Article:

Reber, B. orcid.org/0000-0003-0503-0017 (2017) Does mispricing, liquidity or third-party certification contribute to IPO downside risk? International Review of Financial Analysis, 51. pp. 25-53. ISSN 1057-5219

https://doi.org/10.1016/j.irfa.2017.03.001

Does Mispricing, Liquidity or Third-Party Certification Contribute to IPO Downside Risk?

Beat Reber

Nottingham University Business School
Nottingham
United Kingdom
NG8 1BB
beat.reber@nottingham.ac.uk

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.

Keywords: Initial public offerings; downside risk; initial return; liquidity; third-party certification; quantile regressions
JEL: C21, G12, G32

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 (Ritter, 1991; Loughran, Ritter, and Rydqvist, 1994; Loughran and Ritter, 1995; Jenkinson and Ljungqvist, 2001).[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

[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 (e.g., Jenkinson and Ljungqvist, 2001).

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.

Thirdly, studies such as Hahn, Ligon, and Rhodes (2013) and Eckbo and Norli (2005) 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 (Aggarwal, Krigman, and Womack, 2002; Cao, Field, and Hanka, 2004; Eckbo and 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, Ligon, and Rhodes (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 et al., 2008; Mantecon and Poon, 2009). Hahn, Ligon, and Rhodes (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 and Hwang, 1989). On the other hand, a positive relationship between initial return and downside risk would embody market timing abilities or market over-reaction to overpriced IPOs. Alternatively, liquidity measures capture different aspects of post-issue liquidity (Krigman, Shaw, and Womack, 1999; Michaely and Womack, 1999; Teoh, Welch, and Wong, 1998), while third-party certification in terms of underwriter reputation (Loughran and Ritter, 2004; Carter and Manaster, 1990) and venture-capital backing (Bessler and 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, Ligon, and Rhodes (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

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

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, and 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% percentile and 99% percentile 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 over-reaction 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, Shaw, and Womack (1999), Michaely and Womack (1999), and Teoh, Welch, and Wong (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 and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Chordia, Roll, and Subrahmanyam, 2001; Hahn, Ligon, and Rhodes, 2013; Huberman and Halka, 2001; Rubia and Sanchis-Marco, 2013). In addition, I use price impact based liquidity measures (Brennan and Subrahmanyam, 1996; Glosten and Harris, 1988; Hahn, Ligon, and Rhodes, 2013; Kyle, 1985). Finally, I use trading volume related liquidity measures, including the ratio of returns to trading volume (Amihud, 2002; Hahn, Ligon, and Rhodes, 2013; Rubia and Sanchis-Marco, 2013) and the number of shares traded in relation to the number of shares outstanding (Datar, Naik, and Radcliffe, 1998; Hahn, Ligon, and Rhodes, 2013; Rubia and Sanchis-Marco, 2013).

Thirdly, I test whether an association between downside risk, initial return, liquidity, and third-

[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 and Manzan, 2013; Pedersen, 2015; Rubia and Sanchis-Marco, 2013), risk and stress testing (Bernal, Gnabo, and Guilmin, 2014; Covas, Rump, and Zakrajšek, 2014; Klomp and Haan, 2012), diversification and risk-adjusted performance (Lee and 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.

party certification persists if corrected for potential endogeneity between dependent and state variables. The literature does not provide a conclusive guidance as to whether these stochastic variables are endogenous to downside risk. Some studies observe endogeneity between initial return and post-issue liquidity (Ellul and Pagano, 2006; Hahn, Ligon, and Rhodes, 2013). This suggests that controlling for endogeneity is potentially important in the present context. If stochastic variables are endogenous then they would require instrumenting in the estimation process.

Fourthly, I analyse whether initial, post-issue liquidity, and third-party certification affect the downside risk evenly across the distribution of dependent variables or whether different quantiles better explain downside risk. In particular, I test the predictability of downside risk at various quantiles in the left tail of the conditional distribution. I use quantile regressions to analyse tail-predictability without departing significantly from traditional predictive least squares-based regressions. The latter technique imposes restrictive assumptions on how covariates can influence the conditional distributions of response variables. Quantile regressions relax this limitation. They offer a more complete characterization of the stochastic relationship among initial return, post-issue liquidity, third-party certification, and downside risk. Quantile regressions thus provide more robust and efficient estimates in some non-Gaussian settings. Since the seminal paper of Koenker and Bassett (1978), quantile regression analysis has increasingly become a complementary approach to the conventional mean estimation methods. However, until now, we do not know how initial return, post-issue liquidity, and third-party certification impact on downside risk at different quantiles. My study therefore carries out a more robust empirical test with − in this context − a novel applied estimation method.

2 Relationship to Existing Research

My study relates to various different streams of research and makes several distinct contributions to the existing literature. Previous research has estimated downside risk using different variable definitions and methodologies. Firstly, this study relates to the literature on quantifying downside risk and, more precisely, to the body of research devoted to measure initial return as well as post-issue return and risk. To begin with, information asymmetry between market participants surrounding IPO values leaves the new issues market subject to Akerlof's (1970) classic adverse selection problem. This adverse selection problem manifests itself in persistent average initial return across capital markets and time periods.[6] The literature offers various explanations for persistent average initial return.[7] More specifically, Brav and Gompers (1997), Friesen and Swift (2009), Loughran and Ritter (1995), Ritter (1991), and Teoh, Welch, and Wong (1998) explain initial return as a consequence of mispricing between an issuer and underwriter as a result of overoptimism about firm value that creates excess demand in shares, pushes up prices which then leads to average initial return when post-issue trading begins. Prices then revert back to fundamental firm value post-issue, which then translates into subsequent average long-run post-issue underperformance between three and five years. In addition, studies such as Chen and William Jr (2008), Beneda and Zhang (2009), Falconieri, Murphy, and Weaver (2009), Gleason, Johnston, and Madura (2008), and Neill, Perfect, and Wiles (1999) link post-issue risk with performance. For example, Gleason, Johnston, and Madura (2008) find a correlation between post-issue betas and initial return. These findings imply that IPOs need to offer initial return to compensate post-issue risk in addition to risk that comes from ex ante uncertainty if investors want to purchase in the primary and/or secondary market. Beneda and Zhang (2009) report a negative association between the level of initial idiosyncratic volatility and the post-issue volatility change. Initially, low quality firms have a greater increase in volatility. Their study reports that initial return and post-issue returns have a positive relationship to the corresponding idiosyncratic risk levels. Also, Beneda and Zhang (2009) report that higher long-run post-issue performance has a positive relationship with lower levels of initial risk as well as decreasing risk in the first year after flotation. The study therefore implies firm-specific

[6] Initial return is also known as underpricing. Initial return is the percentage change from the offer price to the post-issue market price on the first day of trading. Evidence of persistent average initial return is available from Banerjee, Dai, and Shrestha (2011), Ritter (2003), and Jay R. Ritter's web site (`http://bear.warrington.ufl.edu/ritter`) that has regular updates of Loughran, Ritter, and Rydqvist (1994).

[7] See, for example, Allen and Faulhaber (1989), Baron (1982), Grinblatt and Hwang (1989), Rock (1986), and Welch (1989).

changes post-issue. Initial return appears to compensate investors for acquiring costly information. In addition, ex post value uncertainty in the post-issue market continues to persist for some time. Falconieri, Murphy, and Weaver (2009) report that controlling for this ex post uncertainty improves the explanatory power of post-issue IPO performance. In their study, they use various definitions of liquidity measures as proxy variables for ex post uncertainty. The literature reports a gradual decline in ex post uncertainty and risk as IPOs become more seasoned. For example, Neill, Perfect, and Wiles (1999) report that individual average IPO betas decline over time. The authors attribute this decline to new issues becoming more seasoned rather than from the delisting of high-value beta IPOs. In a related study, Pástor and Stambaugh (2003) demonstrate that stocks with higher liquidity betas have greater expected returns.

Secondly, this study also relates to the literature on measuring liquidity in general and, more precisely, to the body of research on the impact of liquidity on post-issue IPO performance. The literature offers a range of definitions to capture various aspects of liquidity. These definitions fall into three broad categories: (1) spread based liquidity measures, (2) price impact based liquidity measures, and (3) trading volume based liquidity measures (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Chordia, Roll, and Subrahmanyam, 2001; Falconieri, Murphy, and Weaver, 2009; Eckbo and Norli, 2005; Hahn, Ligon, and Rhodes, 2013; Huberman and Halka, 2001; Rubia and Sanchis-Marco, 2013). To begin with, Hahn, Ligon, and Rhodes (2013) report that initial return increases the liquidity of IPO shares in the secondary market over the first year of trading. These findings are robust regardless of the time horizon used to calculate liquidity after having addressed endogeneity concerns between liquidity and initial return. Hahn, Ligon, and Rhodes (2013) use no fewer than eight different definitions of liquidity that fall into the three broad categories identified above. Before the study of Hahn, Ligon, and Rhodes (2013), Falconieri, Murphy, and Weaver (2009) use spread based liquidity measures and volume based liquidity measures. These ex post measures of uncertainty improve the explanatory power of post-issue IPO performance. In an earlier analysis, Ellul and Pagano (2006) claim that the less liquid the aftermarket and the less predictable post-issue liquidity, the greater will be the initial return of an IPO. When comparing post-issue IPO performance with a seasoned control sample, Eckbo and Norli (2005) claim that IPOs underperform because they are more liquid than their counterparts matched on size and book-to-market. Finally, the findings of Eckbo and Norli (2005) are consistent with those reported previously in Corwin, Harris, and Lipson (2004). In their study, Corwin, Harris, and Lipson (2004) examine the post-issue liquidity of IPOs. The authors find a steady increase of depth relative to volume and percentage spreads increase in the secondary market following an IPO.

Thirdly, this study relates to the literature on third-party certification of firm quality. Agents that participate regularly in the IPO market such as underwriters and venture capitalists can build up reputation capital to certify IPO firm quality. Using more prestigious underwriters and venture-capital backing should reduce the ex ante valuation uncertainty and hence diminish post-issue downside risk. Studies that support the certification role of underwriter reputation in reducing ex ante valuation uncertainty include Megginson and Weiss (1991), Carter and Manaster (1990), and Habib and Ljungqvist (2001). In contrast, Beatty and Welch (1996) find no support for an underwriter certification role. Therefore, it remains to be tested whether the present analysis finds a negative association between underwriter reputation and downside risk. It also remains to be tested whether the size of the underwriting syndicate, measured by the number of participating investment banks, can explain downside risk. The number of syndicate members involved in the underwriting should enhance the visibility and coverage of an IPO and hence reduce downside risk. Analysing the impact of venture-capital backing awaits investigation and is important because of the mixed findings in the extant literature whether or not the presence of venture capitalists reduces or increases ex ante uncertainty surrounding the valuation of firms. On the one hand, studies that report a reduction in ex ante uncertainty and hence initial return include Arthurs et al. (2009), Barry et al. (1990), Brav and Gompers (1997), Krishnan et al. (2011), Lerner (1994), Megginson and Weiss (1991), and Nanda and Rhodes-Kropf (2013). On the other hand, studies that do not find support in favour third-party certification by venture capitalists include Liu and Ritter (2011) and Hamao, Packer, and Ritter (2000).

Fourthly, this study belongs to the literature devoted to downside risk modelling in the general context of quantile regression analysis. Existing research papers in the non-IPO literature use various methodologies. In a recent study, Rubia and Sanchis-Marco (2013) report conditional tail predictability of downside risk using different liquidity measures and trading conditions. The authors apply quantile regression methodology in their analysis. Predictability of downside risk is robust to various representative market portfolios and different testing procedures. However, the extent of predictability varies across different quantiles in the left tail of these conditional return distributions. In addition, Rubia and Sanchis-Marco (2013) report that volume-related variables are good predictors of well-diversified portfolios, including the market portfolio and small-cap stocks, while liquidity measures are more accurate when forecasting the tail of conditional return distributions of value portfolios. Using an alternative model specification, Taylor (2008) employs exponentially weighted quantile regressions to estimate VaR and CVaR. This approach outperforms GARCH-based methods and CAViaR models for a sample of ten stock return series. Some research papers perform more detailed test on the performance of different model specifications. For instance, Bao, Tae-Hwy, and Saltoğlu (2006) investigate the prediction accuracy of various downside risk models, including quantile regression based approaches. The authors report that the RiskMetrics model performs well in tranquil periods, whereas some Extreme Value Theory (EVT) based models perform better during more volatile market periods. In another comparative study, Bao, Tae-Hwy, and Saltoğlu (2006) report that CaViaR quantile regression models of Engle and Managnelli (2004) have predictive power when forecasting VaR. Yet another comparative study is Taylor (2000). He estimates the conditional probability distribution of multiperiod financial returns using quantile regressions. In particular, his methodology involves a neural network approach to estimate non-linear quantiles. This approach offers a potential alternative to GARCH-based quantile estimates.

My study contributes to these strands of the extant literature in several ways. Firstly, this study measures VaR and CVaR to analyse the downside risk of post-issue IPO returns using Extreme Value Theory (EVT) and the Peak over Threshold (POT) approach. The extant literature does not provide any evidence on the downside risk of new issues. Yet, identifying and estimating the downside risk makes an important contribution to existing knowledge on the long-run performance of IPOs. Secondly, my analysis examines whether initial return, post-issue liquidity and/or third-party certification can explain downside risk of IPOs. There is a notable absence in the literature that analyses the relationship between these state variables with downside risk. This study employs different definitions of liquidity to capture various aspects of this measure and its relative importance with IPO downside risk. Thirdly, my study reveals and extends the current knowledge in the literature on whether initial return, post-issue liquidity, and/or third party certification affect downside risk evenly across the distribution of dependent variables and whether quantile regression models improve the tail predictability of VaR and CVaR. Quantile regressions constitute a more robust test of the stochastic relationships among variables than conventional least squares regression analysis.

3 Downside Risk

I use Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) to measure downside risk of post-issue IPO returns. VaR is an estimate of the maximum loss over a given holding period (t) within a fixed confidence level c. Mathematically, VaR at the $100(1-c)\%$ confidence level is defined as the upper $100c$ percentile of the loss distribution X of post-issue IPO returns. Following Artzner et al. (1999), I define VaR at the $100(1-c)\%$ confidence level $[VaR_c(X)]$ as:

$$VaR_c(X) = \sup\{x \mid P[X \geq x] > c\} \tag{1}$$

where $\sup\{x \mid M\}$ is the upper limit of x given event M, while $\sup\{x \mid P[X \geq x] > c\}$ represents the upper $100c$ percentile of the loss distribution X of post-issue IPO returns.

In addition to VaR, I also use CVaR. CVaR is the expected loss beyond the VaR threshold. Following Artzner et al. (1999), I define CVaR as:

$$CVaR_c(X) = E[X \mid X \geq VaR_c(X)] \tag{2}$$

CVaR measures the average loss of post-issue IPO returns when the loss exceeds the VaR level. Artzner et al. (1999) recommend this measure to alleviate the problems inherent in VaR.

The risk of extreme losses of post-issue IPO returns and their relationship is at the heart of this study. Extreme losses represent a significant downside risk to investors. For that reason, I use Extreme Value Theory (EVT) in conjunction with the Peak over Threshold (POT) method to capture extreme losses and downside risk (for details, see, McNeil, Frey, and Embrechts, 2015). EVT provides a conceptual framework that can accommodate extreme observations. To begin with, this approach overcomes unreliable estimates as a result of sparse data on extreme outcomes. In addition, EVT also allows a statistical quantification of extreme events that have values beyond those observable over a limited time interval. The POT method to model exceedances is the most frequently approach used in finance (see, for example, Gupta and Liang, 2005). Suppose X is a random loss with distribution function $F(x)$, and u is a threshold value, then we can define the distribution of excess losses over the threshold u as:

$$F_u\left(x\right) = \Pr\left\{X - u \leq x \,|\, X > u\right\} = \frac{F\left(x+u\right) - F\left(u\right)}{1 - F\left(u\right)} \tag{3}$$

for $x > 0$. As u gets larger, the $F_u\left(x\right)$ distribution converges to a GPD. This convergence follows from the Gnedenko-Pickands-Balkema-deHaan theorem (see, Dowd, 2005). The cumulative distribution function of GPD is:

$$G_{\xi,\beta}\left(x\right) = \begin{cases} 1 - \left(1 + \xi x/\beta\right)^{-1/\xi} & \text{if} \quad \xi \neq 0 \\ 1 - \exp\left(-x/\beta\right) & \phantom{\text{if}} \quad \xi = 0 \end{cases} \tag{4}$$

where $G\left(x\right)$ refer to exceedances, defined for $x \geq 0$ for $\xi \geq 0$ and $0 \leq x \leq -\beta/\xi$ for $\xi < 0$. β is a positive scale parameter. ξ is a shape or tail index parameter which can be positive, zero, or negative. I fit this GDP by means of maximum likelihood method to those observations which exceed the threshold in the tail of the loss distribution. I use a threshold of 0.1 to assign 10% to the tail of the loss distribution.

After fitting the GDP to the exceedances, I use this distribution to calculate VaR and CVaR for the loss distribution of returns. Mathematically, the loss distribution function $F\left(x\right)$ over the threshold u is:

$$F\left(x\right) = \left[1 - F\left(u\right)\right] G_{\xi,\beta}\left(x - u\right) + F\left(u\right) \tag{5}$$

where $x > u$ with $F\left(u\right)$ estimated empirically from post-issue IPO returns. Eq. (5) represents a parametric model for the tail of the original loss distribution above the threshold u.

4 Data

My sample consists of 2,413 U.S. IPOs between 1985−2012 with an aggregate gross proceeds of \$248.7 billion. Four data sources contribute to the construction of this sample. Firstly, the New Issues database from Thomson One Banker provides details on IPOs and their corresponding deal characteristics. I exclude IPOs of Real Estate Investment Trusts, American Depository Receipts, Master Limited Partnerships, closed-end funds, unit offers, and new issues with an offer price smaller than \$5.[8] Secondly, the Centre for Research in Security Prices (CRSP) tapes provide stock market data, including stock prices and trading information to calculate initial return and liquidity measures. Each IPO must have at least 150 days of trading activity following an offer.[9] Thirdly, Compustat from Standard and Poor's database offers complementary financial statement data for those observations that have missing values in Thomson One Banker's New Issues database. Fourthly, Jay Ritter's web

[8] SEC refers to common stock that trade below \$5 as penny shares. These stocks are in the highest risk category for equity investment which involves a speculative element that prompted Congress to pass laws against brokers making buy or sell recommendations on these shares.

[9] Hahn, Ligon, and Rhodes (2013) also impose a 150-day minimum sampling criteria in their analysis to calculate liquidity measures.

site provides information on underwriter reputation, issuer founding dates, and aggregate initial return of IPOs in the new issues market.[10]

Details on sample distribution by year as well as by industry sector are available from Table I and Table II. The sample covers a variety of industry sectors. No single year and no single industry sector dominate the sample distribution which could introduce a sample bias or diminish the generalizability of the findings.

