Does mispricing, liquidity or third-party certification contribute to IPO downside risk?

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ABSTRACT

This study analyses the impact of initial return, post-issue liquidity, and third-party certification on downside risk of initial public offerings (IPOs). Downside risk, measured by value-at-risk (VaR) and conditional value-at-risk (CVaR), draws upon Extreme Value Theory (EVT) and the Peak over Threshold (POT) approach. Initial return and downside risk exhibit a positive association which is consistent with a market-overreaction explanation but contradicts the validity of signalling models in which underpricing acts as a costly and difficult to imitate signal of firm quality. Post-issue liquidity, measured by seven distinct definitions to capture different aspects of liquidity, also has a positive association with downside risk. In contrast, third-party certification, measured by the reputation and size of underwriter syndicate and venture capital-backed IPOs do not persistently explain the variation in downside risk. Quantile regression analysis constitutes more rigour in the testing and offers new insights into the sensitivity among variables and their covariates at different quantiles of downside risk. While initial return affects downside risk evenly across the entire distribution, quantile covariates for liquidity measures are statistically significant and generally outside the confidence interval of least squares regression coefficients. Sensitivity of liquidity measures is greater towards the upper end of the downside risk distribution.

1. Introduction

There is broad consensus in the literature that initial public offerings (IPOs) have historically experienced relatively low stock returns over three to five years following flotation in relation to comparable seasoned firms and the stock market in general (Jenkinson & Ljungqvist, 2001; Loughran & Ritter, 1995; Loughran, Ritter, & Rydqvist, 1994; Ritter, 1991).[1] Existing research offers at least three plausible explanations for this persistent average underperformance. Firstly, a risk-based explanation of low average post-issue returns presumes rational investor behaviour. Studies such as Brav, Geczy, and Gompers (2000) and Eckbo and Norli (2005) show that low average post-issue stock returns is not a distinct anomaly. Rather, these returns are, as advocated in Fama and French (1992), consistent with a more pervasive pattern that is observable in the wider population of publicly listed companies whereby small growth stocks experience lower than expected returns. In this instance, low average post-issue returns are commensurate with the issuers' typical risk profile, captured by existing asset pricing models and their corresponding factors, including firm size and book-to-market ratio.

Secondly, low average post-issue returns presume the ability of market timing and the presence of some irrational investor behaviour. Studies such as Krigman, Shaw, and Womack (1999) and Michaely and Womack (1999) advocate that issuers can time their offerings and raise extra capital from selling overpriced equity, while Teoh, Welch, and Wong (1998) show that IPO firms engage in earnings manipulation in the accounting period leading up to flotation. Both instances generate high initial return, followed by low average post-issue returns due to IPO overvaluation or investor overreaction when prices adjust to a new price equilibrium that reflects the intrinsic value of stocks. In this explanation of long-run IPO underperformance, low stock returns are more indicative of mispricing by issuing firms and their underwriters when pricing offerings or indicative of investor over-optimism rather than that of a risk-based dimension in the aftermarket.

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[1] This new issue puzzle is well documented in developed stock markets around the world. However, in less developed stock markets, the evidence of long-run underperformance is less conclusive. For example, IPOs in some emerging markets appear to outperform rather than underperform the average stock market in the long run (Jenkinson & Ljungqvist, 2001).

Thirdly, studies such as Eckbo and Norli (2005) and Hahn, Ligon, and Rhodes (2013) analyse the impact of liquidity on IPO returns. Generally, more liquid stocks experience minimal delay in the execution of trades. These trades have a minimal impact on price changes. Also, more liquid stocks have smaller transaction costs, including commissions and bid-ask spreads (R. K. Aggarwal, Krigman, & Womack, 2002; Cao, Field, & Hanka, 2004; Eckbo & Norli, 2005). According to Amihud and Mendelson (1986), expected return is an increasing and concave function of the bid-ask spread. In the IPO context, Hahn et al. (2013) argue that issuers may tolerate leaving money on the table when going public through underpricing (initial return) to create a more liquid aftermarket for their shares. Initial return increases liquidity in the secondary market (Bodnaruk, Kandel, Massa, & Simonov, 2008; Mantecon & Poon, 2009). Hahn et al. (2013) make a direct link between initial return, liquidity, and long-run post-issue returns. Eckbo and Norli (2005) also corroborate this link in an earlier study. In their analysis, they show that new issues underperform in the long-run because these IPOs are, on average, more liquid than non-issuing firms when matched on firm size and book-to-market ratio.

