy.

Chapter 8

Marketplace implications

The fair value analysis strongly suggests that the options market inefficiently prices options during a 90-day stock IPO period for stocks in every industry. Market efficiency is crucial for optimal allocation of capital and risk among investors; improving market efficiency is a stated goal of the literature and financial regulation.

8.1 Applications

The IPO period option underpricing problem might be minimized by using three strategies. First, investors might apply the results of this study to create new trading strategies (not unlike the strategy crafted in Chapter 6) to exploit the pricing inefficiency and, over time, reduce it. Second, regulation might be amended to reduce opacity surrounding the option IPO decision, strengthening market expectations. Finally, options trading fee schedules might be altered to the benefit of traders, brokers, and exchanges while reducing market friction, permitting trading strategies like the one tested in Chapter 6 to enhance price discovery in the options market.

8.1.1 Trading strategies

In theory, any free market with adequate liquidity and symmetric information should be characterized by efficient prices and allocations. In the case of the underlying stock IPO period, the absence of either of these prerequisites for efficiency could result in option undervaluation. Attaining robust liquidity may take some time after an option begins trading while investors build their positions. In addition, information about the underlying security is relatively limited in its earliest days of trading.

Although the consistent undervaluation of options in this study may be attributable to a warm-up period during which liquidity and information issues are gradually resolved, it is more likely the result of a poor understanding of the risk associated with IPO-period options among market participants. Following trading strategies based on this study can lead to complete losses of value in a single transaction; what seems to be excessive risk may cause investors to overlook certain opportunities in the options market. In addition, the trading strategy proposed in Chapter 5 ignores company-specific information (besides subsector affiliation) in favor of focusing on historic industry trends; available and relevant information about the traded option, underlying stock, and relevant business are ignored. On the surface, this practice may seem unncessarily risky, as well.

However, if small positions are taken while following the "prudent man rule" — if the potential downside of an investment could lead to bankruptcy, do not invest — and an appropriate risk management strategy is used, an investor purchasing undervalued options is likely to realize outsized returns in the long run. The portfolio simulation in Chapter 6 demonstrates the ability of a simple fixed-ratio investment scheme to effectively hedge against the effects of purchasing options that expire worthless. The Jackwerth (2000) strategy also employs an effective hedging technique to insulate its put-writing strategy from the effects of market crashes.

Of course, this study assumes that historic stock volatility can help to estimate future volatility levels and options market conditions on a relatively accurate basis. While this may or may not prove to be true, the 1996–2010 period includes a comprehensive variety of bull and bear markets (including the "Great Recession") that significantly reduces biases in this study's data and results. The Phase IV out-of-sample test for options in 2011 suggests that, while pricing efficiency may have partially improved, the options market is still characterized by significant inefficiency during the IPO period. As the IPO period's effect on option values becomes better understood, investors should adopt the risk of owning undervalued options while employing appropriate risk management strategies, bid up prices in the process, and move market pricing towards efficiency.

8.1.2 Regulatory amendments

Another solution to the options market pricing problem may lie in regulation. As it stands, the day on which a stock option starts trading is determined behind closed doors by options exchange management. Added consistency and transparency in the option IPO decision-making process may reduce uncertainty in the market and result in improved pricing efficiency. For example, regulations requiring an options exchange to declare a fixed amount of delay between a stock IPO and its option IPO may solidify market expectations, help investors to prepare for option IPOs on a predetermined date, and consequently improve options price discovery.

Of course, all forms of economic regulation risk introducing imperfections to markets that can further disrupt efficiency. The observed options market inefficiency may tempt regulators either to increase their scrutiny of the options exchanges as they decide when to list options or to require longer delays between stock IPOs and option IPOs. While keeping the option market inactive throughout the entire stock IPO period would undoubtedly remove option market inefficiencies by preventing options market development altogether, it is important to recognize the implications of a frozen options market on the market for the underlying stock; as discussed in Subchapter 2.4, studies like Boehmer et al. (2011), Jubinski and Tomljanovich (2006), and de Jong et al. (2006) show that a healthy options market benefits the market for its underlying stock. Without a liquid options market, potential stock investors might be unable to redistribute risk appropriately and, unable to meet their hedging requirements, refrain from investing altogether. Amihud and Mendelson (1986) show that less liquid stocks have lower valuations; consequently, any proposed regulation reducing options market liquidity should be scrutinized.