[Table I]

Both the number of IPOs and gross proceeds across the sample period follow cycles similar to those reported elsewhere in the literature (see, Lowry, 2003; Loughran and Ritter, 2004; Yung, Çolak, and Wei, 2008). We can observe high IPO activity between 1992 and 1999, whereas the period before and after this interval shows fewer new issues and relatively smaller gross proceeds. The highest concentration in the number of offerings occurs in 1996. A total of 260 companies obtain a stock market listing during that year which corresponds to 10.77% of all IPOs in the sample. The highest concentration in gross proceeds occurs in 1999. Gross proceeds amount to $23.2 billion which corresponds to 9.34% of aggregate gross proceeds during that year. The year 1985 has the lowest concentration in both, the number of IPOs as well as the amount of gross proceeds.

[Table II]

IPO concentration across sectors, based on Fama and French's (1992) four-digit industry sector classification, is comparable to those firms trading on national stock exchanges at the time of these new issues. The top three industry sectors, by number of IPOs, are: Computer Software, Retail, and Business Services; while the top three industry sectors, by gross proceeds, are: Computer Software, Trading, and Communication. These industry sectors account for approximately 30% of IPOs by number and by gross proceeds. In contrast, both Precious Metals and Fabricated Products have the fewest number of IPOs as well as the smallest amount of gross proceeds.

4.1 Variable Definitions and Measurements

Variable definitions on downside risk, initial return, liquidity measures, third-party certification proxy measures, proxy variables on ex ante uncertainty surrounding IPO value, deal characteristics, and contemporaneous stock market conditions at the time of flotation along with data sources are available from Table III.

[Table III]

While the existing literature offers several variables that help to explain IPO value and persistent average initial return, we do not know the importance of these stochastic variables on downside risk.[11]

I measure downside risk by value-at-risk (VaR) and conditional value-at-risk (CVaR) for confidence levels $c = \{0.95, 0.99\}$ as shown in Panel A of Table III. Estimates of VaR and CVaR use Extreme Value Theory (EVT) and the Peak over Threshold (POT) approach as explained in Section 3.

To analyse the significance of initial return, stock liquidity, and third-party certification on downside risk, I rely on variables from the literature that explain the long-run performance of IPOs. Initial return in Panel B captures Grinblatt and Hwang's (1989) signalling argument. The relationship between initial return and downside risk awaits investigation. Initial return (underpricing) is a costly and difficult to imitate signal to overcome information asymmetry surrounding IPO value between firm insiders and outside investors. Thus, firms that underprice their IPO should exhibit superior post-listing returns relative to those firms that do not underprice their IPO. However, the majority of empirical studies do not detect superior long-run return performance for underpriced IPOs. For

[10] `http://bear.warrington.ufl.edu/ritter`

[11] I have constructed all variables with a time dimension in Table III over different time frequencies to detect any possible horizon effect among these measures. Using alternative time horizons do not significantly change the findings and conclusions.

example, Ritter (1991), Carter, Dark, and Singh (1998), and Wu and Kwok (2007) report underperformance of IPOs for up to three years post-offering. The findings in Gompers and Lerner (2003) suggest that underperformance, based on cumulative abnormal returns, disappears after five years.

Liquidity measures listed in Panel C, Panel D, and Panel E capture the second set of independent variables. These three distinct categories include spread based liquidity measures, price impact based liquidity measures, and trading volume related liquidity measures. Spread based liquidity measures in Panel C include proportional quoted spread and proportional realised spread (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Chordia, Roll, and Subrahmanyam, 2000; Chordia, Roll, and Subrahmanyam, 2001; Hahn, Ligon, and Rhodes, 2013; Huberman and Halka, 2001; Rubia and Sanchis-Marco, 2013). Price impact based liquidity measures in Panel D quantify the extent to which order flow impacts on prices. These measures originate from Kyle (1985). Existing studies such as, for example, Brennan and Subrahmanyam (1996), Glosten and Harris (1988), and Hahn, Ligon, and Rhodes (2013) use various alternative definitions of Kyle's (1985) original λ measure. Finally, trading volume based liquidity measures in Panel E include the ratio of returns to trading volume (Amihud, 2002; Hahn, Ligon, and Rhodes, 2013; Rubia and Sanchis-Marco, 2013) and the number of shares traded in relation to the number of shares outstanding (Datar, Naik, and Radcliffe, 1998; Hahn, Ligon, and Rhodes, 2013; Rubia and Sanchis-Marco, 2013). The ratio of returns to trading volume is a measure of liquidity. A larger price move for a given trading volume suggests greater illiquidity and hence higher downside risk.

Measures on third-party certification in Panel F capture the third set of state variables. They incorporate underwriter reputation, underwrityer syndicate size, and venture capital backing which should reduce downside risk. Underwriter reputation draws on the ranking of investment banks in tombstone advertisements as advocated in the studies of Loughran and Ritter (2004) and Carter and Manaster (1990). The number of syndicate members involved in the underwriting and distribution of shares enhances the visibility of an IPO and hence improves the aftermarket liquidity of these shares. Syndicate members include the lead manager, co-managers and other members involved in the marketing of IPOs. A dummy variable captures if pre-IPO venture capitalists retain a stake in the post-IPO firm.

To assess the robustness of initial return and liquidity in explaining downside risk, I use two sets of control variables. Panel G includes variables to control for firm and deal characteristics; while Panel H lists controls for contemporaneous market conditions prevalent at the IPO time. I include earnings, assets, and leverage as IPO value drivers to control for firm characteristics. Earnings before interest, tax, depreciation and amortization (EBITDA) is the proxy measure for operating cash flow because the latter is subject to higher annual volatility. In the long term, earnings converge to cash flows as argued in Teoh, Welch, and Wong (1998) and Aggarwal, Bhagat, and Rangan (2009). EBITDADum is a dummy variable coded one if a firm's EBITDA is negative in the accounting period leading up to flotation. Aggarwal, Bhagat, and Rangan (2009) argue that negative earnings are more likely to indicate future growth opportunities rather than current profitability. In their study, firms with greater negative earnings have higher valuations, which would appear to be counter-intuitive from a profitability point of view. Book value of assets during the accounting period before flotation are an indicator of ex ante uncertainty surrounding firm value. Assets quantify a lower bound of firm value. Koop and Li (2001), Hunt-McCool, Koh, and Francis (1996), and Chen, Hung, and Wu (2002) use book value of assets as a value driver. Leverage takes account of financial distress of IPOs at flotation. Firms with higher levels of financial distress have a greater probability of going bankrupt and hence should experience higher downside risk. Koop and Li (2001) report a negative association between leverage and firm value. Sales and firm age control for firm characteristics surrounding ex ante uncertainty surrounding IPO value. Firms with lower sales and shorter operating history should have higher ex ante uncertainty surrounding IPO value. Hunt-McCool, Koh, and Francis (1996), Koop and Li (2001), and Aggarwal, Bhagat, and Rangan (2009) report a positive relationship between sales and IPO value. Hunt-McCool, Koh, and Francis (1996) provide evidence of a positive association between firm age and IPO value.

In addition, I include deal characteristics such as the fraction of equity retained by original owners in the post-IPO firm, the proportion of new money raised at the disposal of the IPO firm, offer price, number of uses of proceeds disclosed in the flotation prospectus, presence of a lock-in agreement, and offer size to control for deal characteristics. Firstly, Leland and Pyle's (1977) equity retention serves as a costly and difficult to imitate signal in which firm insiders convey IPO value to outside investors to overcome Akerlof's (1970) adverse selection problem. Equity retained is a costly and difficult to imitate signal because pre-IPO owners forgo the opportunity to diversify their personal investment portfolio at flotation. Secondly, the fraction of primary shares in relation to total number of shares offered in an IPO signals future capital expenditure of a firm. Downes and Heinkel (1982) and Ritter (1984) use offer proceeds at the disposal of an issuer in conjunction with equity retained as a joint signal of IPO value. Thirdly, offer price signals the variance of a firm's expected cash flows as advocated in Grinblatt and Hwang (1989). Smaller offer prices have higher variance in cash flows. Thus, smaller offer prices should have a positive association with downside risk. Fourthly, the number of uses of IPO proceeds disclosed in the flotation prospectus is a proxy measure for uncertainty surrounding firm value. This variable could be endogenous to the amount of proceeds and hence I control for offer size. Previous studies report mixed evidence of the relationship between the number of uses of proceeds and initial return. On the one hand, Beatty and Ritter (1986) report a positive association. On the other hand, Ljungqvist and Wilhelm (2003) argue that the number of uses of proceeds signifies a more specific disclosure and hence leads to lower initial return. Fifthly, a dummy variable captures the presence of a lock-in agreement. Lock-in agreements prohibit pre-IPO owners from selling shares in the aftermarket for a specified period of time. Brav and Gompers (2003) and Arthurs et al. (2009) convey that demand in shares of IPOs with lock-in agreements should be high because investors have a reduced moral hazard problem during the time interval in which original owners cannot sell their equity stakes in the post-IPO firm. It is only after the lock-in period expires when the supply of shares available for trading increases. An increase in the supply of shares could negatively impact on stock prices as argued in Bradley et al. (2001) and Field and Hanka (2001). Sixthly, offer size captures the total amount of primary as well as secondary money raised at flotation and is an indicator of IPO risk. Smaller IPOs are, on average, riskier than larger issues of more established companies. Beatty and Ritter (1986), Ritter (1987), and Carter (1992) report a negative relationship between offer size and initial return. Seventhly, two dummy variables capture the demand in IPO shares via price revisions between the initial filing price range and the offer price as advocated in Hanley (1993). IPOs at the upper end of the initial price range should perform better than those priced at the lower price range.

Finally, I include variables to capture equity market and new equity issues market activity to control for the downside risk of individual IPOs. The cumulative contemporaneous value-weighted NYSE/AMEX/Nasdaq index return and the volatility of this index takes account of equity market conditions at the time of flotation. Controlling for market conditions is essential because the dependent variables VaR and CVaR use raw returns. A dummy variable captures if an IPO obtains a listing on the Nasdaq. This control variable is necessary since the microstructure of this market differs from that of the NYSE and AMEX. An additional dummy variable identifies if offer date or first trade date are on a Monday. Jones (2009) report that IPOs on a Monday have, on average, greater initial return than those issued on other days. A further dummy variable captures the January 1997 Nasdaq reforms to the order handling rules and subsequent decimalization. Hahn, Ligon, and Rhodes (2013) report, on average, greater initial return for IPOs after this reform. Another dummy variable captures the 1999−2000 IPO bubble. Hahn, Ligon, and Rhodes (2013) argue that liquidity during the bubble period was high, particularly in terms of volume based measures. A further two dummy variables take account of cycles in hot and cold average initial return in the IPO market. I follow the definition provided in Yung, Çolak, and Wei (2008) to differentiate between 'hot', 'cold', and 'normal' average initial return across the sample period. Studies such as, for example, Yung, Çolak, and Wei (2008), Loughran and Ritter (2004), and Brailsford, Heaney, and Shi (2004) report high autocorrelation in average initial return over time.

Panel I lists twelve dummy variables capture industry sector membership based on the classification of Koop and Li (2001). The authors use this classification in the context of IPO and seasoned equity valuation to take account of different ex ante uncertainty and business risk.

4.2 Descriptive Statistics

Summary statistics on downside risk, initial return, liquidity, third-party certification measures, and control variables are available from Table IV.

[Table IV]

My sample consists of 2,413 U.S. IPOs between 1980 and 2012 for which a minimum of 150 trading days and a maximum of six months of daily trading prices post-offering are available. Data availability for price impact based liquidity measures and spread based liquidity measures reduces the sample to 2,409 observations and 2,286 observations, respectively.

Mean of $\text{VaR}_{0.95}$ is 5.98% and 9.74% for $\text{VaR}_{0.99}$. Downside risk, measured by CVaR has a mean of 8.42% for $\text{CVaR}_{0.95}$ and 12.65% for $\text{CVaR}_{0.99}$. All four downside risk measures have asymmetric, leptokurtic distributions. Thus, most values in the distributions are on the left of the mean, with extreme values to the right. In addition, these distributions have thicker tails which implies higher probabilities for extreme values than the normal distribution would predict.

All remaining variables of primary interest, including initial return, liquidity, and third-party certification measures have skewed, leptokurtic distributions. Mean initial return raw return is 19.61% with a median of 8.04%, confirming that IPOs are, on average, underpriced. Interestingly, IPOs in the first quantile of observations have market prices equal to their offer prices. The initial return distribution is asymmetric, right skewed and leptokurtic. All liquidity measures and third-party certification variables also show evidence of asymmetric, leptokurtic distributions.

5 Impact of State Variables on Downside Risk

Evidence on the impact of initial return, liquidity, and third-party certification measures on downside risk are available from Table V to Table VIII. Overall, my findings provide the first evidence that initial return and liquidity in the aftermarket simultaneously explain IPO downside risk, while third-party certification has no persistent explanatory power. These findings are robust across all estimation models using different specifications.

Firstly, initial return is positive and statistically significant in explaining downside risk. Thus, firms with higher initial return suffer greater downside risk. This relationship casts doubt on the validity of signalling models in which firms use underpricing as a costly and difficult to imitate signal to convey IPO value to outside investors (Allen and Faulhaber, 1989; Grinblatt and Hwang, 1989; Welch, 1989). Instead, my findings are consistent with those reported in the literature on market-overreaction. I observe high average initial return, followed greater downside risk which is consistent with the literature on the long-run average return underperformance as reported in Aggarwal and Rivoli (1990), Ritter (1991), Loughran and Ritter (1995), and Ritter and Welch (2002).

Secondly, liquidity of IPO shares in the aftermarket also explains downside risk. More liquid shares have greater downside risk. These findings are consistent across seven distinct liquidity based proxy measures. My findings are consistent with those studies in the non-IPO literature that examine the relationship between liquidity and downside risk of stocks such as Rubia and Sanchis-Marco (2013).

Thirdly, none of the proxy measures that capture third-party certification can persistently explain downside risk. We therefore have to conclude that underwriter reputation, the number of underwriters in the underwriting syndicate, and venture-capital backing appear not to reduce the downside risk of IPO firms in the aftermarket. My findings are therefore consistent with those reported in Beatty and Welch (1996) who find no evidence in support of a certification effect by which more reputable underwriters should reduce the ex ante information asymmetry between issuers and outside investors.

Fourthly, tests for endogeneity of initial return, post-issue liquidity, and third-party certification measures in regression models using the Durbin-Wu-Hausman test (Wooldridge, 1995) find no evidence that these stochastic variables are endogenous with respect to downside risk for the cross-section of IPOs. Thus, instrumenting these variables is not necessary and would only reduce the efficiency of the estimates. Multicollinearity tests using Variance Inflation Factors (VIF) do not provide evidence of unstable parameter estimates which would make it problematic to assess the effect of predictor variables on downside risk.

5.1 Initial Return

Details on positive and statistically significant relationships between initial return and downside risk are available from Models (1) across Table V to Table VIII. On the one hand, my findings contradict the signalling arguments offered by Grinblatt and Hwang (1989). They argue that issuers underprice their IPOs to signal high IPO value to outside investors. Thus, greater underpricing should signify better performance and lower downside risk. On the other hand, my findings are consistent with those reported elsewhere in the empirical literature. For example, Ritter (1991) reports a negative correlation between initial return and the three-year raw return, measured from the first aftermarket closing share price to the earlier of the three-year anniversary or the firm's CRSP delisting date. Carter, Dark, and Singh (1998) also show evidence of positive initial return followed by long-run negative market adjusted returns. These patterns are not unique to the US IPO market (see, for example, Jenkinson and Ljungqvist, 2001, for an overview of the literature).

5.2 Liquidity

Details on positive and statistically significant correlations between liquidity based proxy measures and downside risk are available from Models (2) to Models (8) across Table V to Table VIII. Although the existing IPO literature does not provide any direct evidence of the relationship between liquidity based proxy measures and downside risk, while controlling for firm and deal characteristics, my findings are consistent with comparable tests of liquidity and downside risk reported elsewhere in the literature.

Firstly, spread based liquidity measures, including proportional quoted spread and proportional realised spread, have positive and statistically significant coefficients in Models (2) and Models (3) across all definitions of downside risk. Studies such as, for example, Hahn, Ligon, and Rhodes (2013) and Booth and Chua (1996) argue that greater initial return can boost the aftermarket liquidity of IPOs. More to the point, Rubia and Sanchis-Marco (2013) show that market liquidity explains the tail of the conditional distribution of daily market returns of value portfolios. In an earlier study, Amihud and Mendelson (1986) report that market-observed expected return is an increasing function of the bid-ask spread.

Secondly, proportional price impact based measures of liquidity, including Kyle's (1985) proportional λ as well as versions adjusted for the number of shares $\lambda\ CN$ and the number of trades $\lambda\ CQ$ have without exception positive relationships in Models (4), Models (5), and Models (6) across all definitions of downside risk. Hahn, Ligon, and Rhodes (2013) report partial support of a significant correlation between initial return and price impact based liquidity measures, but the evidence is not as overwhelming as that for the proportional spread based liquidity measures.

Thirdly, volume related liquidity measures, including the average ratio of absolute returns to trading volume (*Illiquidity*), and the number of shares traded ($Turnover$) all have positive relationships in Models (7) and Models (8). The coefficient on *Illiquidity* is positive. Thus, a larger price move for a given trading volume suggests greater illiquidity and hence higher downside risk. Amihud (2002), Datar, Naik, and Radcliffe (1998), and Brennan, Chordia, and Subrahmanyam (1998) report a positive relationship between illiquidity and return. The positive coefficient on $Turnover$ indicates that higher proportions of shares traded with respect to the number of shares outstanding creates a more liquid market in which prices can adjust more quickly and increases the downside risk. These findings are therefore consistent with those reported in existing IPO studies and the wider literature. More specifically, Eckbo and Norli (2005) and Hahn, Ligon, and Rhodes (2013) find that high initial return has a negative correlation with returns for a given dollar trading volume. Brennan and Subrahmanyam (1996) report that required rates of return are greater for illiquid stocks.

5.3 Third-Party Certification

Details on the absence of third-party certification in explaining downside risk are available from Models (1) to Models (8) across across Table V to Table VIII. We have to reject third-party certification on the basis that underwriter reputation, size of underwriting syndicate, and venture-capital backing variables change their statistical significance depending on model specification or never achieve statistical significance in the first instance.

Underwriter reputation never achieves statistical significance in conjunction with initial return across Models (1) which tests initial return as a signal of firm value or as market overreaction in relation to downside risk. Models (2) to Models (8) report mixed results in relation to underwriter reputation and liquidity. The reputation variable changes its statistical significance depending on model specification or never achieves statistical significance in the first instance. On the basis of this inconsistency, we have to reject the validity of a third-party certification effect between underwriter reputation and downside risk. My findings are therefore in line with the notion reported in Beatty and Welch (1996) that underwriter reputation does not reduce ex ante uncertainty surrounding firm quality.