While existing studies have analysed the risk-return profile of IPOs, including the validity of signalling models, liquidity, and third-party certification, the literature leaves several as of yet unanswered questions. To begin with, we do not know much about IPO downside risk post-offering. Yet, identifying and estimating downside risk is essential for risk management and asset allocation purposes. Only very few studies employ dedicated risk measures. A notable exception is Neill, Perfect, and Wiles (1999). They use firm-specific betas as estimates of systematic IPO risk. No study in the extant literature applies any of the more conventional measures of downside risk such as, for example, value-at-risk (VaR) or conditional value-at-risk (CVaR).[2]

In addition, we do not know whether initial return, post-issue liquidity, and third-party certification, or indeed all three state variables simultaneously explain downside risk. On the one hand, high initial return, followed by low post-issue downside risk would be consistent with the signalling of firm quality (Grinblatt & Hwang, 1989). On the other hand, a positive relationship between initial return and downside risk would embody market timing abilities or market overreaction to overpriced IPOs. Alternatively, liquidity measures capture different aspects of post-issue liquidity (Krigman et al., 1999; Michaely & Womack, 1999; Teoh et al., 1998), while third-party certification in terms of underwriter reputation (R. Carter & Manaster, 1990; Loughran & Ritter, 2004) and venture-capital backing (Bessler & Seim, 2012) should reduce downside risk. There is a notable absence in the literature that analyses the relationship between these state variables and downside risk, while controlling for firm and deal characteristics as well as contemporaneous stock market conditions.

Finally, not only do we not have an understanding of the impact of initial return, liquidity, and third-party certification on downside risk, we also do not know whether and how the state variables impact on different quantiles of the downside risk distribution. Traditional estimation techniques such as ordinary least squares (OLS) and two-stage least squares (2SLS) applied in Hahn et al. (2013) can only offer a conditional mean view of the relationship among variables. These traditional techniques impose restrictive assumptions on how covariates can influence the conditional distribution of state variables. Quantile regressions relax this limitation and offer a more complete characterization of the stochastic relationship among variables. A more complete characterization in quantile regression analysis is possible because we estimate the relationship between independent and dependent variables conditional on quantiles of the dependent variable. Since the seminal paper of Koenker and Bassett (1978), quantile regression has increasingly become a complementary approach to the conventional mean estimation techniques.[3] To-date, we have no clear understanding of the underlying characterization of the stochastic relationship between the three state variables and downside risk of IPOs.

In light of these unanswered questions, my study makes the following, distinct contributions. Firstly, I use VaR and CVaR to analyse the downside risk of post-offering IPO returns. Diagnostic tests reveal skewed, leptokurtic (heavy-tailed) stock return distributions. More specifically, while extreme negative stock returns are relatively rare, they occur more frequently and are larger in size than the Gaussian distribution would predict. To overcome the distributional characteristics of post-issue stock returns, I use Extreme Value Theory (EVT) and the Peak over Threshold (POT) approach to fit these distributions using the maximum likelkihood method to calculate the downside risk (see McNeil, Frey, & Embrechts, 2015). POT is the preferred method in the present context because this approach uses data more efficiently than alternative approaches.[4] I estimate conventional 95% and 99% confidence levels of the return distributions to measure downside risk.[5] Estimating downside risk of post-issue IPO stock returns in the context of this study has not attracted any attention in the extant literature.

Secondly, I analyse whether initial return, post-offering liquidity and/or third party certification, while controlling for firm and deal characteristics as well as contemporary stock market conditions, can explain downside risk. To the best of my knowledge, my study is the first to analyse this relationship. Estimating the impact of these two stochastic variables on IPO downside risk is essential for risk-management and asset allocation purposes. On the one hand, a negative association between initial return and downside risk would be consistent with the signalling argument of Grinblatt and Hwang (1989). On the other hand, a positive association between initial return and downside risk would be consistent with a market overreaction on the side of investors or mispricing on the side of issuing firms and their underwriters. Observing such a positive relationship would also corroborate earlier empirical findings reported in studies such as Krigman et al. (1999), Michaely and Womack (1999), and Teoh et al. (1998). A positive association between liquidity and downside risk would be consistent with studies such as Eckbo and Norli (2005). Their study reports an inverse relationship between liquidity and post-issue stock returns. New issues underperform in the long-run because IPOs have greater liquidity than comparable seasoned firms. Unfortunately, liquidity is difficult to define. Accordingly, I use different definitions to capture various aspects of liquidity and to better understand its impact on downside risk. To begin with, I use spread based liquidity measures, including proportional quoted spread and proportional realised spread (Amihud & Mendelson, 1986; Brennan & Subrahmanyam, 1996; Chordia, Roll, & Subrahmanyam, 2001; Hahn et al., 2013; Huberman & Halka, 2001; Rubia & Sanchis-Marco, 2013). In addition, I use price

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[2] CVaR is also known as Expected Shortfall or Expected Tail Loss.

[3] Previous applications of quantile regressions to value-at-risk include the studies of Bao, Tae-Hwy, and Saltoğlu (2006) , Fuertes and Olmo (2013), and Jeon and Taylor (2013). Other applications of quantile regressions include the modelling of return distributions, volatility and equity premium (Hua & Manzan, 2013; Pedersen, 2015; Rubia & Sanchis-Marco, 2013), risk and stress testing (Bernal, Gnabo, & Guilmin, 2014; Covas, Rump, & Zakrajšek, 2014; Klomp & de Haan, 2012), diversification and risk-adjusted performance (Lee & Li, 2012), and foreign exchange rates (Baur, 2013; Nikolaou, 2008).

[4] Alternative approaches consist of fitting one of the three standard extreme value distributions (Frechet, Weibull or Gumbel).

[5] 95% comes from RiskMetrics and 99% comes from Basel Accord.