8.1.3 Rethinking fee schedules

The common practice of charging option transaction fees on a per-contract basis may discourage investment in undervalued options securities when their nominal value is very low. For example, a low fee of \$1 per contract reaches the 10% fee threshold for portfolio profitability described in Subchapter 6.2 for a \$10 contract. If investors are aware of the options underpricing problem but do not exploit it because of fixed-amount per-contract fees, a broker offering fixed-percentage fees on option trades might provide investors with greater incentive to invest in undervalued options while winning new clients and building its own market share. If transaction fees charged by options exchanges necessitate the per-contract retail fee schedule,[1] exchanges might similarly rethink their own fee schedules to increase trading volume and increase market share.

8.2 Further study

In addition to this study's immediate applications, avenues for further study abound. First, modifications to this study may further clarify the options underpricing prob-

[1]CBOE details a per-contract fixed-amount fee schedule on its website.

lem. In addition, this study has highlighted the potential link between listed option variety and underlying security markets.

8.2.1 Variations on this study

While the results of this study strongly suggest an options underpricing problem during the IPO period, a number of methodological changes might bolster their credibility and provide added insight into the fair valuation of options securities.

First, Phase I might be revised to instead calculate industry volatility on a basis relative to the broader market. For example, volatility can be calculated for each event day during the IPO period on a market-adjusted basis. Daily market volatility can be measured using the VIX, S&P 500, or some other benchmark so that specific market conditions do not bias results.

Increasing observation period granularity may expose correlation between broader market conditions and options pricing efficiency. For example, a look at each individual year during the 1996–2010 observation period might show increased returns associated with bear markets when investors are more cautious and demand for options abates. Increased volatility yearly could let underpricing build. Although the results of this study establish that option underpricing occurs, its causes might be better understood with more thorough investigation.

In addition, criteria other than industry sector or subsector group might be used to classify stocks and options. For example, stocks might be classified by market capitalization, capital structure, geographic market, or some other criteria. If sample sizes remain adequately large and over-controlling is avoided by running out-of-sample tests, categorization by multiple criteria might further increase the accuracy of the Phase I quasi-hyperbolic IPO volatility model in predicting actual intraday volatility for specific stocks. Adding specificity to the division of stock and options data might shed light on the effects of numerous factors on stock volatility during the IPO period.

"Insider" investors who hold shares in IPO companies are typically subject to a lockup period of 180 days[2] following an IPO during which they cannot sell shares. A new model might be used to examine the effects of lockup period expiration on stock volatility.

$$\widehat{v_t} = \kappa + \frac{\lambda}{1 + \mu * (t - 1)} + \frac{\xi}{1 + \pi * |180 - t|} + \varepsilon_t \tag{8.1}$$

Results of regressions approximating κ, λ, μ, ξ, and π in Equation 8.1 during a 270-day period can be used to reflect the effects of both the IPO and lockup expiration events on stock volatility. Just as quasi-hyperbolic regression results from Phase I were applied in Phases II and III in this study to detect option underpricing, regression results using the Equation 8.1 model could be used to examine option pricing efficiency around the lockup expiration date. Incorporation of a possible change in intraday volatility associated with the lockup expiration event can also improve annualized volatility forecasts for stocks on days in the original 90-day IPO period.