Similar to underwriter reputation, the findings on the size of the underwriter syndicate also provides mixed results. While more models show a statistically significant relationship between the size of underwriter syndicate and downside risk than in terms of underwriter reputation capital, we do not observe consistently statistically significant coefficients.

Venture-capital backing achieves no statistical significance in any of the regression models. We therefore have to conclude that the presence of venture capitalists at IPO have no impact on reducing the ex ante uncertainty and hence risk post-flotation. My findings are therefore consistent with the conclusions in Liu and Ritter (2011) and Hamao, Packer, and Ritter (2000).

5.4 Control Variables

Among the control variables, we observe persistent statistically significant associations between downside risk and negative EBITDA, assets, fraction of primary shares in relation to total shares offered, lock-in agreements by original owners, contemporaneous equity market returns and volatility, Nasdaq IPOs, and whether an IPO occurred during the 1999−2000 bubble years. Firstly, firms with negative EBITDA in the accounting period leading up to flotation experience greater post-IPO downside risk than firms with positive earnings. A consistent positive coefficient on this dummy variable across all model specification is therefore perhaps more intuitive than the view expressed by Aggarwal, Bhagat, and Rangan (2009). They argue that negative earnings are more likely to indicate future growth opportunities rather than current profitability. Secondly, firms with a larger asset base have smaller downside risk. Thirdly, a consistent positive relationship between downside risk and the fraction of primary shares in relation to the total number of shares offered in an IPO may at first seem counterintuitive. It would perhaps be obvious to argue that higher levels of funds at the disposal of an issuing firm signals confidence about shareholder wealth generation from future net present value projects. However, these new projects are often inherent to downside risk which may explain consistent positive coefficients on this variable across all model specifications. Fourthly, lock-in agreements that prohibit pre-IPO owners from selling shares in the aftermarket increase downside risk. It is therefore more likely that an increase in the supply of shares after the lock-in period expires could negatively impact on stock prices as argued in Bradley et al. (2001) and Field and Hanka (2001). Fifthly, downside risk diminishes for higher cumulative contemporaneous value-weighted NYSE/AMEX/Nasdaq index returns and the lower stock market volatility. Controlling for stock market conditions is essential because downside risk across the models rely on raw returns. Sixthly, persistent negative coefficients on the Nasdaq dummy variable shows an increased downside risk for IPOs on this market. The microstructure for Nasdaq differs from that of the NYSE and AMEX. Seventhly, new issues during the 1999−2000 IPO bubble experience greater downside risk. Hahn, Ligon, and Rhodes (2013) argue that liquidity during the bubble period was high. Eighthly, IPO firms belong to Computers, Electrical Equipment, Utilities, and Retail sectors explain some of the variance in downside risk. On the one hand, we can observe a positive relationship between downside risk and firms operating in Computers, Electrical Equipment, and Retail sectors. On the other hand, firms in the Utilities sector exhibit lower downside risk. All remaining control variables change their statistical significance depending on model specification or never achieve statistical significance in the first instance. I do not delete statistically insignificant control variables from the analysis for several reasons. The aim of the analysis is not to maximize the explanatory power of regression models but to assess the impact of initial return and liquidity measures on downside risk using an identical set of control variables. Even if these controls are not persistently statistically significant in my regression models, these variables are normally part of the analysis in IPO research. Finally, my sample is large and hence insignificant control variables do not use up precious degrees of freedom.

6 Impact of State Variables on Downside Risk at Different Quantiles

The evidence thus far shows that both initial return and liquidity explain downside risk of post-IPO returns, while there is no persistent evidence in support for a third-party certification effect. In this section, I use quantile regressions to analyse whether the relationships between downside risk, initial return, liquidity, and third-party certification are representative across an entire range of values or whether the impact in the lower and upper distributions of the dependent variables change. It is possible that the covariates of independent variables could change their sensitivity at different quantiles of downside risk. Therefore, quantile regressions provide a more comprehensive picture of the relationship among variables than simple least squares regression analysis.

My findings reveal differences on how initial return and liquidity correlate with downside risk at different quantiles as shown in Figure 1 to Figure 8. The coefficients of third-party certification variables in Figure 9 to Figure 11 reject any support for a third-party certification effect in explaining downside risk. Firstly, initial return covariates at different quantiles are representative of the average least squares coefficients. The majority of quantile covariates for initial return are inside the 90% confidence interval of least squares regression coefficients. Secondly, downside risk is more sensitive to liquidity at the upper end of the distribution without any exception. The majority of quantile covariates are outside the 90% confidence interval of least squares regression coefficients and statistically significant. Thirdly, with the exception of a few cases, the majority of quantile regression coefficients that capture third-party certification are either statistically insignificant or outside the 90% confidence interval of least squares regression coefficients. This finding provides a more robust result for the rejection of a third-party certification effect.

6.1 Initial Return

Figure 1 provides details of the relationship between downside risk and initial return at different quantiles of the dependent variable. A positive association supports the notion of market timing abilities and market over-reaction to overpriced IPOs, consistent with the studies of Aggarwal and Rivoli (1990), Ritter (1991), Loughran and Ritter (1995), Carter, Dark, and Singh (1998), and Ritter and Welch (2002).

[Figure 1]

There are very few occasions in which quantile regression covariates fall outside the confidence interval of least squares regression coefficients. Graphs in the top row show the regression covariates at different quantiles for VaR and CVaR for confidence levels $c = \{0.95, 0.99\}$. In the vast majority, quantile regression covariates (continues black lines) fall inside the 90% confidence interval of least squares regression coefficients (dashed red lines). Grey areas indicate the 90% confidence levels of quantile regression coefficients at different quantiles τ. Tables across the middle row show the actual values of the regression coefficients at various quantiles τ. Tables across the middle row show the actual values of the regression coefficents at various quantiles τ. All quantile regression coefficients are statistically significant across VaR and CVaR as well as their corresponding confidence levels with the exception of $\tau = 0.95$ for $\text{CVaR}_{0.95}$, $\tau = \{0.90, 0.95\}$ for $\text{VaR}_{0.99}$, $\tau = \{0.90, 0.95\}$ for $\text{CVaR}_{0.95}$, and $\tau = \{0.85, 0.90, 0.95\}$ for $\text{CVaR}_{0.99}$. Tables across the bottom row report tests of equality of quantile regression coefficients across different levels of τ. F-tests across all τ quantiles show statistically significant differences.

6.2 Liquidity

Figure 2 to Figure 8 show the associations between downside risk and liquidity for regression coefficients at different quantiles. The findings allow me to draw several conclusions. Firstly, post-issue liquidity does not affect downside risk evenly across the entire distribution. Secondly, quantile regressions are superior at predicting the tail of the conditional distribution of downside risk. This estimation technique therefore offers a more complete characterization of the stochastic relationship between downside risk and liquidity than traditional least squares regression models. I base these conclusions on the following evidence. To begin with, we can observe positive correlations between downside risk and various definitions of post-issue liquidity at different quantiles. In addition, we can observe more sensitive correlations among the variables towards the upper end of the distribution of downside risk. Furthermore, these differences in the size of covariates between the upper part and the lower end of the distribution are statistically significant. Moreover, the majority of quantile regression covariates are outside the 90% confidence intervals of least squares regression coefficients. These findings are consistent across spread based liquidity measures, price impact based liquidity measures, and trading volume related liquidity measures.

Firstly, Figure 2 and Figure 3 provide details on the relationship between downside risk, quoted spread and realised spread.

[Figure 2]

[Figure 3]

Greater spread-based liquidity stocks experience higher downside risk, measured by post-issue IPO returns. Both spread-based liquidity measures consistently show statistically significant correlations with VaR and CVaR across confidence levels $c = \{0.95, 0.99\}$. More significantly, the vast majority of quantile regression covariates fall outside the 90% confidence interval of least squares coefficients. Downside risk in the upper end of the distribution appears to be particularly pronounced for those stocks with increasing liquidity. While coefficients in the lower part of the distribution have values less than those predicted by least squares regressions, quantile covariates in the upper end of the distribution of downside risk have greater sensitivity than those predicted by least squares. F-tests measuring differences between coefficients across all τ quantiles are statistically significant. Even though my study is the first to make the link between spread-based liquidity and downside risk, the findings resemble the conclusions in other related studies such as Amihud and Mendelson (1986) and Rubia and Sanchis-Marco (2013).

Secondly, Figure 4, Figure 5, and Figure 6 show details on the association between downside risk and proportional price impact based liquidity measures. They are: Kyle's λ (Figure 4), Kyle's λ CN (Figure 5), and Kyle's λ CQ (Figure 6). Overall, we can observe that price impact based liquidity measures can explain downside risk, but the evidence is not as strong as for spread based liquidity measures.

[Figure 4]

[Figure 5]

[Figure 6]

To begin with, not all regression covariates of Kyle's λ in Figure 4 are statistically significant at each quantile for VaR and CVaR. However, the majority of coefficients are outside the 90% confidence interval of least squares regression coefficients. Quantile covariates are statistically significant at the upper end of the distribution of downside risk, while at the lower end the explanatory power of Kyle's λ is statistically not significant. I therefore conclude that the impact and sensitivity of Kyle's λ becomes more prominent for those stocks with an increased downside risk. This piece of evidence helps to explain the marginal statistical significance of the least squares regression coefficient on Kyle's λ reported in Model (4) of Table V, Table VI, Table VII, and Table VIII.

In addition, we can observe a similar pattern between Kyle's λ CN in Figure 5 and downside risk, particularly for CVaR. The majority of quantile regression covariates are outside the 90% confidence interval of least squares coefficients and gain increasing statistical significance as well as sensitivity in the upper end of the downside risk distribution. This effect in the case of Kyle's λ CN is not as pronounced as that for Kyle's λ and hence the least squares coefficients in Model (5) of Table V, Table VI, Table VII, and Table VIII are statistically significant at the 1% level.

Finally, the results for Kyle's λ CQ in Figure 6 show statistically significant covariates at each regression quantile. The majority of quantile regression covariates are outside the 90% confidence interval of least squares regression coefficients. Also, the sensitivity of the impact of Kyle's λ CQ increases at the upper end of the downside risk distribution. F-statistics tests for pairwise equality of slope coefficients show that differences between upper and lower quantiles are statistically significant.

Thirdly, Figure 7 and Figure 8 present details on the relationship between downside risk and trading volume related liquidity measures.

[Figure 7]

[Figure 8]

Greater illiquidity and turnover experience higher downside risk. Both trading volume based liquidity measures show statistically significant correlations with VaR and CVaR. In a similar way to spread based and price impact based liquidity measures, the vast majority of quantile regression covariates fall outside the 90% confidence interval of least squares coefficients. On average, downside risk in the upper end of the VaR and CVaR distributions have greater sensitivity than those predicted by least squares. F-tests across all τ quantiles show that differences in covariates are statistically significant. These findings are consistent with those reported in Eckbo and Norli (2005). The authors associate high trading volume with IPO underperformance because these stocks are more liquid than a seasoned control sample matched on size and book-to-market.

6.3 Third-Party Certification

Figure 9 to Figure 11 provide details on the relationship between third-party certification and downside risk. I find no evidence to support a third-party certification effect on downside risk. With the exception of a few instances, the majority of quantile regression coefficients for underwriter reputation, the number of underwriters in the underwriting syndicate, and venture-capital backing measures are either statistically insignificant or outside the 90% confidence interval of least squares regression coefficients. These findings provide a more robust test of the rejection of a third-party certification effect than the results presented in Table V to Table VIII.

Firstly, the majority of quantile regression coefficients for underwriter reputation are statistically insignificant and/or outside the 90% confidence interval of least squares regression coefficients.

[Figure 9]

Figure 9 in conjunction with Table V to Table VIII therefore reject the notion of a third-party certification effect using a more robust test. My findings are consistent with the view held in Beatty and Welch (1996) and inconsistent with conclusion reported in the studies of Megginson and Weiss (1991), Carter and Manaster (1990), and Habib and Ljungqvist (2001) which claim that underwriter reputation help to reduce ex ante valuation uncertainty.

Secondly, all quantile regression coefficients for the number of underwriters in the underwriting syndicate are either statistically insignificant and/or outside the 90% confidence interval of least squares regression coefficients.

[Figure 10]

Figure 10 together with Table V to Table VIII provide further evidence that there is no evidence in support for a third-party certification effect.

Thirdly, none of the quantile regression coefficients for venture-capital backing is statistically significant and/or outside the 90% confidence interval of least squares regression coefficients.

[Figure 11]

Figure 11 confirms the findings reported in Table V to Table VIII that there is no third-party certification from venture capital-backed IPOs. My findings therefore corroborate earlier conclusions offered in the studies of Liu and Ritter (2011) and Hamao, Packer, and Ritter (2000), but contradict opposing views held in Arthurs et al. (2009), Barry et al. (1990), Brav and Gompers (1997), Krishnan et al. (2011), Lerner (1994), Megginson and Weiss (1991), and Nanda and Rhodes-Kropf (2013).

7 Concluding Remarks and Extensions

This study analyses the impact of initial return, post-issue liquidity, and third-party certification on downside risk of IPOs. I use Extreme Value Theory (EVT) and the Peak over Threshold (POT) approach to calculate value-at-risk (VaR) and conditional value-at-risk (CVaR). Initial return and downside risk exhibit a positive association which is consistent with a market-overreaction explanation but contradicts the validity of IPO signalling models in which underpricing acts as a costly and difficult to imitate signal of firm quality. Post-issue liquidity also has a positive association with downside risk. My findings do not support the notion that third-party certification at flotation reduces IPO downside risk. While some of my findings are in agreement with certain strands of the empirical literature, a more robust estimation technique with supplementary control variables invalidates some of the findings reported in earlier studies. Therefore, my findings add to the understanding of both the conceptual and empirical literature.

More specifically, my study contributes to the extant literature in several ways. To begin with, existing studies do not provide any evidence on the association between downside risk and initial return. My analysis reveals that IPOs with higher initial return have greater downside risk. These findings are consistent with the literature on market-overreaction (Aggarwal and Rivoli, 1990; Ritter, 1991; Loughran and Ritter, 1995; Ritter and Welch, 2002). My findings therefore cast doubt on the validity of signalling models in which firms use underpricing as a costly and difficult to imitate signal to convey IPO value to outside investors (Allen and Faulhaber, 1989; Grinblatt and Hwang, 1989; Welch, 1989).

In addition, the literature offers no evidence on the relationship between downside risk and post-issue liquidity of IPOs. I use seven distinct measures to capture various aspects of liquidity, while controlling for firm and deal characteristics as well as contemporaneous market conditions. Post-issue liquidity has a positive association with downside risk. My findings are consistent with comparable studies on liquidity and downside risk reported elsewhere in the non-IPO literature. Firstly, quoted spread and realised spread liquidity measures explain the tail conditional distribution of post-issue daily stock market returns. This observed impact is consistent with earlier studies (Amihud and Mendelson, 1986; Rubia and Sanchis-Marco, 2013). Secondly, price impact based liquidity measures also explain downside risk. Thirdly, volume related liquidity measures all have positive associations with all definitions of downside risk. These findings are consistent with those reported elsewhere in the literature (Amihud and Mendelson, 1986; Brennan, Chordia, and Subrahmanyam, 1998; Datar, Naik, and Radcliffe, 1998; Rubia and Sanchis-Marco, 2013).

Furthermore, none of the proxy measures that capture third-party certification can persistently explain downside risk. I conclude that underwriter reputation, the number of underwriters in the underwriting syndicate, and venture-capital backing appear not to reduce the downside risk of IPOs in the aftermarket. These findings are similar to those reported in Beatty and Welch (1996).

My final contribution comes from the use of quantile regressions. They help in the analysis whether the relationships between downside risk, initial return, and third-party certification are representative across an entire range of values or whether the impact in the lower and upper distributions of the dependent variable change. Quantile regressions therefore provide a more robust test of the relationships among variables than simple least squares regression analysis. Quantile regressions allow for the possibility that the covariates of stochastic variables could change their sensitivity at different quantiles of downside risk.

While initial return covariates at different quantiles are representative of the average least squares coefficients, the majority of quantile covariates are outside the confidence interval of least squares regression coefficients and statistically significant. Post-issue liquidity does not affect downside evenly across the distribution. Downside risk is more sensitive to post-issue liquidity at the upper end of the distribution. Therefore, quantile regressions improve the tail predictability of downside risk because this method offers a more complete characterization of the stochastic relationship than traditional least squares regression models. Quantile regression coefficients that capture third-party certification are either statistically insignificant and/or outside the confidence interval of least squares regression coefficients. This finding provides a more robust result for the rejection of a third-part certification effect.

Future research can extend the present study in several directions. More comprehensive datasets from different developed or less developed stock markets will help to corroborate or reject the findings in the present study. Extended back-testing of out-of-sample tail predictability using quantile regressions will help to identify the effectiveness of initial return and liquidity in forecasting downside risk for the purpose of portfolio management and asset allocation decisions.

References

Aggarwal, Rajesh, Sanjay Bhagat, and Srinivasan Rangan (2009). The impact of fundamentals on IPO valuation. *Financial Management* 38(2): 253–284.

Aggarwal, Rajesh K., Laurie Krigman, and Kent L. Womack (2002). Strategic IPO underpricing, information momentum, and lockup expiration selling. *Journal of Financial Economics* 66(1): 105–137.

Aggarwal, Reena and Pietra Rivoli (1990). Fads in the initial public offering market? *Financial Management* 19(4): 45–57.

Akerlof, George A. (1970). The market for 'lemons': Quality uncertainty and the market mechanism. *Quarterly Journal of Economics* 84(3): 488–500.

Allen, Franklin and Gerald R. Faulhaber (1989). Signalling by underpricing in the IPO market. *Journal of Financial Economics* 23(2): 303–323.

Amihud, Yakov and Haim Mendelson (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics* 17(2): 223–249.

Amihud, Yakow (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets* 5(1): 31–56.

Arthurs, Jonathan D. et al. (2009). Signaling and initial public offerings: The use and impact of the lockup period. *Journal of Business Venturing* 24(4): 360–372.

Artzner, Philippe et al. (1999). Coherent measures of risk. *Mathematical Finance* 9(3): 203–228.

Banerjee, Suman, Lili Dai, and Keshab Shrestha (2011). Cross-country IPOs: What explains differences in underpricing? *Journal of Corporate Finance* 17(5): 1289–1305.

Bao, Yong, Lee Tae-Hwy, and Saltoğlu (2006). Evaluating predictive performance of value-at-risk models in emerging markets: A reality check. *Journal of Forecasting* 25(2): 101–128.

Baron, David P. (1982). A model of the demand for investment banking advising and distribution services for new issues. *Journal of Finance* 37(4): 955–976.

Barry, Christopher B. et al. (1990). The role of venture capital in the creation of public companies: Evidence from the going-public process. *Journal of Financial Economics* 27(2): 447–471.

Baur, Dirk G. (2013). The structure and degree of dependence: A quantile regression approach. *Journal of Banking & Finance* 37(3): 786–798.

Beatty, Randolph P. and Jay R. Ritter (1986). Investment banking, reputation, and the underpricing of initial public offerings. *Journal of Financial Economics* 15(1-2): 213–232.

Beatty, Randolph P. and Ivo Welch (1996). Issuer expenses and legal liability in initial public offerings. *Journal of Law and Economics* 39(2): 545–602.

Beneda, Nancy and Yilei Zhang (2009). Heterogeneous relationship between IPO return and risk across idiosyncratic variance characteristics. *The Quarterly Review of Economics and Finance* 49(4): 1298–1316.

Bernal, Oscar, Jean-Yves Gnabo, and Grégory Guilmin (2014). Assessing the contribution of banks, insurance and other financial services to systemic risk. *Journal of Banking & Finance* 47 270–287.

Bessler, Wolfgang and Martin Seim (2012). The performance of venture-backed IPOs in Europe. *Venture Capital* 14(4): 215–239.

Bodnaruk, Andriy et al. (2008). Shareholder diversification and the decision to go public. *Review of Financial Studies* 21(6): 2779–2824.

Booth, James R. and Lena Chua (1996). Ownership dispersion, costly information, and IPO underpricing. *Journal of Financial Economics* 41(2): 291–310.

Bradley, Daniel J. et al. (2001). Venture capital and IPO lockup expiration: An empirical analysis. *Journal of Financial Research* 24(4): 465–493.

Brailsford, Tim, Richard Heaney, and Jing Shi (2004). Modelling the behaviour of the new issue market. *International Review of Financial Analysis* 13(2): 119–132.

Brav, Alon, Christopher Geczy, and Paul A. Gompers (2000). Is the abnormal return following equity issuances anomalous? *Journal of Financial Economics* 56(2): 209–249.

Brav, Alon and Paul A. Gompers (1997). Myth or reality? The long-run underperformance of initial public offerings: Evidence from venture and nonventure capital-backed companies. *Journal of Finance* 52(5): 1791–1821.

Brav, Alon and Paul A. Gompers (2003). The role of lockups in initial public offerings. *Review of Financial Studies* 16(1): 1–29.
Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics* 49(3): 345–373.
Brennan, Michael J. and Avanidhar Subrahmanyam (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics* 41(3): 441–464.
Cao, Charles, Laura Casares Field, and Gordon Hanka (2004). Does insider trading impair market liquidity? Evidence from IPO lockup expirations. *Journal of Financial & Quantitative Analysis* 39(1): 25–46.
Carter, Richard and Steven Manaster (1990). Initial public offerings and underwriter reputation. *Journal of Finance* 45(4): 1045–1067.
Carter, Richard B. (1992). Underwriter reputation and repetitive public offerings. *Journal of Financial Research* 15(4): 341–354.
Carter, Richard B., Frederick H. Dark, and Ajai K. Singh (1998). Underwriter reputation, initial returns, and the long-run performance of IPO stocks. *Journal of Finance* 53(1): 285–311.
Chen, Anlin, Chen Dhein Hung, and Chin-Shun Wu (2002). The underpricing and excess returns of initial public offering in Taiwan based on noisy trading: a stochastic frontier model. *Review of Quantitative Finance & Accounting* 18(2): 139–159.
Chen, Zhaohui and William J. William Jr (2008). A theory of the transition to secondary market trading of IPOs. *Journal of Financial Economics* 90(3): 219–236.
Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam (2000). Commonality in liquidity. *Journal of Financial Economics* 56(1): 3–28.
— (2001). Market liquidity and trading activity. *Journal of Finance* 56(2): 501–530.
Corwin, Shane A., Jeffrey H. Harris, and Marc L. Lipson (2004). The development of secondary market liquidity for NYSE-listed IPOs. *Journal of Finance* 59(5): 2339–2373.
Covas, Francisco B., Ben Rump, and Egon Zakrajšek (2014). Stress-testing US bank holding companies: A dynamic panel quantile regression approach. *International Journal of Forecasting* 30(3): 691–713.
Datar, Vinay T., Y. Naik Narayan, and Robert Radcliffe (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets* 1(2): 203–219.
Dowd, Kevin (2005). *Measuring market risk*. Second edition. Chichester, England: John Wiley & Sons.
Downes, David H. and Robert Heinkel (1982). Signaling and the valuation of unseasoned new issues. *Journal of Finance* 37(1): 1–10.
Eckbo, B. Espen and Ø yvind Norli (2005). Liquidity risk, leverage and long-run IPO returns. *Journal of Corporate Finance* 11(1-2): 1–35.
Ellul, Andrew and Marco Pagano (2006). IPO underpricing and after-market liquidity. *Review of Financial Studies* 19(2): 381–421.
Engle, Robert F. and Simone Managnelli (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business & Economic Statistics* 22(4): 367–381.
Falconieri, Sonia, Albert Murphy, and Daniel Weaver (2009). Underpricing and ex post value uncertainty. *Financial Management* 38(2): 285–300.
Fama, Eugene F. and Kenneth R. French (1992). The cross-section of expected stock returns. *Journal of Finance* 47(2): 427–465.
— (1997). Industry costs of equity. *Journal of Financial Economics* 43(2): 153–193.
Field, Laura Casares and Gordon Hanka (2001). The expiration of IPO share lockups. *Journal of Finance* 56(2): 471–500.
Friesen, Geoffrey C. and Christopher Swift (2009). Overreaction in the thrift IPO market. *Journal of Banking & Finance* 33(7): 1285–1298.
Fuertes, Ana-Maria and Jose Olmo (2013). Optimally harnessing inter-day and intra-day information for daily value-at-risk prediction. *International Journal of Forecasting* 29(1): 28–42.

Gleason, K., J. Johnston, and J. Madura (2008). What factors drive IPO aftermarket risk. *Applied Financial Economics* 18(13): 1099–1110.

Glosten, Lawrence R. and Lawrence E. Harris (1988). Estimating the components of the bid/ask spread. *Journal of Financial Economics* 21(1): 123–142.

Gompers, Paul A. and Josh Lerner (2003). The really long-run performance of initial public offerings: The pre-Nasdaq evidence. *Journal of Finance* 58(4): 1355–1392.

Grinblatt, Mark and Yang Hwang (1989). Signalling and the pricing of new issues. *Journal of Finance* 44(2): 393–420.

Gupta, Anurag and Bing Liang (2005). Do hedge funds have enough capital? A value-at-risk approach. *Journal of Financial Economics* 77(1): 219–253.

Habib, Michel A. and Alexander P. Ljungqvist (2001). Underpricing and entrepreneurial wealth losses in IPOs: Theory and evidence. *Review of Financial Studies* 14(2): 433–458.

Hahn, TeWhan, James A. Ligon, and Heather Rhodes (2013). Liquidity and initial public offering underpricing. *Journal of Banking and Finance* 37(12): 4973–4988.

Hamao, Yasushi, Frank Packer, and Jay R. Ritter (2000). Institutional affiliation and the role of venture capital: Evidence from initial public offerings in Japan. *Pacific-Basin Finance Journal* 8(5): 529–558.

Hanley, Kathleen Weiss (1993). The underpricing of initial public offerings and the partial adjustment phenomenon. *Journal of Financial Economics* 34(2): 231–250.

Hua, Jian and Sebastiano Manzan (2013). Forecasting the return distribution using high-frequency volatility measures. *Journal of Banking & Finance* 37(11): 4381–4403.

Huberman, Gur and Dominika Halka (2001). Systematic liquidity. *Journal of Financial Research* 24(2): 161–178.

Hunt-McCool, Janet, Samuel C. Koh, and Bill B. Francis (1996). Testing for deliberate underpricing in the IPO premarket: a stochastic frontier approach. *Review of Financial Studies* 9(4): 1251–1269.

Jenkinson, Tim and Alexander Ljungqvist (2001). *Going public: The theory and evidence on how companies raise equity finance*. Second edition. Oxford: Oxford Press.

Jeon, Jooyoung and James W. Taylor (2013). Using CAViaR Models with Implied Volatility for Value-at-Risk Estimation. *Journal of Forecasting* 32(1): 62–74.

Jones, Travis L. (2009). The day of the week effect in IPO initial returns. *The Quarterly Review of Economics and Finance* 49(1): 110–127.

Klomp, Jeroen and Jakob de Haan (2012). Banking risk and regulation: Does one size fit all? *Journal of Banking & Finance* 36(12): 3197–3212.

Koenker, Roger and Gilbert Bassett (1978). Regression quantiles. *Econometrica* 46 33–50.

Koop, Gary and Kai Li (2001). The valuation of IPO and SEO firms. *Journal of Empirical Finance* 8(4): 375–401.

Krigman, Laurie, Wayne H. Shaw, and Kent L. Womack (1999). The persistence of IPO mispricing and the predictive power of flipping. *Journal of Finance* 54(3): 1015–1044.

Krishnan, C.N.V. et al. (2011). Venture capital reputation, post-IPO performance, and corporate governance. *Journal of Financial & Quantitative Analysis* 46(5): 1295–1333.

Kyle, Albert (1985). Continuous auctions and insider trading. *Econometrica* 53(6): 1315–1335.

Lee, Bong Soo and Ming-Yuan Leon Li (2012). Diversification and risk-adjusted performance: A quantile regression approach. *Journal of Banking & Finance* 36(7): 2157–2173.

Leland, Hayne E. and David H. Pyle (1977). Informational asymmetries, financial structure, and financial intermediation. *Journal of Finance* 32(2): 371–387.

Lerner, Joshua (1994). Venture capitalists and the decisions to go public. *Journal of Financial Economics* 35(3): 293–316.

Liu, Xiaoding and Jay R. Ritter (2011). Local underwriter oligopolies and IPO underpricing. *Journal of Financial Economics* 102(3): 579–601.

Ljungqvist, Alexander L. and Jr William Wilhelm (2003). IPO pricing in the dot-com bubble. *Journal of Finance* 58(2): 723–752.

Loughran, Tim and Jay Ritter (2004). Why has IPO underpricing changed over time? *Financial Management* 33(3): 5–37.

Loughran, Tim and Jay R. Ritter (1995). The new issues puzzle. *Journal of Finance* 50(1): 23–51.
Loughran, Tim, Jay R. Ritter, and Kristian Rydqvist (1994). Initial public offerings: International insights. *Pacific-Basin Finance Journal* 2(2-3): 165–199.
Lowry, Michelle (2003). Why does IPO volume fluctuate so much? *Journal of Financial Economics* 67(1): 3–40.
Mantecon, Tomas and Percy Poon (2009). An analysis of the liquidity benefits provided by secondary markets. *Journal of Banking & Finance* 33(2): 335–346.
McNeil, Alexander J., Rüdiger Frey, and Paul Embrechts (2015). *Quantitative risk management: Concepts, techniques and tools*. Revised edition. Princeton University Press.
Megginson, William L. and Kathleen A. Weiss (1991). Venture capitalist certification in initial offerings. *Journal of Finance* 46(3): 879–903.
Michaely, Roni and Kent L. Womack (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies* 12(4): 653–685.
Nanda, Ramana and Matthew Rhodes-Kropf (2013). Investment cycles and startup innovation. *Journal of Financial Economics* 110(2): 403–418.
Neill, John D, Steven B. Perfect, and Kenneth W. Wiles (1999). The time-series behavior of IPO betas. *Review of Quantitative Finance and Accounting* 13(3): 261–275.
Nikolaou, Kleopatra (2008). The behaviour of the real exchange rate: Evidence from regression quantiles. *Journal of Banking & Finance* 32(5): 664–679.
Pástor, Ľuboš and Robert F. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political Economy* 111(3): 642–685.
Pedersen, Thomas Q. (2015). Predictable Return Distributions. *Journal of Forecasting* 34(2): 114–132.
Ritter, Jay R. (1984). Signaling and the valuation of unseasoned new issues: A comment. *Journal of Finance* 39(4): 1231–1237.
— (1987). The costs of going public. *Journal of Financial Economics* 19(2): 269–281.
— (1991). The long-run performance of initial public offerings. *Journal of Finance* 46(1): 3–27.
— (2003). Investment banking and securities issuance. In: *Handbook of the economics of finance*. Ed. by George Constantinides, Milton Harris, and René Stultz. North-Holland, pp. 253–304.
Ritter, Jay R. and Ivo Welch (2002). Review of IPO activity, pricing, and allocations. *Journal of Finance* 57(4): 1795–1828.
Rock, Kevin (1986). Why new issues are underpriced. *Journal of Financial Economics* 15(1-2): 187–212.
Rubia, Antonio and Lidia Sanchis-Marco (2013). On downside risk predictability through liquidity and trading activity: A dynamic quantile approach. *International Journal of Forecasting* 29(1): 202–219.
Taylor, James W. (2000). A quantile regression neural network approach to estimating the conditional density of multiperiod returns. *Journal of Forecasting* 19(4): 299–311.
— (2008). Using exponentially weighted quantile regression to estimate value at risk and expected shortfall. *Journal of Financial Econometrics* 6(3): 382–406.
Teoh, Stew Hong, Ivo Welch, and T. J. Wong (1998). Earnings management and the long-run market performance of initial public offerings. *Journal of Finance* 53(6): 1935–1974.
Welch, Ivo (1989). Seasoned offerings, imitation costs, and the underpricing of initial public offerings. *Journal of Finance* 44(2): 421–449.
Wooldridge, Jeffrey M. (1995). Score diagnostics for linear models estimated by two stage least squares. In: *Advances in econometrics and quantitative economics: Essays in Honor of Professor C.R. Rao*. Ed. by G.S. Maddala, T.N. Srinivasan, and Peter C.B. Phillips. Oxford: Blackwell, pp. 66–87.
Wu, Congsheng and Chuck C.Y. Kwok (2007). Long-run performance of global versus domestic initial public offerings. *Journal of Banking and Finance* 31(3): 609–627.
Yung, Chris, Gönül Çolak, and Wang Wei (2008). Cycles in the IPO market. *Journal of Financial Economics* 89(1): 192–208.

Table I: Sample Distribution of Initial Public Offerings by Year, 1985–2012

The sample consists of 2,413 U.S. IPOs between 1985 and 2012 with an aggregate gross proceeds of $248.7 billion, identified from Thomson One Banker. Sample observations exclude Real Estate Investment Trusts, American Depository Receipts, Master Limited Partnerships, closed-end funds, unit offers, and issues with an offer price smaller than $5. Column one lists the calendar year. Column two reports the number of IPOs for each calendar year. Column three shows the percentage of IPOs per year with respect to the total number of IPOs in the sample. Column four provides the aggregate IPO gross proceeds in $million per calendar year. Column five shows the percentage of gross proceeds per year with respect to the total gross proceeds of the sample.

Year	Number of IPOs	Number of IPOs in %	Gross Proceeds in $million	Gross Proceeds in %
1985	1	0.04	42.50	0.02
1986	117	4.85	2,368.62	0.95
1987	92	3.81	3,273.19	1.32
1988	35	1.45	1,233.79	0.50
1989	26	1.08	819.89	0.33
1990	11	0.46	613.84	0.25
1991	73	3.03	3,893.98	1.57
1992	140	5.80	6,057.57	2.44
1993	160	6.63	7,749.97	3.12
1994	146	6.05	6,143.17	2.47
1995	175	7.25	9,179.18	3.69
1996	260	10.77	15,943.79	6.41
1997	165	6.84	8,689.90	3.49
1998	125	5.18	12,393.36	4.98
1999	174	7.21	23,222.31	9.34
2000	87	3.61	8,159.08	3.28
2001	32	1.33	3,368.37	1.35
2002	42	1.74	5,755.85	2.31
2003	33	1.37	5,269.29	2.12
2004	96	3.98	15,881.41	6.39
2005	95	3.94	15,831.38	6.37
2006	97	4.02	19,593.49	7.88
2007	84	3.48	21,788.64	8.76
2008	12	0.50	3,689.99	1.48
2009	29	1.20	9,243.18	3.72
2010	54	2.24	7,983.88	3.21
2011	39	1.62	1,2556.52	5.05
2012	13	0.54	17,953.94	7.22
Total	2,413	100.00	248,700.08	100.00

Table II: Sample Distribution of Initial Public Offerings by Industry Classification

Column one lists the industry sector, based on Fama and French's (1997) updated four-digit Industry Classification (SIC) code available from Ken French's web site [`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french`]. Column two reports the number of IPOs for each industry. Column three gives the percentage of the number of IPOs for each industry with respect to the total number of IPOs in the sample. Column four lists the aggregate gross proceeds in $million for each industry. Aggregate gross proceeds exclude funds from overallotment options. Column five reports the percentage of gross proceeds for each industry with respect to the total gross proceeds of the sample.

Industry	Number of IPOs	Number of IPOs in %	Proceeds in $million	Proceeds in %
Agriculture	6	0.25	301.01	0.12
Aircraft	7	0.29	1,570.58	0.63
Apparel	33	1.37	3,319.13	1.33
Automobiles and Trucks	32	1.33	3,788.56	1.52
Banking	79	3.27	10,368.63	4.17
Beer & Liquor	8	0.33	279.83	0.11
Business Services	180	7.46	14,532.56	5.84
Business Supplies	9	0.37	579.02	0.23
Candy & Soda	3	0.12	232.92	0.09
Chemicals	22	0.91	4,280.76	1.72
Coal	7	0.29	2,397.70	0.96
Communication	90	3.73	15,529.99	6.24
Computer Hardware	70	2.90	3,745.04	1.51
Computer Software	359	14.88	42,379.70	17.04
Construction	23	0.95	1,000.80	0.40
Construction Materials	27	1.12	1,502.30	0.60
Consumer Goods	31	1.28	1,816.44	0.73
Electrical Equipment	18	0.75	1,733.03	0.70
Electronic Equipment	142	5.88	9,888.80	3.98
Entertainment	39	1.62	5,156.16	2.07
Fabricated Products	2	0.08	224.35	0.09
Food Products	36	1.49	3,276.55	1.32
Healthcare	64	2.65	3,937.48	1.58
Insurance	61	2.53	7,823.71	3.15
Machinery	61	2.53	4,829.13	1.94
Measuring and Control Equipment	53	2.20	2,193.07	0.88
Medical Equipment	89	3.69	4,697.11	1.89
Non-Metallic and Industrial Metal Mining	6	0.25	1,483.67	0.60
Other	25	1.04	2,784.81	1.12
Personal Services	33	1.37	3,244.96	1.30
Petroleum and Natural Gas	73	3.03	11,996.46	4.82
Pharmaceutical Products	127	5.26	8,197.54	3.30
Precious Metals	2	0.08	215.50	0.09
Printing and Publishing	10	0.41	1,859.32	0.75
Real Estate	10	0.41	568.25	0.23
Recreation	24	0.99	924.02	0.37
Restaurants, Hotels, Motels	50	2.07	4,298.20	1.73
Retail	197	8.16	13,677.14	5.50
Rubber and Plastic Products	20	0.83	944.43	0.38
Shipbuilding and Railroad Equipment	6	0.25	483.00	0.19
Shipping Containers	5	0.21	718.03	0.29
Steel Works etc.	35	1.45	3,654.55	1.47
Textiles	15	0.62	593.60	0.24
Tobacco Products	3	0.12	290.80	0.12
Trading	53	2.20	18,744.00	7.54
Transportation	58	2.40	8,345.70	3.36
Utilities	17	0.70	8,029.65	3.23
Wholesale	93	3.85	6,262.09	2.52
Total	2,413	100.00	248,700.08	100.00

Table III: Variable Definitions and Data Sources

Column one reports variable labels. Column two provides details on the definition and measurement of variables. *Thomson* refers to the New Issues database in Thomson One Banker. *Compustat* refers to Standard and Poor's database and provides financial statement data. *CRSP* denotes the Center for Research in Security Prices and provides stock market data. *Ritter* refers to Jay Ritter's web site [http://bear.warrington.ufl.edu/ritter] which provides information on underwriter tombstone rankings which is the proxy measure for reputation. Panel A lists variables on downside risk. Panel B provides the definition on initial return. Panel C reports spread based liquidity measures. Panel D shows price impact based liquidity measures. Panel E provides trading volume related liquidity measures. Panel F includes third-party certification variables. Panel G lists variables on ex-ante uncertainty surrounding an IPO and corresponding deal characteristics. Panel H provides variables on stock market conditions. Panel I lists Koop and Li's (2001) industry sector classification.