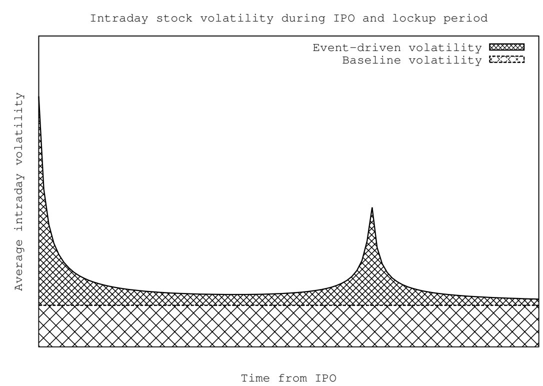


Figure 8.1: Equation 8.1 can be used to forecast increases in stock volatility associated with the lockup expiration event.

Finally, Phases II and III of this study only reflect the purchase of apparently undervalued options. Further experiments might examine the success of selling options that the market overprices and buying them in offsetting orders when they depreciate to fair value. Although this study's findings suggest that the market underprices options, problems with price discovery may not be one-sided. The hedging technique employed in the Jackwerth (2000) put-selling strategy may be relevant for

[2]For simplicity, lockup periods are assumed to expire after 180 trading days in this illustration. Adjustments would likely have to be made for lockup periods lasting 180 calendar days and for other period lengths.

evaluating portfolio returns from selling overpriced options.

8.2.2 Options variety and underlying securities

Since listed options are managed by the exchanges, the number, type, and other qualities of listed options for a given security are selected subjectively. Any of these factors may affect the market of the underlying security. For example, if the number of different strike prices for available puts and calls on a given stock increases, the market for the underlying stock might benefit from added liquidity and improved price discovery. In addition, these factors may affect the corresponding over-the-counter (OTC) options market; reduced variety in strike prices for listed options may increase OTC market activity as investors struggle to meet their needs in centralized exchanges. Finally, the availability of FLEX options and other securities designed to help centralized exchanges compete with OTC markets might similarly impact underlying securities and corresponding OTC markets. Studies analyzing the attributes of listed options and their effects on underlying securities and OTC markets can help investors and exchange management to make more informed decisions when investing in and listing options; as a result, further market efficiency gains may be achieved.

Chapter 9

Options underpricing: A broader problem?

While the results of the study do support the hypothesis that options are inefficiently priced during the 90-day stock IPO period, it is unclear whether the option underpricing problem is, in fact, unique to the IPO period. Jackwerth (2000) observed pricing inefficiency throughout a stock's life that may still prevail in current market conditions. Moreover, small but significant positive correlation was observed between observed Phase II trade returns and the the number of days separating stock IPO from options purchase date.[1] This suggests that the quasi-hyperbolic model may be best suited not for accurately estimating the effects of the IPO period on volatility but instead for predicting the "baseline" intraday volatility asymptote that the model approaches as time from stock IPO increases.

If this is so, some measure of "normal" volatility may be used as a Black-Scholes input to calculate the fair value of options on any day; perhaps annualized baseline industry volatility ($255 * \kappa_j$) as calculated in Subchapter 4.2 or some comparable mea-

[1] An ordinary least squares regression estimating the effect of options purchase time (measured in days from stock IPO t) on the natural logarithm of trade outcome as a percentage of initial value shows a 0.31% expected increase in the natural logarithm of trade return α plus one ($ln(\alpha + 1)$) for each additional day from IPO t. A t-score of 19.90 implies significant correlation.

sure of long-term average stock volatility can be used to calculate fair option values accurately at any time. Fair value analysis may produce more accurate valuations of options than the market outside of the IPO period and allow for outsized investment returns similar to those observed in Phase III.

As shown in Table 4.2 (Subchapter 4.2), the increase in predicted annualized stock volatility attributable to the IPO event appears to account for a relatively small portion of first-year volatility. Furthermore, IPO-driven volatility diminishes rapidly during the first few days of stock trading. With a significant decay in IPO-driven stock volatility after the unofficial 5-day minimum delay between stock IPO and option IPO, the annualized volatility approximations used in this study closely approached industry baseline levels ($255 * \kappa_j$).

If the options market inefficiency observed during the IPO period *does* persist throughout a stock's lifetime, it is likely symptomatic of some structural problem in the options market: universally inefficient fees, severely restricted liquidity, or another substantial issue. This study may only expose the tip of an iceberg. While it confirms the IPO period underpricing phenomenon, it poses many new questions about price discovery in the options market for scholars and investors to explore.

Appendix A

Data preparation scripts

Stata was used to run Phase I regressions and to prepare combined stock-options data sets for use in Phases II, III, and IV. Prior to using each script, the appropriate data set must be loaded in Stata. Where input file names must be modified, `INSERT_FILE_NAME_HERE` is used as a placeholder.

- For Phase I, `regress.do` runs the quasi-hyperbolic regression. This script must be used for each industry data set individually. Results are produced for 30-day and 90-day observation periods — only the 90-day results were used in this study.

- For stock data sets, `ipos.do` detects each individual stock's IPO day and prepares a new data set with IPO days only. This new data set is later used in `theMerge.do` to calculate number of days from IPO t for use in fair value anlayses.

- The `primeTarget.do` script modifies stock data so that it can be properly merged with options data for use in Phase II using `theMerge.do`. Input and output file names must be modified in the script prior to use.

- For Phase II, `theMerge.do` merges appropriate option and stock data sets that have been prepared with the `primeTarget.do` script. The new data set is exported for use with MATLAB simulations. Input and output file names must be modified in the script prior to use.

A.1 regress.do

```
drop if ticker==""
drop if prc==.
sort permno date
replace divamt = 0 if missing(divamt)
replace divamt = divamt/cfacshr
sort permno date
by permno:generate cumdiv = sum(divamt)
replace bidlo = abs(bidlo)
replace askhi = abs(askhi)
replace prc = abs(prc)
replace bidlo = bidlo/cfacpr
replace askhi = askhi/cfacpr
replace prc = prc/cfacpr
replace bidlo = bidlo + cumdiv
replace askhi = askhi + cumdiv
replace prc = prc + cumdiv
generate v = ((askhi - bidlo) / (2 * prc))^2
sort permno date
by permno:generate counter=_n
sort counter
drop if counter > 90
```

```
nl (v = {C1} + {C2}/(1+{C3}*(counter-1))), ///
initial (C1 0.05 C2 0.2 C3 1.75)
predict a
graph twoway (scatter v counter) (line a counter)
nl (v = {C1} + {C2}/(1+{C3}*(counter-1))) ///
if counter < 31, initial (C1 0.05 C2 0.2 C3 1.75)
predict b
graph twoway (scatter v counter) (line b counter) ///
if counter < 31
```

A.2 ipos.do

```
drop if ticker==""
drop if prc==.
drop if vol==.
sort permno date
by permno:generate counter=_n
sort counter
drop if date<td(01jan1996)
drop if counter>1
drop permno divamt bidlo askhi prc ///
vol cfacpr cfacshr counter
```

A.3 primeTarget.do

```
drop permno divamt bidlo askhi vol cfacpr cfacshr
drop if date<td(01jan1996)
drop if ticker == ""
```

```
duplicates drop ticker date, force
```

A.4 theMerge.do

```
drop issuer
drop if ticker == ""

merge m:1 ticker date using "INSERT_FILE_NAME_HERE" // stock data
drop if _merge<3
drop _merge

merge m:1 ticker using "INSERT_FILE_NAME_HERE" // ticker and ipo dates
drop if _merge<3
drop _merge
gen counter = date - ipo

drop secid
drop index_flag
drop ipo
drop if counter > 90

merge m:1 date using "INSERT_FILE_NAME_HERE" // risk-free rates
drop if _merge<3
drop _merge
sort optionid date

outsheet date exdate cp_flag strike_price best_bid best_offer ///
```

```
optionid ticker exercise_style prc counter r using ///
"INSERT_FILE_NAME_HERE", comma replace
```