Variable	Definition and data sources
	Panel A
VaR	Value-at-risk is the maximum loss of stock i over period m that can occur at confidence level $c = \{0.95, 0.99\}$. Confidence levels reflect those used by RiskMetrics ($c = 95\%$) and Basel Accords ($c = 99\%$). Daily stock returns for a minimum period of $m = 150$ days and a maximum period of $m = 6$ months are from $CRSP$. Section 3 provides more details on the calculations.
CVaR	Conditional value-at-risk is the loss beyond the VaR threshold of an individual stock at confidence level $c = \{0.95, 0.99\}$. Confidence levels reflect those used by RiskMetrics ($c = 95\%$) and Basel Accords ($c = 99\%$). Daily stock returns for a minimum period of $m = 150$ days and a maximum period of $m = 6$ months are from $CRSP$. Section 3 provides more details on the calculations.
	Panel B
InitRtn	Initial return: $InitRtn = P_i/OP_i - 1$, where P is the closing price of stock i at the end of the first day of trading from $CRSP$, and OP is the offer price from $Thomson$.
	Panel C
QuotedSp	Average proportional quoted spread is the difference between the closing quoted ask price and the quoted bid price divided by the quote midpoint price: $$Quoted\ Spread_{i,m} = \frac{1}{D_{i,m}} \sum_{d=1}^{D} \frac{Ask_{i,m,d} - Bid_{i,m,d}}{(Ask_{i,m,d} + Bid_{i,m,d})/2} \quad (6)$$ where D is the total number of days d for which trading data are available for stock i over a period of $m = 6$ months post-IPO, $Ask_{i,m,d}$ is the closing ask quote, $Bid_{i,m,d}$ is the closing bid quote. Bid and ask price data are available from $CRSP$.
RealSp	Average proportional realised spread is twice the absolute value of the difference between the most recent transaction price (i.e. the closing price) and the quote midpoint prevailing after the trade divided by the quote midpoint price: $$Realised\ Spread_{i,m} = \frac{1}{D_{i,m}} \sum_{d=1}^{D} \frac{2 \times \lvert P_{i,m,d} - ((Ask_{i,m,d} + Bid_{i,m,d})/2)\rvert}{(Ask_{i,m,d} + Bid_{i,m,d})/2} \quad (7)$$ where D is the total number of days d for which trading data are available for stock i over a period of $m = 6$ months post-IPO, $Ask_{i,m,d}$ is the closing ask quote, $Bid_{i,m,d}$ is the closing bid quote. Price data are available from $CRSP$.
	Panel D
Kyle λ	Kyle's (1985) proportional λ measures the extent to which order flow impacts on prices: $$Kyle's\ \lambda_{i,m} = \frac{0.5 \times (\sigma^2_{\mu,i,m}/\Sigma_{O,i,m})^{-0.5}}{P_{\mu,i,m}} \quad (8)$$ where $\sigma^2_{\mu,i,m}$ is the variance of daily trading volume, $\Sigma_{O,i,m}$ is the variance of daily closing prices, and $P_{\mu,i,m}$ is the mean closing price of stock i over period $m = 6$ months after the offering. Trading volume and price data are available from $CRSP$.
Kyle λ CN	Kyle's (1985) proportional λ adjusted for the number of shares outstanding: $$CN_{i,m} = \lambda_{i,m} \times N_{\mu,i,m} \quad (9)$$ where $\lambda_{i,m}$ is Kyle's (1985) proportional measure of liquidity and $N_{\mu,i,m}$ is the mean number of shares outstanding for stock i over period $m = 6$ months. Number of shares outstanding and price data are available from $CRSP$.
Kyle λ CQ	Kyle's (1985) proportional λ adjusted for the number of trades: $$CQ_{i,m} = \lambda_{i,m} \times Q_{\mu,i,m} \quad (10)$$ where $\lambda_{i,m}$ is Kyle's (1985) proportional measure of liquidity and $Q_{\mu,i,m}$ is the mean number of shares traded for stock i over period $m = 6$ months. Number of shares traded and price data are available from $CRSP$.

Table III — *Continued*

Variable	Definition and data sources
	Panel E
Illiquidity	Average ratio of absolute daily returns to the (dollar) trading volume on that day: $$Illiq_{i,m} = \frac{1}{D_{i,m}} \sum_{d=1}^{D} \frac{\lvert r_{i,m,d} \rvert}{VOLD_{i,m,d}} \quad (11)$$ where D is the number of days for which data are available for stock i in period $m = 6$ months, $r_{i,m,d}$ is the return on stock and $VOLD_{i,m,d}$ is the respective daily trading volume in dollars. Return data and trading volume are available from *CRSP*.
Turnover	Average number of shares traded daily: $$Turnover_{i,m} = \frac{1}{D_{i,m}} \sum_{d=1}^{D} \frac{Q_{i,m,d}}{N_{i,m,d}} \quad (12)$$ where D is the number of days for which data are available for stock i in period $m = 6$ months, $Q_{i,m,d}$ is the number of shares traded, $N_{i,m,d}$ is the respective number of shares outstanding. Data on Q and N are available from *CRSP*.
	Panel F
UwRank	Average underwriter reputation rank is the Loughran and Ritter (2004) update of the Carter and Manaster (1990) measures ranging from zero for lowest quality to 9.1 for highest quality underwriters and is available from *Ritter*.
NumUw	Number of underwriters in a syndicate, including lead manager, co-managers and members of the syndicate that are involved in the distribution and sales of IPO sales. Data are available from *Thomson*.
VC-backed	Dummy variable coded one if pre-IPO venture capitalists retain a stake in the post-IPO firm, else coded zero. *Thomson* discloses if an IPO has VC-backing.
	Panel G
EBITDA	Earnings before interest, tax, depreciation, and amortization in \$million in the accounting period before flotation available from *Thomson*. *Compustat* is the secondary data source for those observations with missing values in *Thomson*.
EBITDA Dum	Dummy variable, coded one if EBITDA is negative in the accounting period before flotation.
Assets	Total assets at book value in \$million in the accounting period before flotation available from *Compustat*.
Leverage	Long-term debt divided by total assets at book value in the accounting period before flotation available from *Compustat*.
Sales	Sales in \$million for the last full fiscal year prior to flotation available from *Thomson*. *Compustat* is the secondary data source for those observations with missing values in *Thomson*.
Age	Age of firm in years between foundation date and date of flotation available from *Ritter*. *Compustat* is the secondary data source for those observations with missing values from *Ritter*.
$\widehat{\alpha}$	Leland and Pyle's (1977) signal of equity retained: $\widehat{\alpha} = EqRet + \log(1 - EqRet)$, where $EqRet$ is the proportion of equity retained by pre-IPO shareholders in the post-IPO firm available from *Thomson*.
Omega	Fraction of primary shares in relation to total shares offered in IPO available from *Thomson*.
OfferPrice	Offer (subscription) price per share in \$ is available from *Thomson*.
Use	Number of uses of IPO proceeds disclosed in the prospectus available from *Thomson*.
Lock-in	Dummy variable coded one if the prospectus discloses a 'lock-in' agreement, else coded zero. *Thomson* indicates the presence of a lock-in agreement.
Offer size	Amount of primary plus secondary money raised in \$million available from *Thomson*.
AboDum	Dummy variable coded one if the final offer price is above the initial filing price range, else coded zero. Data on filing price ranges are available from *Thomson*.
BelDum	Dummy variable coded one if the final offer price is below the initial filing price range, else coded zero. Data on filing price ranges are available from *Thomson*.

Table III — *Continued*

Variable	Definition and data sources
	Panel H
MktRet	Cumulative contemporaneous value-weighted NYSE/AMEX/Nasdaq index covers a maximum of six months post-offering for which data are available from *CRSP*.
MktRisk	Variance of the value-weighted NYSE/AMEX/Nasdaq index covers a maximum of six months post-offering for which data are available from *CRSP*.
Nasdaq	Dummy variable coded one if a firm lists IPO to trade on Nasdaq, else coded zero. Details on stock markets are available from *Thomson*.
Monday	Dummy variable coded one if the offering and first aftermarket trade is on a Monday, else coded zero. Dates are available from *Thomson* and *CRSP*.
Nasdaq Ref	Dummy variable coded one if an IPO occurs after January 1, 1997 to capture the Nasdaq reform in the order handling rules and subsequent decimalization, else coded zero. Dates are available from *Thomson* and *CRSP*.
MktBubble	Dummy variable coded one to capture the 1999−2000 IPO bubble years, else coded zero. Dates are available from *Thomson* and *CRSP*.
HotMkt	Dummy variable coded one if the average initial return in a quarter is 50% greater than the three-monthly moving average, else coded zero. Aggregate IPO data are available from *Ritter*.
ColdMkt	Dummy variable coded one if the average initial return in a quarter is 50% smaller than the three-monthly moving average, else coded zero. Aggregate IPO data are available from *Ritter*.
	Panel I
OilGas	Dummy variable coded one if an IPO belongs to the oil and gas industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
ChemProd	Dummy variable coded one if an IPO belongs to the chemical products industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
Manuf	Dummy variable coded one if an IPO belongs to the manufacturing industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
Computers	Dummy variable coded one if an IPO belongs to the computers industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
ElectEq	Dummy variable coded one if an IPO belongs to the electronic equipment industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
Transp	Dummy variable coded one if an IPO belongs to the transportation industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
ScientifInst	Dummy variable coded one if an IPO belongs to the scientific instruments industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
Communic	Dummy variable coded one if an IPO belongs to the communication industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
Utilities	Dummy variable coded one if an IPO belongs to the utilities industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
Retail	Dummy variable coded one if an IPO belongs to the retail industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
FinServ	Dummy variable coded one if an IPO belongs to the financial services industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.
Health	Dummy variable coded one if an IPO belongs to the health industry sector, else coded zero. Industry membership uses the classification of Koop and Li (2001), based on SIC available from *Thomson*.

Table IV: Descriptive Statistics on Initial Public Offerings, 1980–2012

VaR is the value-at-risk for confidence levels $c = \{0.95, 0.99\}$. $CVaR$ is the conditional value at risk for confidence levels $c = \{0.95, 0.99\}$. $InitRtn$ is the return after the first day of trading. $QuotedSp$ is the average proportional quoted spread. $RealSp$ is the average proportional realised spread. $Kyle\ \lambda$ is Kyle's (1985) measure of the extent to which order flow impacts on prices. $Kyle\ \lambda\ CN$ is Kyle's (1985) proportional λ adjusted for the number of shares outstanding and closing prices. $Kyle\ \lambda\ CQ$ is Kyle's (1985) proportional λ adjusted for the number of trades and closing prices. $Illiquidity$ is the average ratio of absolute daily returns to trading volume. $Turnover$ is the average number of shares traded. $UwRank$ measures underwriter reputation. $NumUw$ is the number of underwriters in the IPO. $VC-backed$ indicates venture capital backed IPO. $EBITDA$ are earnings before interest, tax, depreciation, and amortization. $EBITDADum$ is a dummy variable, coded one if $EBITDA$ is negative. $Assets$ are assets at book value. $Leverage$ is long-term debt divided by total assets. $Sales$ is annual sales. Age is firm age. $\hat{\alpha}$ is Leland and Pyle's (1977) signal of equity retained. $Omega$ is the fraction of primary shares offered. $OfferPrice$ is the offer price. Use is the number of uses of proceeds. $Lock-in$ indicates the presence of a lock-in period. $OfferSize$ is the amount of primary and secondary money raised. $AboDum$ indicates if $OfferPrice$ is above the initial filing price range. $BelDum$ indicates if $OfferPrice$ is below the initial filing price range. $MktRet$ is the cumulative NYSE/AMEX/Nasdaq index return. $MktRisk$ is the variance of $MktRet$. $Nasdaq$ indicates if an IPO is a Nasdaq issue. $Monday$ indicates if an IPO is issued or started trading on a Monday. $NasdaqRef$ indicates if an IPO is issued after January 1997. $MktBubble$ indicates if an IPO is issued during the bubble period. $HotMkt$ indicates if an IPO is issued during a hot new issue period. $ColdMkt$ indicates if an IPO is issued during a cold new issue period. Industry sector dummy variables capture differences in the cost of capital and business risk across industry sectors based on Koop and Li's (2001) 12-industry sector classification: $OilGas$ is oil and gas, $ChemProd$ is chemical products, $Manuf$ is manufacturing, $Computers$ is computers, $ElectEq$ is electronic equipment, $Transp$ is transportation, $ScientifInst$ is scientific instruments, $Communic$ is communication, $Utilities$ is utilities, $Retail$ is retail, $FinServ$ is financial services, $Health$ is health. Details on variable definitions are available from Table III.

Variable	Observations	Unit	1st Quartile	Median	Mean	3rd Quartile	Std. Dev.	Skewness	Kurtosis
$VaR_{0.95}$	2,413		0.0406	0.0542	0.0598	0.0729	0.0274	1.2192	4.8672
$VaR_{0.99}$	2,413		0.0638	0.0866	0.0974	0.1219	0.0470	1.2304	5.0912
$CVaR_{0.95}$	2,413		0.0556	0.0751	0.0842	0.1045	0.0399	1.2057	4.9278
$CVaR_{0.99}$	2,413		0.0759	0.1075	0.1265	0.1567	0.0726	1.5494	6.2124
InitRtn	2,413		0.0000	0.0804	0.1961	0.2300	0.4415	5.5829	48.2932
QuotedSp	2,286		0.0085	0.0217	0.0261	0.0367	0.0224	2.0303	11.8246
RealSp	2,286		0.0066	0.0160	0.0197	0.0287	0.0159	1.4385	6.3685
Kyle λ	2,409	Kyle $\lambda \times 10^6$	0.3465	0.7030	1.2356	1.3057	2.0832	6.9368	73.7667
Kyle λ CN	2,409		5.1447	8.6150	11.7674	14.4706	11.9317	5.5358	66.2523
Kyle λ CQ	2,409		0.0306	0.0485	0.0627	0.0790	0.0485	2.1505	9.6609
Illiquidity	2,413	Illiquidity$\times 10^6$	0.0169	0.0786	0.5092	0.3461	1.5587	8.8401	117.0808
Turnover	2,413		0.0036	0.0059	0.0076	0.0091	0.0078	7.3446	105.1255
UwRank	2,413		7.0010	8.0010	7.6878	9.0010	1.6698	−1.8808	6.4525
NumUw	2,413	Integer	1	1	1.2254	1	0.6739	4.4168	29.3229
VC-backed	2,413	Zero-one dummy	0	0	0.1289	0	0.3351	2.2179	5.9191
EBITDA	2,413	\$million	0.5610	5.5750	42.3055	21.4520	384.7985	37.4343	1,622.3410
EBITDADum	2,413	Zero-one dummy	0	0	0.2292	0	0.4204	1.2903	2.6663
Assets	2,413	\$million	15.8390	41.7680	480.6342	179.1660	4,766.1880	39.7575	1,786.2260
Leverage	2,413		0.0449	0.2010	0.2686	0.4379	0.2513	0.8641	2.8034
Sales	2,413	\$million	18.1210	51.3500	281.7479	167.4510	1,119.5640	13.2312	235.8592
Age	2,413	Years	5	10	18.6867	20	23.2708	2.3782	8.8852
$\hat{\alpha}$	2,413		−0.7360	−0.5226	−0.5816	−0.3526	0.3674	−1.8930	11.0592
Omega	2,413		0.7773	1.0000	0.8664	1.0000	0.2172	−2.0351	7.2879
OfferPrice	2,413	\$	10.0000	13.0000	13.5279	16.0000	5.6709	3.5535	39.8180
Use	2,413		1	2	2.2586	3	1.7965	1.5014	4.9651
Lock-in	2,413	Zero-one dummy	1	1	0.7584	1	0.4281	−1.2088	2.4626
OfferSize	2,413	\$million	22.9500	45.0000	110.1034	97.7500	406.9870	27.1196	990.0332

Table IV — *Continued*

Variable	Observations	Unit	1st Quartile	Median	Mean	3rd Quartile	Std. Dev.	Skewness	Kurtosis
AboDum	2,413	Zero-one dummy	0	0	0.1774	0	0.3821	1.6913	3.8615
BelDum	2,413	Zero-one dummy	0	0	0.1720	0	0.3774	1.7406	4.0305
MktRtn	2,413		0.0166	0.0670	0.0585	0.1143	0.0883	-0.9031	5.1473
MktRisk	2,413	MktRisk$\times 10^3$	0.0379	0.0570	0.1005	0.1252	0.1121	3.2110	18.3771
Nasdaq	2,413	Zero-one dummy	1	1	0.7725	1	0.4193	-1.3015	2.6954
Monday	2,413	Zero-one dummy	0	0	0.0953	0	0.2937	2.7596	8.6145
NasdaqRef	2,413	Zero-one dummy	0	0	0.4849	1	0.4999	0.0606	1.0057
MktBubble	2,413	Zero-one dummy	0	0	0.1082	0	0.3107	2.5263	7.3818
HotMkt	2,413	Zero-one dummy	0	0	0.0431	0	0.2031	4.5053	21.2911
ColdMkt	2,413	Zero-one dummy	0	0	0.0199	0	0.1397	6.8854	48.3913
OilGas	2,413	Zero-one dummy	0	0	0.0303	0	0.1713	5.4919	31.1505
ChemProd	2,413	Zero-one dummy	0	0	0.0634	0	0.2437	3.5876	13.8677
Manufact	2,413	Zero-one dummy	0	0	0.0352	0	0.1844	5.0486	26.4796
Computers	2,413	Zero-one dummy	0	0	0.2445	0	0.4299	1.1904	2.4185
ElectEq	2,413	Zero-one dummy	0	0	0.0717	0	0.2580	3.3246	12.0502
Transp	2,413	Zero-one dummy	0	0	0.0477	0	0.2131	4.2518	19.0721
ScientifInst	2,413	Zero-one dummy	0	0	0.0622	0	0.2415	3.6312	14.1823
Comunic	2,413	Zero-one dummy	0	0	0.0373	0	0.1895	4.8897	24.9014
Utilities	2,413	Zero-one dummy	0	0	0.0174	0	0.1308	7.3896	55.5852
Retail	2,413	Zero-one dummy	0	0	0.0688	0	0.2532	3.4116	12.6362
FinServ	2,413	Zero-one dummy	0	0	0.0841	0	0.2776	3.0002	9.9993
Health	2,413	Zero-one dummy	0	0	0.0265	0	0.1607	5.9006	35.8045