Appendix B

Simulation code

MATLAB was used to run all trading and portfolio simulations throughout Phases II, III, and IV. The `runAllTrades.m` program (which uses the `calcVols.m` function) loads data from Phase I regression results and combined stock-option data sets prepared using Stata to simulate the purchase and sale of options for the Phase II fair value analysis. Phase III uses `portfolioSim.m` to run portfolio simulations for ranges of investment ratios and transaction fee percentages. It takes an input `returns.dat` that includes all returns observed in the Phase II simulation. Where input file names must be modified, `INSERT_FILE_NAME_HERE` is used as a placeholder. Other simulations run throughout the study use partly modified MATLAB files which are not included in this Appendix.

B.1 `runAllTrades.m`

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%% runAllTrades runs the Phase II fair value analysis
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%


clear all
```

```
industrySet = [2, 3, 5, 6, 8, 9, 11, 12, 13, 15, 16, 18, 19, 20, 22, 23,...
    24 26 27 28 29 31 32];

allReturns = [];
balance = zeros([3 1]);

for industrySwitch = industrySet

    % SWITCH TO SET INDUSTRY TYPE

    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %
    % INDUSTRY KEY
    %
    % 1  Oil & Gas
    % 2      Oil & Gas Producers
    % 3      Oil & Gas Equipment and Distribution
    % 4  Basic Materials
    % 5      Basic Resources
    % 6      Chemicals
    % 7  Industrials
    % 8      Construction & Materials
    % 9      Industrial Goods & Services
    % 10 Consumer Goods
    % 11    Automobiles & Parts
```

```
% 12    Food & Beverage
% 13    Personal & Household Goods
% 14 Healthcare
% 15    Healthcare Equipment & Services
% 16    Pharmaceuticals & Biotechnology
% 17 Consumer Services
% 18    Media
% 19    Retail
% 20    Travel & Leisure
% 21 Telecommunications
% 22    Fixed Line Telecommunications
% 23    Mobile Telecommunications
% 24 Utilities
% 25 Financials
% 26    Banks
% 27    Financial Services
% 28    Insurance
% 29    Real Estate
% 30 Technology
% 31    Software & Computer Services
% 32    Technology Hardware & Equipment
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

returns = [];

% Imports regression results from CSV
```

```
% NOTE: must change file name
cValues = fopen(...
    'INSERT_FILE_NAME_HERE');
cTable = textscan(cValues,'%s %f %f %f', 'delimiter',',');
fclose('all');

industryName = cTable{1}{industrySwitch};

fprintf('Running simulation for %s industry\n\n',industryName)

% Use appropriate Phase I regression result values
C1 = cTable{2}(industrySwitch);
C2 = cTable{3}(industrySwitch);
C3 = cTable{4}(industrySwitch);

clear cTable;

filename = strcat(...
    'INSERT_FILE_NAME_HERE', ...
    industryName,'.raw');
raw = fopen(filename);
import1 = textscan(raw,'%s %s %s %f %f %f %u %s %s %f %u %f', ...
    'delimiter',',','HeaderLines', 1);
fclose('all');

% PARSE DATA (simple matrices)
tickers = import1{8};         % ticker symbol of underlying stock
```

```
optionid = import1{7};        % option security identifier
pcFlags = import1{3};         % put or call flag
K = import1{4} / 1000;        % strike price
S = import1{10};              % spot price
r = import1{12};              % risk-free rate
counter = import1{11};        % days from IPO
sigmas = calcVols(C1,C2,C3);  % annualized volatility
dates = datestr(import1{1});  % trading dates
exps = datestr(import1{2});   % expiration dates
TTM = wrkdydif(dates,exps) / 255;           % time to maturity
availPrice = (import1{5} + import1{6}) / 2; % market price
clear exps import1;

runLength = length(tickers);

% Test for "bad tickers"
% Purge all tickers containing a 0 counter value (non-IPO)

badTickers = [];

for i = 1:runLength
    if (counter(i) <= 0)
        badTickers = [badTickers ; tickers(i)];
    end
end

badTickers = unique(badTickers); % remove duplicate entries
```

```
fprintf('%u false IPOs detected\n', numel(badTickers))

deletions = [];

% identify index numbers to delete
for i = 1:numel(badTickers)
    deletions = [deletions ; find(strcmp(badTickers(i),tickers))];
end

% delete false IPO entries
tickers(deletions) = [];
K(deletions) = [];
S(deletions) = [];
r(deletions) = [];
counter(deletions) = [];
TTM(deletions) = [];
availPrice(deletions) = [];
pcFlags(deletions) = [];
dates(deletions) = [];
optionid(deletions) = [];

deletions = find(counter>90);
tickers(deletions) = [];
K(deletions) = [];
S(deletions) = [];
r(deletions) = [];
counter(deletions) = [];
```

```
TTM(deletions) = [];
availPrice(deletions) = [];
pcFlags(deletions) = [];
dates(deletions) = [];
optionid(deletions) = [];

fprintf('%u observations deleted\n\n',(runLength-numel(tickers)))
runLength = numel(tickers);

% Ensure that "bad ticker" test worked
for i = 1:runLength
    if (strcmp(tickers(i),badTickers))
        disp('ERROR: MISSED BAD TICKERS')
    end
    if (strcmp(tickers(i),''))
        disp('ERROR: EMPTY ENTRIES')
    end
end

clear badTickers

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%% Begin fair value analysis
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

fairValues = zeros(runLength,1,'double');
d1 = zeros(runLength,1,'double');
```

```
d2 = zeros(runLength,1,'double');

% CALCULATE FAIR VALUE MATRIX
for i = 1:runLength

    % calculate d1
    d1(i) = (log(S(i)/K(i))+(r(i)...
        +((sigmas(counter(i))^2)/2))*TTM(i)) ...
        /(sigmas(counter(i))*(TTM(i)^.5));

    % calculate d2
    d2(i) = d1(i)-sigmas(counter(i))*(TTM(i)^.5);

    % call calculation
    % C(S,t) = N(d1)S-N(d2)Ke^(-r(T-t))
    if (strcmp(pcFlags{i},'"C"'))
        %disp('call')
        fairValues(i) = normcdf(d1(i))*S(i)...
            -normcdf(d2(i),0,1)*K(i)*exp(-r(i)*TTM(i));
    end

    % put calculation
    % N(-d2)Ke^(-r(T-t))-N(-d1)S
    if (strcmp(pcFlags{i},'"P"'))
        %disp('put');
        fairValues(i) = normcdf(-d2(i))*K(i)...
            *exp(-r(i)*TTM(i))-normcdf(-d1(i))*S(i);
```

```
    end
end

% RUN TRADES

basis = 0; % purchase price (0 if no inventory)



% first read
if (availPrice(1) < fairValues(1))
    basis = availPrice(1);
end



% loop through options
for i=2:(runLength-1)

    % NO INVENTORY
    if (basis == 0)
        if (availPrice(i) < fairValues(i))
            basis = availPrice(i);
        end
    end

    % HOLDING INVENTORY
    if (basis > 0)
```

```
% Sell inventory
if (availPrice(i) > fairValues(i))
    thisReturn = (availPrice(i)/basis - 1);
    returns = [returns , thisReturn];
    if (thisReturn > 0)
        balance(1) = balance(1) + 1;
    else if (thisReturn < 0)
            balance(3) = balance(3) + 1;
        else
            balance(2) = balance(2) + 1;
        end
    end
    basis = 0;

    % Hold inventory (no change)

    % forced sale on expiration
else if (optionid(i) ~= optionid(i+1))
        thisReturn = (availPrice(i)/basis - 1);
        returns = [returns , thisReturn];
        if (thisReturn > 0)
            balance(1) = balance(1) + 1;
        else if (thisReturn < 0)
                balance(3) = balance(3) + 1;
            else
                balance(2) = balance(2) + 1;
            end
```