Table V: Initial Return, Liquidity and Vaule-at-Risk for Confidence Level $c = 0.95$

VaR is the value-at-risk for confidence level $c = 0.95$. $InitRtn$ is the return after the first day of trading. $QuotedSp$ is the average proportional quoted spread. $RealSp$ is the average proportional realised spread. $Kyle\ \lambda$ is Kyle's (1985) measure of the extent to which order flow impacts on prices. $Kyle\ \lambda\ CN$ is Kyle's (1985) proportional λ adjusted for the number of shares outstanding and closing prices. $Kyle\ \lambda\ CQ$ is Kyle's (1985) proportional λ adjusted for the number of trades and closing prices. $Illiquidity$ is the average ratio of absolute daily returns to trading volume. $Turnover$ is the average number of shares traded. $UwRank$ measures underwriter reputation. $NumUw$ is the number of underwriters in the IPO. $VC-backed$ indicates venture capital backed IPO. $EBITDA$ are earnings before interest, tax, depreciation, and amortization. $EBITDADum$ is a dummy variable, coded one if $EBITDA$ is negative. $Assets$ are assets at book value. $Leverage$ is long-term debt divided by total assets. $Sales$ is annual sales. Age is firm age. $\hat{\alpha}$ is Leland and Pyle's (1977) signal of equity retained. $Omega$ is the fraction of primary shares offered. $OfferPrice$ is the offer price. Use is the number of uses of proceeds. $Lock-in$ indicates the presence of a lock-in period. $OfferSize$ is the amount of primary and secondary money raised. $AboDum$ indicates if $OfferPrice$ is above the initial filing price range. $BelDum$ indicates if $OfferPrice$ is below the initial filing price range. $MktRet$ is the cumulative NYSE/AMEX/Nasdaq index return. $MktRisk$ is the variance of $MktRet$. $Nasdaq$ indicates if an IPO is a Nasdaq issue. $Monday$ indicates if an IPO is issued or started trading on a Monday. $NasdaqRef$ indicates if an IPO is issued after January 1997. $MktBubble$ indicates if an IPO is issued during the bubble period. $HotMkt$ indicates if an IPO is issued during a hot new issue period. $ColdMkt$ indicates if an IPO is issued during a cold new issue period. Industry sector dummy variables capture differences in the cost of capital and business risk across industry sectors based on Koop and Li's (2001) 12-industry sector classification: $OilGas$ is oil and gas, $ChemProd$ is chemical products, $Manuf$ is manufacturing, $Computers$ is computers, $ElectEq$ is electronic equipment, $Transp$ is transportation, $ScientifInst$ is scientific instruments, $Communic$ is communication, $Utilities$ is utilities, $Retail$ is retail, $FinServ$ is financial services, $Health$ is health. Details on variable definitions are available from Table III. ***, **, * denote 1%, 5%, and 10% significance, respectively.

	$VaR_{0.95}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InitRtn	0.0065***							
	(0.0012)							
QuotedSp		0.5475***						
		(0.0513)						
RealSp			0.9458***					
			(0.0372)					
Kyle λ				0.0007*				
				(0.0004)				
Kyle λ CN					0.0003***			
					(0.0001)			
Kyle λ CQ						0.1766***		
						(0.0110)		
Illiquidity							0.0030***	
							(0.0005)	
Turnover								0.4214***
								(0.0854)
UwRank	−0.0005	0.0003	0.0004*	−0.0004	−0.0005*	−0.0006**	−0.0002	−0.0004
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
NumUw	−0.0005	−0.0005	−0.0019***	−0.0006	−0.0002	−0.0005	−0.0009	−0.0008
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
VC-backed	0.0005	0.0004	−0.0001	0.0003	0.0002	0.0001	0.0004	0.0010
	(0.0011)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0011)
log(EBITDA)	−0.0009*	−0.0016***	−0.0020***	−0.0010*	−0.0010*	−0.0005	−0.0013**	−0.0010*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
EBITDADum	0.0158***	0.0197***	0.0221***	0.0165***	0.0163***	0.0107***	0.0182***	0.0168***
	(0.0038)	(0.0038)	(0.0036)	(0.0040)	(0.0039)	(0.0035)	(0.0039)	(0.0039)
log(Assets)	−0.0028***	−0.0027***	−0.0025***	−0.0031***	−0.0033***	−0.0026***	−0.0031***	−0.0025***
	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
log(Leverage)	−0.0003	−0.0005**	−0.0005**	−0.0004	−0.0004	−0.0001	−0.0005**	−0.0002
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)

Table V — *Continued*

	$VaR_{0.95}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Sales)	−0.0003	−0.0004	−0.0003	−0.0003	−0.0002	−0.0001	−0.0002	−0.0005
	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
log(Age)	−0.0001	−0.0005	-0.0006^{*}	−0.0002	−0.0003	−0.0001	−0.0001	−0.00002
	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
$\hat{\alpha}$	-0.0043^{***}	-0.0071^{***}	-0.0072^{***}	-0.0054^{***}	-0.0027^{**}	-0.0026^{**}	-0.0054^{***}	-0.0056^{***}
	(0.0011)	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0010)	(0.0012)	(0.0012)
Omega	0.0059^{***}	0.0052^{***}	0.0062^{***}	0.0061^{***}	0.0061^{***}	0.0051^{***}	0.0065^{***}	0.0057^{***}
	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0013)	(0.0014)	(0.0014)
log(OfferPrice)	-0.0105^{***}	-0.0053^{***}	-0.0040^{***}	-0.0096^{***}	-0.0080^{***}	-0.0083^{***}	-0.0085^{***}	-0.0104^{***}
	(0.0017)	(0.0016)	(0.0016)	(0.0017)	(0.0017)	(0.0015)	(0.0017)	(0.0018)
log(1+Use)	-0.0036^{***}	−0.0015	-0.0017^{*}	-0.0042^{***}	-0.0043^{***}	-0.0036^{***}	-0.0042^{***}	-0.0035^{***}
	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)
Lock-in	0.0051^{***}	0.0038^{***}	0.0036^{***}	0.0051^{***}	0.0047^{***}	0.0036^{***}	0.0055^{***}	0.0045^{***}
	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)
log(OfferSize)	0.0037^{***}	0.0074^{***}	0.0083^{***}	0.0047^{***}	0.0042^{***}	0.0022^{***}	0.0054^{***}	0.0029^{***}
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0007)	(0.0008)	(0.0008)
AboDum	0.0021^{**}	0.0039^{***}	0.0041^{***}	0.0033^{***}	0.0036^{***}	0.0023^{**}	0.0032^{***}	0.0032^{***}
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0011)
BelDum	−0.0008	-0.0022^{**}	−0.0014	−0.0013	-0.0018^{*}	−0.0012	-0.0017^{*}	−0.0009
	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
MktRtn	-0.0339^{***}	-0.0296^{***}	-0.0240^{***}	-0.0339^{***}	-0.0328^{***}	-0.0387^{***}	-0.0299^{***}	-0.0364^{***}
	(0.0057)	(0.0054)	(0.0051)	(0.0057)	(0.0056)	(0.0050)	(0.0055)	(0.0056)
MktRisk	0.0670^{***}	0.0564^{***}	0.0534^{***}	0.0622^{***}	0.0582^{***}	0.0477^{***}	0.0603^{***}	0.0659^{***}
	(0.0060)	(0.0053)	(0.0050)	(0.0060)	(0.0061)	(0.0055)	(0.0056)	(0.0059)
Nasdaq	0.0079^{***}	0.0089^{***}	0.0015	0.0089^{***}	0.0099^{***}	0.0078^{***}	0.0084^{***}	0.0068^{***}
	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0008)	(0.0009)	(0.0009)
Monday	0.0029^{**}	0.0024^{**}	0.0018	0.0029^{**}	0.0029^{**}	0.0031^{***}	0.0031^{**}	0.0030^{**}
	(0.0013)	(0.0012)	(0.0011)	(0.0013)	(0.0013)	(0.0012)	(0.0013)	(0.0013)
NasdaqRef	-0.0049^{***}	0.0045^{***}	0.0070^{***}	-0.0041^{***}	-0.0040^{***}	-0.0037^{***}	-0.0039^{***}	-0.0046^{***}
	(0.0011)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0011)
MktBubble	0.0289^{***}	0.0291^{***}	0.0282^{***}	0.0307^{***}	0.0305^{***}	0.0234^{***}	0.0312^{***}	0.0292^{***}
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0016)	(0.0018)	(0.0019)

Table V — *Continued*

	VaR$_{0.95}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HotMkt	0.0023	0.0035*	0.0032*	0.0030	0.0027	0.0019	0.0031*	0.0031*
	(0.0018)	(0.0018)	(0.0017)	(0.0019)	(0.0018)	(0.0017)	(0.0018)	(0.0018)
ColdMkt	0.0054*	0.0030	0.0035	0.0052*	0.0058*	0.0057**	0.0057*	0.0052*
	(0.0031)	(0.0028)	(0.0027)	(0.0030)	(0.0030)	(0.0026)	(0.0030)	(0.0030)
OilGas	−0.0017	−0.0008	−0.0019	−0.0022	−0.0024	−0.0031*	−0.0020	−0.0016
	(0.0020)	(0.0020)	(0.0019)	(0.0020)	(0.0020)	(0.0018)	(0.0020)	(0.0020)
ChemProd	−0.0012	−0.0017	−0.0020	−0.0021	−0.0025	−0.0004	−0.0022	−0.0010
	(0.0018)	(0.0017)	(0.0016)	(0.0018)	(0.0018)	(0.0017)	(0.0018)	(0.0018)
Manuf	0.0008	0.0026*	0.0032**	0.0016	0.0016	0.0012	0.0020	0.0012
	(0.0018)	(0.0015)	(0.0014)	(0.0018)	(0.0018)	(0.0017)	(0.0017)	(0.0018)
Computers	0.0049***	0.0071***	0.0070***	0.0054***	0.0054***	0.0031***	0.0060***	0.0049***
	(0.0012)	(0.0010)	(0.0010)	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0012)
ElectEq	0.0073***	0.0093***	0.0089***	0.0075***	0.0079***	0.0051***	0.0077***	0.0070***
	(0.0017)	(0.0015)	(0.0015)	(0.0017)	(0.0017)	(0.0016)	(0.0016)	(0.0017)
Transp	−0.0013	0.0008	0.0004	−0.0012	−0.0009	−0.0010	−0.0007	−0.0013
	(0.0015)	(0.0014)	(0.0013)	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0015)
ScientificInst	0.0017	0.0021	0.0021	0.0016	0.0016	0.0022	0.0018	0.0020
	(0.0017)	(0.0016)	(0.0016)	(0.0018)	(0.0017)	(0.0016)	(0.0017)	(0.0017)
Communic	0.0007	−0.0013	−0.0025	−0.0003	0.0009	0.0011	−0.0010	−0.0007
	(0.0020)	(0.0018)	(0.0017)	(0.0021)	(0.0020)	(0.0019)	(0.0020)	(0.0020)
Utilities	−0.0084***	−0.0068***	−0.0079***	−0.0086***	−0.0084***	−0.0072***	−0.0076***	−0.0083***
	(0.0022)	(0.0018)	(0.0018)	(0.0022)	(0.0022)	(0.0021)	(0.0021)	(0.0022)
Retail	0.0016	0.0050***	0.0045***	0.0014	0.0015	−0.0002	0.0023*	0.0013
	(0.0014)	(0.0013)	(0.0012)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
FinServ	−0.0023	−0.0018	−0.0021	−0.0022	−0.0020	−0.0013	−0.0022	−0.0019
	(0.0016)	(0.0015)	(0.0014)	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0016)
Health	−0.0018	−0.0003	−0.00003	−0.0017	−0.0019	−0.0022	−0.0011	−0.0016
	(0.0021)	(0.0018)	(0.0018)	(0.0021)	(0.0021)	(0.0019)	(0.0020)	(0.0020)
Constant	0.0653***	0.0126**	0.0078*	0.0597***	0.0579***	0.0608***	0.0512***	0.0658***
	(0.0042)	(0.0055)	(0.0043)	(0.0048)	(0.0044)	(0.0040)	(0.0044)	(0.0044)
Observations	2,413	2,286	2,286	2,409	2,409	2,409	2,413	2,413
Adjusted R^2	0.6022	0.6819	0.7078	0.5956	0.6026	0.6578	0.6178	0.6056
F Statistic	97.0901***	129.9146***	146.6713***	94.3250***	97.1065***	122.8335***	103.5879***	98.4576***

Table VI: Initial Return, Liquidity and Vaule-at-Risk for Confidence Level $c = 0.99$

VaR is the value-at-risk for confidence level $c = 0.95$. $InitRtn$ is the return after the first day of trading. $QuotedSp$ is the average proportional quoted spread. $RealSp$ is the average proportional realised spread. $Kyle\ \lambda$ is Kyle's (1985) measure of the extent to which order flow impacts on prices. $Kyle\ \lambda\ CN$ is Kyle's (1985) proportional λ adjusted for the number of shares outstanding and closing prices. $Kyle\ \lambda\ CQ$ is Kyle's (1985) proportional λ adjusted for the number of trades and closing prices. $Illiquidity$ is the average ratio of absolute daily returns to trading volume. $Turnover$ is the average number of shares traded. $UwRank$ measures underwriter reputation. $NumUw$ is the number of underwriters in the IPO. $VC-backed$ indicates venture capital backed IPO. $EBITDA$ are earnings before interest, tax, depreciation, and amortization. $EBITDADum$ is a dummy variable, coded one if $EBITDA$ is negative. $Assets$ are assets at book value. $Leverage$ is long-term debt divided by total assets. $Sales$ is annual sales. Age is firm age. $\hat{\alpha}$ is Leland and Pyle's (1977) signal of equity retained. $Omega$ is the fraction of primary shares offered. $OfferPrice$ is the offer price. Use is the number of uses of proceeds. $Lock-in$ indicates the presence of a lock-in period. $OfferSize$ is the amount of primary and secondary money raised. $AboDum$ indicates if $OfferPrice$ is above the initial filing price range. $BelDum$ indicates if $OfferPrice$ is below the initial filing price range. $MktRet$ is the cumulative NYSE/AMEX/Nasdaq index return. $MktRisk$ is the variance of $MktRet$. $Nasdaq$ indicates if an IPO is a Nasdaq issue. $Monday$ indicates if an IPO is issued or started trading on a Monday. $NasdaqRef$ indicates if an IPO is issued after January 1997. $MktBubble$ indicates if an IPO is issued during the bubble period. $HotMkt$ indicates if an IPO is issued during a hot new issue period. $ColdMkt$ indicates if an IPO is issued during a cold new issue period. Industry sector dummy variables capture differences in the cost of capital and business risk across industry sectors based on Koop and Li's (2001) 12-industry sector classification: $OilGas$ is oil and gas, $ChemProd$ is chemical products, $Manuf$ is manufacturing, $Computers$ is computers, $ElectEq$ is electronic equipment, $Transp$ is transportation, $ScientifInst$ is scientific instruments, $Communic$ is communication, $Utilities$ is utilities, $Retail$ is retail, $FinServ$ is financial services, $Health$ is health. Details on variable definitions are available from Table III. ***, **, * denote 1%, 5%, and 10% significance, respectively. Significance levels are adjusted for robust standard errors.