```
                end
                basis = 0;
            end
        end
    end
end

% FINAL SALE
if (basis > 0)
    thisReturn = (availPrice(i)/basis - 1);
    returns = [returns , thisReturn];
    if (thisReturn > 0)
        balance(1) = balance(1) + 1;
    else if (thisReturn < 0)
            balance(3) = balance(3) + 1;
        else
            balance(2) = balance(2) + 1;
        end
    end
    basis = 0;
end

csvwrite(industryName,returns)

allReturns = [allReturns , returns]

end
```

```
allReturns = allReturns * 100;

csvwrite(...
    'INSERT_FILE_NAME_HERE'...
    ,returns)

fprintf('\nTrades executed: %u\n',length(allReturns))
fprintf('\nMean return: %f%%\n',mean(allReturns))
fprintf('\nMedian return: %f%%\n',median(allReturns))
fprintf('\nMaximum return: %f%%\n',max(allReturns))
fprintf('\nMinimum return: %f%%\n',min(allReturns))
fprintf('\nStandard deviation of return: %f%%\n',std2(allReturns))
fprintf('\n%u positive, %u neutral, %u negative trades\n', ...
    balance(1),balance(2),balance(3))
```

B.1.1 Function: `calcVols.m`

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%% calcVols returns an array with projected annualized volatility
%%%%%%% for each day from IPO for an industry with quasi-hyperbolic
%%%%%%% coefficients C1, C2, and C3.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%


function indVols = calcVols(C1, C2, C3)

ipoPeriod = 255;
```

```
tradingDays = 255;

dailies = zeros(tradingDays + ipoPeriod,1);
indVols = zeros(ipoPeriod,1);

% Calculate daily projected intraday volatility
for i = 1:(tradingDays + ipoPeriod)
    dailies(i,1) = C1 + C2 / (1 + C3 * (i - 1));
end

% Convert daily volatility predictions to annnualized volatility
% for each day from IPO
for i = 1:ipoPeriod
    for j = i:(i + tradingDays)
        indVols(i) = indVols(i) + dailies(j);
    end
    indVols(i) = (indVols(i))^.5;
end
end
```

B.2 portfolioSim.m

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%% portfolioSim runs a portfolio simulation for a range of
%%%%%%% fixed investment ratios and transaction fee percentages
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

clear all

distFile = 'returns.dat';

medians = zeros(35,16);
stds = zeros(35,16);
ratios = zeros(35,16);

for k = 1:35

    for j = 1:16

        playMoney = k/100;
        feeRate = (j - 1)/100;

        N = 255;
        trials = 500;

        results = [];

        returnDist = importdata(distFile);
```

```
for trial=1:trials

    endowment = zeros(N,1);
    endowment(1) = 1000000;

    shuffleKeys = randperm(length(returnDist));
    returnDist = returnDist(shuffleKeys);

    for i=1:N
        inPlay = endowment(i) * playMoney;        % amount to risk
        endowment(i+1) = endowment(i) - inPlay;   % withdraw
        inPlay = inPlay * (1 - feeRate);          % pay fee
        inPlay = inPlay * (1 + returnDist(i));    % invest
        inPlay = inPlay * (1 - feeRate);          % pay fee (again)
        endowment(i+1) = endowment(i+1) + inPlay; % cash out
    end

    results(trial) = endowment(N);

end

medians(k,j) = median(results);
stds(k,j) = std(results);
ratios(k,j) = stds(k,j)/medians(k,j);

outName = strcat('./output/use',num2str(playMoney*100),'pay',...
```

```
            num2str(feeRate*100),'.csv');
        dlmwrite(outName, results, 'delimiter', ',', 'precision', 9);

    end
end

dlmwrite('medians.csv', medians, 'delimiter', ',', 'precision', 9);
dlmwrite('stds.csv', stds, 'delimiter', ',', 'precision', 9);
dlmwrite('ratios.csv', ratios, 'delimiter', ',', 'precision', 9);
```

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