	$VaR_{0.95}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InitRtn	0.0077***							
	(0.0023)							
QuotedSp		0.7719***						
		(0.0793)						
RealSp			1.2794***					
			(0.0757)					
Kyle λ				0.0016**				
				(0.0007)				
Kyle λ CN					0.0004***			
					(0.0001)			
Kyle λ CQ						0.2923***		
						(0.0212)		
Illiquidity							0.0039***	
							(0.0008)	
Turnover								0.6581***
								(0.1556)
UwRank	0.0001	0.0013**	0.0014***	0.0003	0.00005	0.000001	0.0005	0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
NumUw	−0.0019	−0.0022**	−0.0041***	−0.0022*	−0.0014	−0.0020*	−0.0024**	−0.0024**
	(0.0012)	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0010)	(0.0012)	(0.0010)
VC-backed	0.0019	0.0013	0.0006	0.0016	0.0015	0.0013	0.0018	0.0027
	(0.0019)	(0.0018)	(0.0018)	(0.0020)	(0.0019)	(0.0018)	(0.0019)	(0.0019)
log(EBITDA)	−0.0020**	−0.0029***	−0.0035***	−0.0021**	−0.0022**	−0.0013	−0.0025***	−0.0021**
	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
EBITDADum	0.0290***	0.0341***	0.0371***	0.0296***	0.0295***	0.0201***	0.0320***	0.0301***
	(0.0070)	(0.0070)	(0.0070)	(0.0071)	(0.0070)	(0.0064)	(0.0071)	(0.0070)
log(Assets)	−0.0056***	−0.0052***	−0.0051***	−0.0060***	−0.0064***	−0.0051***	−0.0059***	−0.0050***
	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0010)
log(Leverage)	−0.0003	−0.0007	−0.0006	−0.0004	−0.0004	0.0001	−0.0005	−0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)

Table VI — *Continued*

	$\text{VaR}_{0.99}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Sales)	0.0007	0.0005	0.0006	0.0007	0.0010	0.0010	0.0008	0.0004
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
log(Age)	−0.0008	−0.0014**	−0.0014**	−0.0010	−0.0011	−0.0008	−0.0008	−0.0007
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0007)
$\hat{\alpha}$	−0.0065***	−0.0104***	−0.0105***	−0.0080***	−0.0033	−0.0032*	−0.0078***	−0.0082***
	(0.0021)	(0.0023)	(0.0023)	(0.0020)	(0.0020)	(0.0018)	(0.0020)	(0.0021)
Omega	0.0101***	0.0089***	0.0103***	0.0103***	0.0102***	0.0086***	0.0108***	0.0097***
	(0.0027)	(0.0027)	(0.0027)	(0.0028)	(0.0027)	(0.0026)	(0.0027)	(0.0027)
log(OfferPrice)	−0.0127***	−0.0057*	−0.0042	−0.0122***	−0.0093***	−0.0098***	−0.0103***	−0.0131***
	(0.0033)	(0.0032)	(0.0032)	(0.0033)	(0.0033)	(0.0030)	(0.0033)	(0.0034)
log(1+Use)	−0.0058***	−0.0034*	−0.0038**	−0.0069***	−0.0069***	−0.0056***	−0.0065***	−0.0055***
	(0.0018)	(0.0019)	(0.0018)	(0.0018)	(0.0018)	(0.0017)	(0.0018)	(0.0018)
Lock-in	0.0074***	0.0066***	0.0064***	0.0079***	0.0069***	0.0051***	0.0080***	0.0066***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0018)	(0.0019)	(0.0019)
log(OfferSize)	0.0052***	0.0111***	0.0120***	0.0074***	0.0060***	0.0027**	0.0074***	0.0040***
	(0.0015)	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0014)	(0.0015)	(0.0015)
AboDum	0.0032*	0.0051***	0.0054***	0.0047**	0.0051***	0.0030*	0.0045**	0.0045**
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0018)	(0.0019)	(0.0020)
BelDum	−0.0001	−0.0019	−0.0009	−0.0008	−0.0016	−0.0005	−0.0013	−0.0001
	(0.0020)	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0018)	(0.0019)	(0.0020)
MktRtn	−0.0587***	−0.0548***	−0.0475***	−0.0592***	−0.0569***	−0.0669***	−0.0536***	−0.0629***
	(0.0112)	(0.0110)	(0.0108)	(0.0112)	(0.0111)	(0.0103)	(0.0110)	(0.0112)
MktRisk	0.1271***	0.1082***	0.1050***	0.1181***	0.1133***	0.0964***	0.1187***	0.1258***
	(0.0124)	(0.0120)	(0.0118)	(0.0125)	(0.0128)	(0.0118)	(0.0120)	(0.0122)
Nasdaq	0.0112***	0.0133***	0.0032	0.0131***	0.0144***	0.0107***	0.0118***	0.0095***
	(0.0017)	(0.0019)	(0.0019)	(0.0019)	(0.0018)	(0.0016)	(0.0017)	(0.0017)
Monday	0.0031	0.0023	0.0016	0.0031	0.0031	0.0034	0.0033	0.0033
	(0.0022)	(0.0022)	(0.0022)	(0.0023)	(0.0022)	(0.0021)	(0.0022)	(0.0022)
NasdaqRef	−0.0036	0.0101***	0.0129***	−0.0025	−0.0025	−0.0019	−0.0023	−0.0033
	(0.0022)	(0.0024)	(0.0022)	(0.0022)	(0.0022)	(0.0021)	(0.0022)	(0.0022)
MktBubble	0.0408***	0.0408***	0.0397***	0.0431***	0.0426***	0.0309***	0.0436***	0.0407***
	(0.0033)	(0.0032)	(0.0031)	(0.0033)	(0.0032)	(0.0030)	(0.0033)	(0.0033)

Table VI — *Continued*

	$VaR_{0.99}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HotMkt	0.0035	0.0049	0.0045	0.0044	0.0037	0.0024	0.0044	0.0044
	(0.0033)	(0.0034)	(0.0034)	(0.0035)	(0.0035)	(0.0032)	(0.0034)	(0.0033)
ColdMkt	0.0074	0.0029	0.0036	0.0073	0.0082^{*}	0.0081^{*}	0.0078	0.0072
	(0.0050)	(0.0047)	(0.0047)	(0.0049)	(0.0049)	(0.0043)	(0.0050)	(0.0049)
OilGas	−0.0043	−0.0029	−0.0045	−0.0050	−0.0053	-0.0064^{**}	−0.0046	−0.0039
	(0.0035)	(0.0036)	(0.0035)	(0.0035)	(0.0035)	(0.0032)	(0.0035)	(0.0035)
ChemProd	−0.0012	−0.0020	−0.0024	−0.0023	−0.0029	0.0005	−0.0024	−0.0006
	(0.0032)	(0.0034)	(0.0034)	(0.0032)	(0.0032)	(0.0029)	(0.0032)	(0.0031)
Manuf	0.0004	0.0033	0.0040	0.0016	0.0015	0.0008	0.0018	0.0008
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0030)	(0.0030)	(0.0030)
Computers	0.0087^{***}	0.0118^{***}	0.0115^{***}	0.0094^{***}	0.0095^{***}	0.0057^{***}	0.0100^{***}	0.0086^{***}
	(0.0022)	(0.0021)	(0.0021)	(0.0022)	(0.0022)	(0.0021)	(0.0022)	(0.0022)
ElectEq	0.0118^{***}	0.0145^{***}	0.0139^{***}	0.0119^{***}	0.0127^{***}	0.0079^{***}	0.0121^{***}	0.0112^{***}
	(0.0031)	(0.0029)	(0.0029)	(0.0031)	(0.0031)	(0.0029)	(0.0030)	(0.0031)
Transp	−0.0026	0.0003	−0.0003	−0.0024	−0.0019	−0.0022	−0.0018	−0.0027
	(0.0032)	(0.0032)	(0.0031)	(0.0032)	(0.0032)	(0.0030)	(0.0031)	(0.0032)
ScientificInst	0.0042	0.0042	0.0042	0.0041	0.0041	0.0051^{*}	0.0044	0.0047
	(0.0033)	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0029)	(0.0033)	(0.0032)
Communic	0.0012	−0.0013	−0.0027	−0.0003	0.0020	0.0023	−0.0009	−0.0007
	(0.0036)	(0.0034)	(0.0033)	(0.0037)	(0.0036)	(0.0034)	(0.0036)	(0.0037)
Utilities	-0.0124^{***}	-0.0114^{***}	-0.0130^{***}	-0.0126^{***}	-0.0123^{***}	-0.0103^{**}	-0.0113^{***}	-0.0121^{***}
	(0.0046)	(0.0042)	(0.0043)	(0.0045)	(0.0045)	(0.0044)	(0.0044)	(0.0045)
Retail	0.0058^{**}	0.0103^{***}	0.0094^{***}	0.0056^{**}	0.0057^{**}	0.0028	0.0066^{***}	0.0053^{**}
	(0.0026)	(0.0026)	(0.0025)	(0.0026)	(0.0026)	(0.0025)	(0.0025)	(0.0026)
FinServ	−0.0027	−0.0031	−0.0034	−0.0027	−0.0021	−0.0011	−0.0026	−0.0022
	(0.0029)	(0.0027)	(0.0027)	(0.0030)	(0.0030)	(0.0027)	(0.0030)	(0.0029)
Health	−0.0019	0.0008	0.0010	−0.0018	−0.0022	−0.0026	−0.0011	−0.0017
	(0.0048)	(0.0044)	(0.0045)	(0.0048)	(0.0047)	(0.0045)	(0.0047)	(0.0047)
Constant	0.0943^{***}	0.0173^{*}	0.0138	0.0836^{***}	0.0827^{***}	0.0879^{***}	0.0765^{***}	0.0958^{***}
	(0.0075)	(0.0099)	(0.0087)	(0.0083)	(0.0077)	(0.0070)	(0.0078)	(0.0077)
Observations	2,413	2,286	2,286	2,409	2,409	2,409	2,413	2,413
Adjusted R^2	0.5272	0.5798	0.5915	0.5260	0.5317	0.5824	0.5364	0.5330
F Statistic	71.7667^{***}	83.9742^{***}	88.0654^{***}	71.3325^{***}	72.9485^{***}	89.3605^{***}	74.4509^{***}	73.4306^{***}

Table VII: Initial Return, Liquidity and Conditional Vaule-at-Risk for Confidence Level $c = 0.95$

$CVaR$ is the conditional value-at-risk for confidence level $c = 0.95$. $InitRtn$ is the return after the first day of trading. $QuotedSp$ is the average proportional quoted spread. $RealSp$ is the average proportional realised spread. $Kyle\ \lambda$ is Kyle's (1985) measure of the extent to which order flow impacts on prices. $Kyle\ \lambda\ CN$ is Kyle's (1985) proportional λ adjusted for the number of shares outstanding and closing prices. $Kyle\ \lambda\ CQ$ is Kyle's (1985) proportional λ adjusted for the number of trades and closing prices. $Illiquidity$ is the average ratio of absolute daily returns to trading volume. $Turnover$ is the average number of shares traded. $UwRank$ measures underwriter reputation. $NumUw$ is the number of underwriters in the IPO. $VC-backed$ indicates venture capital backed IPO. $EBITDA$ are earnings before interest, tax, depreciation, and amortization. $EBITDADum$ is a dummy variable, coded one if $EBITDA$ is negative. $Assets$ are assets at book value. $Leverage$ is long-term debt divided by total assets. $Sales$ is annual sales. Age is firm age. $\hat{\alpha}$ is Leland and Pyle's (1977) signal of equity retained. $Omega$ is the fraction of primary shares offered. $OfferPrice$ is the offer price. Use is the number of uses of proceeds. $Lock-in$ indicates the presence of a lock-in period. $OfferSize$ is the amount of primary and secondary money raised. $AboDum$ indicates if $OfferPrice$ is above the initial filing price range. $BelDum$ indicates if $OfferPrice$ is below the initial filing price range. $MktRet$ is the cumulative NYSE/AMEX/Nasdaq index return. $MktRisk$ is the variance of $MktRet$. $Nasdaq$ indicates if an IPO is a Nasdaq issue. $Monday$ indicates if an IPO is issued or started trading on a Monday. $NasdaqRef$ indicates if an IPO is issued after January 1997. $MktBubble$ indicates if an IPO is issued during the bubble period. $HotMkt$ indicates if an IPO is issued during a hot new issue period. $ColdMkt$ indicates if an IPO is issued during a cold new issue period. Industry sector dummy variables capture differences in the cost of capital and business risk across industry sectors based on Koop and Li's (2001) 12-industry sector classification: $OilGas$ is oil and gas, $ChemProd$ is chemical products, $Manuf$ is manufacturing, $Computers$ is computers, $ElectEq$ is electronic equipment, $Transp$ is transportation, $ScientifInst$ is scientific instruments, $Communic$ is communication, $Utilities$ is utilities, $Retail$ is retail, $FinServ$ is financial services, $Health$ is health. Details on variable definitions are available from Table III. ***, **, * denote 1%, 5%, and 10% significance, respectively. Significance levels are adjusted for robust standard errors.

	$CVaR_{0.95}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InitRtn	0.0070^{***}							
	(0.0018)							
QuotedSp		0.6905^{***}						
		(0.0688)						
RealSp			1.1485^{***}					
			(0.0615)					
Kyle λ				0.0013^{**}				
				(0.0006)				
Kyle λ CN					0.0004^{***}			
					(0.0001)			
Kyle λ CQ						0.2514^{***}		
						(0.0176)		
Illiquidity							0.0036^{***}	
							(0.0007)	
Turnover								0.5817^{***}
								(0.1321)
UwRank	-0.0001	0.0010^{**}	0.0010^{**}	0.00004	-0.0001	-0.0002	0.0003	0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
NumUw	-0.0015	-0.0017^{*}	-0.0034^{***}	-0.0017^{*}	-0.0010	-0.0016^{*}	-0.0019^{**}	-0.0019^{**}
	(0.0010)	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0009)
VC-backed	0.0014	0.0010	0.0004	0.0011	0.0010	0.0009	0.0013	0.0021
	(0.0016)	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0016)
log(EBITDA)	-0.0016^{**}	-0.0024^{***}	-0.0029^{***}	-0.0016^{**}	-0.0017^{**}	-0.0009	-0.0020^{***}	-0.0016^{**}
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0008)
EBITDADum	0.0237^{***}	0.0283^{***}	0.0309^{***}	0.0242^{***}	0.0241^{***}	0.0161^{***}	0.0264^{***}	0.0247^{***}
	(0.0058)	(0.0058)	(0.0058)	(0.0059)	(0.0058)	(0.0053)	(0.0059)	(0.0059)
log(Assets)	-0.0047^{***}	-0.0044^{***}	-0.0043^{***}	-0.0050^{***}	-0.0054^{***}	-0.0043^{***}	-0.0050^{***}	-0.0042^{***}
	(0.0009)	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0009)	(0.0009)
log(Leverage)	-0.0003	-0.0006^{*}	-0.0005	-0.0003	-0.0004	0.0001	-0.0005	-0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)

Table VII — *Continued*

	CVaR$_{0.95}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Sales)	0.0004	0.0003	0.0004	0.0005	0.0007	0.0008	0.0005	0.0002
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0007)
log(Age)	−0.0006	−0.0011**	−0.0012**	−0.0007	−0.0009	−0.0006	−0.0006	−0.0005
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
$\hat{\alpha}$	−0.0055***	−0.0090***	−0.0092***	−0.0069***	−0.0029*	−0.0028*	−0.0068***	−0.0071***
	(0.0017)	(0.0020)	(0.0020)	(0.0017)	(0.0017)	(0.0015)	(0.0017)	(0.0018)
Omega	0.0088***	0.0077***	0.0090***	0.0090***	0.0088***	0.0075***	0.0094***	0.0084***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0022)	(0.0023)	(0.0023)
log(OfferPrice)	−0.0119***	−0.0056**	−0.0042	−0.0114***	−0.0089***	−0.0093***	−0.0097***	−0.0122***
	(0.0027)	(0.0027)	(0.0026)	(0.0028)	(0.0027)	(0.0025)	(0.0027)	(0.0028)
log(1+Use)	−0.0050***	−0.0028*	−0.0032**	−0.0059***	−0.0059***	−0.0049***	−0.0057***	−0.0047***
	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0014)	(0.0015)	(0.0015)
Lock-in	0.0065***	0.0056***	0.0054***	0.0069***	0.0060***	0.0045***	0.0070***	0.0058***
	(0.0016)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)
log(OfferSize)	0.0045***	0.0097***	0.0105***	0.0063***	0.0053***	0.0024**	0.0065***	0.0034***
	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0013)	(0.0011)	(0.0013)	(0.0013)
AboDum	0.0029*	0.0047***	0.0050***	0.0043***	0.0046***	0.0029*	0.0041**	0.0041**
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0016)
BelDum	−0.0004	−0.0020	−0.0010	−0.0010	−0.0017	−0.0008	−0.0014	−0.0004
	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0016)	(0.0015)	(0.0016)	(0.0016)
MktRtn	−0.0506***	−0.0470***	−0.0404***	−0.0509***	−0.0491***	−0.0576***	−0.0460***	−0.0543***
	(0.0094)	(0.0091)	(0.0089)	(0.0093)	(0.0092)	(0.0086)	(0.0091)	(0.0093)
MktRisk	0.1069***	0.0896***	0.0867***	0.0994***	0.0949***	0.0803***	0.0992***	0.1057***
	(0.0101)	(0.0096)	(0.0094)	(0.0102)	(0.0104)	(0.0096)	(0.0097)	(0.0100)
Nasdaq	0.0097***	0.0117***	0.0026	0.0113***	0.0125***	0.0094***	0.0103***	0.0082***
	(0.0015)	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0013)	(0.0015)	(0.0015)
Monday	0.0025	0.0018	0.0012	0.0025	0.0025	0.0028	0.0027	0.0027
	(0.0019)	(0.0018)	(0.0018)	(0.0019)	(0.0019)	(0.0018)	(0.0019)	(0.0019)
NasdaqRef	−0.0037**	0.0085***	0.0111***	−0.0028	−0.0028	−0.0023	−0.0026	−0.0035*
	(0.0018)	(0.0020)	(0.0018)	(0.0018)	(0.0018)	(0.0017)	(0.0018)	(0.0018)
MktBubble	0.0362***	0.0363***	0.0353***	0.0383***	0.0379***	0.0279***	0.0388***	0.0362***
	(0.0028)	(0.0027)	(0.0026)	(0.0027)	(0.0027)	(0.0025)	(0.0027)	(0.0028)

Table VII — *Continued*

	$\text{CVaR}_{0.95}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HotMkt	0.0029	0.0043	0.0039	0.0037	0.0031	0.0020	0.0037	0.0038
	(0.0027)	(0.0028)	(0.0028)	(0.0029)	(0.0029)	(0.0026)	(0.0028)	(0.0028)
ColdMkt	0.0064	0.0027	0.0034	0.0062	0.0071^{*}	0.0069^{*}	0.0068	0.0062
	(0.0042)	(0.0040)	(0.0039)	(0.0041)	(0.0041)	(0.0036)	(0.0041)	(0.0041)
OilGas	−0.0039	−0.0025	−0.0039	−0.0045	−0.0048	-0.0057^{**}	−0.0041	−0.0036
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0027)	(0.0030)	(0.0029)
ChemProd	−0.0010	−0.0016	−0.0019	−0.0019	−0.0024	0.0005	−0.0020	−0.0005
	(0.0027)	(0.0028)	(0.0029)	(0.0027)	(0.0027)	(0.0025)	(0.0028)	(0.0027)
Manuf	0.0006	0.0032	0.0038	0.0016	0.0016	0.0010	0.0019	0.0010
	(0.0027)	(0.0026)	(0.0025)	(0.0027)	(0.0027)	(0.0026)	(0.0026)	(0.0026)
Computers	0.0074^{***}	0.0102^{***}	0.0100^{***}	0.0080^{***}	0.0081^{***}	0.0048^{***}	0.0086^{***}	0.0073^{***}
	(0.0019)	(0.0017)	(0.0017)	(0.0019)	(0.0019)	(0.0017)	(0.0018)	(0.0018)
ElectEq	0.0102^{***}	0.0127^{***}	0.0122^{***}	0.0103^{***}	0.0110^{***}	0.0069^{***}	0.0105^{***}	0.0097^{***}
	(0.0026)	(0.0024)	(0.0024)	(0.0026)	(0.0026)	(0.0024)	(0.0025)	(0.0026)
Transp	−0.0021	0.0006	0.0001	−0.0019	−0.0014	−0.0017	−0.0014	−0.0022
	(0.0027)	(0.0026)	(0.0026)	(0.0026)	(0.0027)	(0.0025)	(0.0026)	(0.0027)
ScientificInst	0.0033	0.0036	0.0035	0.0033	0.0033	0.0041^{*}	0.0035	0.0038
	(0.0027)	(0.0026)	(0.0026)	(0.0027)	(0.0027)	(0.0024)	(0.0027)	(0.0027)
Communic	0.0009	−0.0013	−0.0026	−0.0003	0.0016	0.0018	−0.0010	−0.0007
	(0.0030)	(0.0028)	(0.0027)	(0.0031)	(0.0031)	(0.0029)	(0.0030)	(0.0031)
Utilities	-0.0110^{***}	-0.0097^{***}	-0.0111^{***}	-0.0112^{***}	-0.0109^{***}	-0.0093^{**}	-0.0101^{***}	-0.0107^{***}
	(0.0038)	(0.0035)	(0.0035)	(0.0037)	(0.0037)	(0.0037)	(0.0036)	(0.0037)
Retail	0.0045^{**}	0.0086^{***}	0.0078^{***}	0.0043^{**}	0.0045^{**}	0.0019	0.0053^{**}	0.0041^{*}
	(0.0022)	(0.0021)	(0.0021)	(0.0022)	(0.0022)	(0.0021)	(0.0021)	(0.0022)
FinServ	−0.0027	−0.0029	−0.0032	−0.0027	−0.0023	−0.0014	−0.0027	−0.0023
	(0.0025)	(0.0023)	(0.0022)	(0.0025)	(0.0025)	(0.0023)	(0.0025)	(0.0024)
Health	−0.0018	0.0005	0.0007	−0.0017	−0.0020	−0.0024	−0.0010	−0.0016
	(0.0040)	(0.0037)	(0.0038)	(0.0040)	(0.0040)	(0.0038)	(0.0039)	(0.0040)
Constant	0.0849^{***}	0.0161^{*}	0.0128^{*}	0.0759^{***}	0.0748^{***}	0.0792^{***}	0.0685^{***}	0.0861^{***}
	(0.0063)	(0.0083)	(0.0072)	(0.0070)	(0.0065)	(0.0059)	(0.0066)	(0.0065)
Observations	2,413	2,286	2,286	2,409	2,409	2,409	2,413	2,413
Adjusted R^2	0.5427	0.6007	0.6142	0.5407	0.5467	0.5987	0.5535	0.5486
F Statistic	76.3135^{***}	91.4705^{***}	96.7299^{***}	75.5923^{***}	77.4380^{***}	95.5589^{***}	79.6783^{***}	78.1431^{***}

Table VIII: Initial Return, Liquidity and Conditional Vaule-at-Risk for Confidence Level $c = 0.99$

$CVaR$ is the conditional value-at-risk for confidence level $c = 0.99$. $InitRtn$ is the return after the first day of trading. $QuotedSp$ is the average proportional quoted spread. $RealSp$ is the average proportional realised spread. $Kyle\ \lambda$ is Kyle's (1985) measure of the extent to which order flow impacts on prices. $Kyle\ \lambda\ CN$ is Kyle's (1985) proportional λ adjusted for the number of shares outstanding and closing prices. $Kyle\ \lambda\ CQ$ is Kyle's (1985) proportional λ adjusted for the number of trades and closing prices. $Illiquidity$ is the average ratio of absolute daily returns to trading volume. $Turnover$ is the average number of shares traded. $UwRank$ measures underwriter reputation. $NumUw$ is the number of underwriters in the IPO. $VC-backed$ indicates venture capital backed IPO. $EBITDA$ are earnings before interest, tax, depreciation, and amortization. $EBITDADum$ is a dummy variable, coded one if $EBITDA$ is negative. $Assets$ are assets at book value. $Leverage$ is long-term debt divided by total assets. $Sales$ is annual sales. Age is firm age. $\hat{\alpha}$ is Leland and Pyle's (1977) signal of equity retained. $Omega$ is the fraction of primary shares offered. $OfferPrice$ is the offer price. Use is the number of uses of proceeds. $Lock-in$ indicates the presence of a lock-in period. $OfferSize$ is the amount of primary and secondary money raised. $AboDum$ indicates if $OfferPrice$ is above the initial filing price range. $BelDum$ indicates if $OfferPrice$ is below the initial filing price range. $MktRet$ is the cumulative NYSE/AMEX/Nasdaq index return. $MktRisk$ is the variance of $MktRet$. $Nasdaq$ indicates if an IPO is a Nasdaq issue. $Monday$ indicates if an IPO is issued or started trading on a Monday. $NasdaqRef$ indicates if an IPO is issued after January 1997. $MktBubble$ indicates if an IPO is issued during the bubble period. $HotMkt$ indicates if an IPO is issued during a hot new issue period. $ColdMkt$ indicates if an IPO is issued during a cold new issue period. Industry sector dummy variables capture differences in the cost of capital and business risk across industry sectors based on Koop and Li's (2001) 12-industry sector classification: $OilGas$ is oil and gas, $ChemProd$ is chemical products, $Manuf$ is manufacturing, $Computers$ is computers, $ElectEq$ is electronic equipment, $Transp$ is transportation, $ScientifInst$ is scientific instruments, $Communic$ is communication, $Utilities$ is utilities, $Retail$ is retail, $FinServ$ is financial services, $Health$ is health. Details on variable definitions are available from Table III. ***, **, * denote 1%, 5%, and 10% significance, respectively. Significance levels are adjusted for robust standard errors.

	$CVaR_{0.99}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
InitRtn	0.0068^{*}							
	(0.0037)							
QuotedSp		0.9117^{***}						
		(0.1185)						
RealSp			1.4148^{***}					
			(0.1381)					
Kyle λ				0.0024^{**}				
				(0.0011)				
Kyle λ CN					0.0006^{***}			
					(0.0002)			
Kyle λ CQ						0.3830^{***}		
						(0.0370)		
Illiquidity							0.0042^{***}	
							(0.0012)	
Turnover								0.8871^{***}
								(0.2510)
UwRank	0.0008	0.0023^{**}	0.0022^{**}	0.0011	0.0008	0.0007	0.0013	0.0011
	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0009)
NumUw	-0.0038^{*}	-0.0044^{**}	-0.0064^{***}	-0.0044^{**}	-0.0032	-0.0040^{**}	-0.0043^{**}	-0.0044^{**}
	(0.0020)	(0.0019)	(0.0020)	(0.0020)	(0.0020)	(0.0019)	(0.0020)	(0.0018)
VC-backed	0.0032	0.0021	0.0013	0.0029	0.0028	0.0026	0.0031	0.0043
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0033)	(0.0034)	(0.0034)
log(EBITDA)	-0.0025^{*}	-0.0036^{**}	-0.0042^{***}	-0.0026^{*}	-0.0028^{*}	-0.0016	-0.0031^{**}	-0.0026^{*}
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0014)	(0.0015)	(0.0015)
EBITDADum	0.0359^{***}	0.0410^{***}	0.0441^{***}	0.0362^{***}	0.0361^{***}	0.0239^{**}	0.0389^{***}	0.0368^{***}
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0115)	(0.0110)	(0.0117)	(0.0116)
log(Assets)	-0.0085^{***}	-0.0079^{***}	-0.0078^{***}	-0.0089^{***}	-0.0094^{***}	-0.0078^{***}	-0.0088^{***}	-0.0076^{***}
	(0.0018)	(0.0018)	(0.0017)	(0.0018)	(0.0018)	(0.0017)	(0.0018)	(0.0017)
log(Leverage)	-0.0001	-0.0006	-0.0005	-0.0001	-0.0001	0.0006	-0.0003	0.0003
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)

Table VIII — *Continued*

	CVaR$_{0.99}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Sales)	0.0023*	0.0020	0.0022	0.0024*	0.0028**	0.0029**	0.0025*	0.0021
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0013)	(0.0014)	(0.0014)
log(Age)	−0.0018	−0.0025**	−0.0025**	−0.0021*	−0.0022*	−0.0018	−0.0018	−0.0016
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
$\hat{\alpha}$	−0.0069*	−0.0117***	−0.0116***	−0.0085**	−0.0022	−0.0022	−0.0082**	−0.0088**
	(0.0036)	(0.0039)	(0.0039)	(0.0035)	(0.0035)	(0.0033)	(0.0035)	(0.0036)
Omega	0.0145***	0.0129***	0.0145***	0.0145***	0.0143***	0.0123**	0.0152***	0.0138***
	(0.0049)	(0.0050)	(0.0050)	(0.0049)	(0.0049)	(0.0048)	(0.0049)	(0.0049)
log(OfferPrice)	−0.0138**	−0.0056	−0.0043	−0.0141**	−0.0099*	−0.0107**	−0.0115**	−0.0150***
	(0.0057)	(0.0058)	(0.0058)	(0.0058)	(0.0057)	(0.0054)	(0.0057)	(0.0058)
log(1+Use)	−0.0075**	−0.0056*	−0.0063*	−0.0089***	−0.0088***	−0.0071**	−0.0082**	−0.0069**
	(0.0032)	(0.0033)	(0.0032)	(0.0032)	(0.0032)	(0.0031)	(0.0032)	(0.0032)
Lock-in	0.0086***	0.0089***	0.0087**	0.0098***	0.0082**	0.0058*	0.0093***	0.0077**
	(0.0033)	(0.0034)	(0.0034)	(0.0033)	(0.0033)	(0.0032)	(0.0033)	(0.0033)
log(OfferSize)	0.0055**	0.0132***	0.0138***	0.0087***	0.0066**	0.0022	0.0078***	0.0038
	(0.0027)	(0.0028)	(0.0029)	(0.0029)	(0.0027)	(0.0025)	(0.0027)	(0.0027)
AboDum	0.0048	0.0062*	0.0064*	0.0061*	0.0066*	0.0039	0.0058*	0.0058
	(0.0035)	(0.0036)	(0.0036)	(0.0035)	(0.0035)	(0.0034)	(0.0035)	(0.0035)
BelDum	0.0003	−0.0013	−0.0001	−0.0004	−0.0013	0.0001	−0.0008	0.0005
	(0.0036)	(0.0035)	(0.0035)	(0.0036)	(0.0035)	(0.0034)	(0.0035)	(0.0036)
MktRtn	−0.0832***	−0.0828***	−0.0752***	−0.0841***	−0.0809***	−0.0940***	−0.0778***	−0.0891***
	(0.0205)	(0.0205)	(0.0204)	(0.0205)	(0.0203)	(0.0198)	(0.0204)	(0.0205)
MktRisk	0.1819***	0.1486***	0.1466***	0.1697***	0.1648***	0.1430***	0.1730***	0.1805***
	(0.0214)	(0.0211)	(0.0210)	(0.0216)	(0.0220)	(0.0212)	(0.0210)	(0.0211)
Nasdaq	0.0116***	0.0159***	0.0045	0.0141***	0.0156***	0.0107***	0.0122***	0.0091***
	(0.0033)	(0.0035)	(0.0036)	(0.0034)	(0.0033)	(0.0031)	(0.0032)	(0.0033)
Monday	−0.0001	−0.0010	−0.0017	−0.0001	−0.0001	0.0003	0.0001	0.0002
	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0034)	(0.0036)	(0.0036)
NasdaqRef	−0.00004	0.0174***	0.0196***	0.0012	0.0011	0.0018	0.0012	0.0001
	(0.0040)	(0.0043)	(0.0042)	(0.0040)	(0.0040)	(0.0039)	(0.0040)	(0.0040)
MktBubble	0.0472***	0.0469***	0.0458***	0.0495***	0.0488***	0.0335***	0.0499***	0.0462***
	(0.0058)	(0.0056)	(0.0056)	(0.0057)	(0.0057)	(0.0056)	(0.0057)	(0.0058)

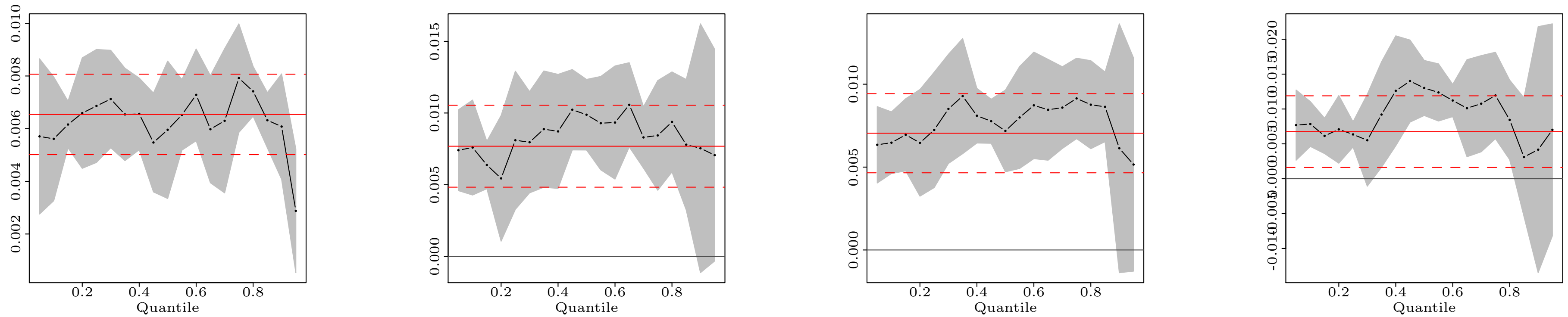
Table VIII — *Continued*

	CVaR$_{0.99}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HotMkt	0.0034	0.0053	0.0048	0.0042	0.0033	0.0016	0.0042	0.0043
	(0.0057)	(0.0060)	(0.0060)	(0.0058)	(0.0059)	(0.0055)	(0.0058)	(0.0057)
ColdMkt	0.0070	0.0014	0.0023	0.0068	0.0081	0.0078	0.0074	0.0067
	(0.0077)	(0.0077)	(0.0077)	(0.0077)	(0.0077)	(0.0072)	(0.0078)	(0.0076)
OilGas	−0.0097*	−0.0074	−0.0092	−0.0104*	−0.0108*	−0.0123**	−0.0099*	−0.0090
	(0.0058)	(0.0060)	(0.0060)	(0.0058)	(0.0058)	(0.0055)	(0.0058)	(0.0057)
ChemProd	0.0003	−0.0005	−0.0008	−0.0006	−0.0014	0.0030	−0.0008	0.0015
	(0.0064)	(0.0068)	(0.0069)	(0.0064)	(0.0064)	(0.0061)	(0.0065)	(0.0063)
Manuf	0.00004	0.0044	0.0051	0.0014	0.0012	0.0002	0.0014	0.0002
	(0.0060)	(0.0065)	(0.0065)	(0.0060)	(0.0060)	(0.0060)	(0.0060)	(0.0059)
Computers	0.0120***	0.0157***	0.0152***	0.0129***	0.0130***	0.0079**	0.0133***	0.0115***
	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0038)	(0.0039)	(0.0039)
ElectEq	0.0150***	0.0188***	0.0180***	0.0151***	0.0162***	0.0099*	0.0153***	0.0140**
	(0.0056)	(0.0055)	(0.0055)	(0.0056)	(0.0055)	(0.0054)	(0.0055)	(0.0056)
Transp	−0.0032	0.0007	−0.0002	−0.0030	−0.0023	−0.0027	−0.0024	−0.0035
	(0.0063)	(0.0064)	(0.0064)	(0.0062)	(0.0062)	(0.0060)	(0.0062)	(0.0062)
ScientificInst	0.0064	0.0065	0.0064	0.0066	0.0066	0.0079	0.0067	0.0073
	(0.0056)	(0.0057)	(0.0057)	(0.0056)	(0.0056)	(0.0053)	(0.0057)	(0.0056)
Communic	0.0012	−0.0011	−0.0025	−0.0005	0.0027	0.0030	−0.0009	−0.0009
	(0.0062)	(0.0060)	(0.0060)	(0.0062)	(0.0062)	(0.0061)	(0.0060)	(0.0062)
Utilities	−0.0155*	−0.0146*	−0.0165*	−0.0156*	−0.0152*	−0.0127	−0.0143*	−0.0150*
	(0.0084)	(0.0084)	(0.0085)	(0.0083)	(0.0083)	(0.0082)	(0.0082)	(0.0083)
Retail	0.0107**	0.0158***	0.0145***	0.0106**	0.0108**	0.0069	0.0117**	0.0101**
	(0.0049)	(0.0050)	(0.0050)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)
FinServ	−0.0043	−0.0055	−0.0060	−0.0042	−0.0035	−0.0021	−0.0042	−0.0036
	(0.0049)	(0.0046)	(0.0046)	(0.0049)	(0.0049)	(0.0047)	(0.0049)	(0.0049)
Health	−0.0019	0.0022	0.0023	−0.0016	−0.0021	−0.0026	−0.0009	−0.0016
	(0.0095)	(0.0092)	(0.0094)	(0.0095)	(0.0094)	(0.0091)	(0.0094)	(0.0094)
Constant	0.1191***	0.0234	0.0252	0.1043***	0.1049***	0.1120***	0.1003***	0.1223***
	(0.0135)	(0.0173)	(0.0163)	(0.0145)	(0.0135)	(0.0129)	(0.0139)	(0.0137)
Observations	2,413	2,286	2,286	2,409	2,409	2,409	2,413	2,413
Adjusted R^2	0.3607	0.3915	0.3935	0.3625	0.3660	0.4021	0.3659	0.3668
F Statistic	36.8143***	39.6896***	40.0083***	37.0273***	37.5803***	43.6116***	37.6291***	37.7720***

Figure 1: Quantile Regressions for Initial Return

Graphs plot Initial Return ($InitRtn$) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ and for conditional value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for Initial Return ($InitRtn$) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.

$VaR_{0.95}$ | $VaR_{0.99}$ | $CVaR_{0.95}$ | $CVaR_{0.99}$



$VaR_{0.95}$

τ	Coefficient	p-value
0.05	0.0057	0.0015
0.10	0.0056	0.0001
0.15	0.0062	0.0000
0.20	0.0066	0.0000
0.25	0.0069	0.0000
0.30	0.0071	0.0000
0.35	0.0065	0.0000
0.40	0.0066	0.0000
0.45	0.0055	0.0000
0.50	0.0060	0.0002
0.55	0.0065	0.0000
0.60	0.0073	0.0000
0.65	0.0060	0.0000
0.70	0.0063	0.0002
0.75	0.0079	0.0000
0.80	0.0074	0.0000
0.85	0.0063	0.0000
0.90	0.0061	0.0000
0.95	0.0029†	0.0439
OLS	0.0065	0.0000
	CI: 0.0050, 0.0081	

$VaR_{0.99}$

τ	Coefficient	p-value
0.05	0.0074	0.0000
0.10	0.0076	0.0002
0.15	0.0064	0.0000
0.20	0.0054	0.0414
0.25	0.0081	0.0058
0.30	0.0080	0.0002
0.35	0.0089	0.0003
0.40	0.0087	0.0003
0.45	0.0102	0.0000
0.50	0.0099	0.0000
0.55	0.0093	0.0000
0.60	0.0093	0.0001
0.65	0.0106†	0.0000
0.70	0.0083	0.0000
0.75	0.0084	0.0003
0.80	0.0094	0.0000
0.85	0.0078	0.0049
0.90	0.0075	0.1533
0.95	0.0071	0.1160
OLS	0.0077	0.0007
	CI: 0.0048, 0.0105	

$CVaR_{0.95}$

τ	Coefficient	p-value
0.05	0.0063	0.0000
0.10	0.0065	0.0000
0.15	0.0070	0.0000
0.20	0.0065	0.0010
0.25	0.0072	0.0006
0.30	0.0085	0.0000
0.35	0.0093	0.0000
0.40	0.0081	0.0000
0.45	0.0078	0.0000
0.50	0.0072	0.0000
0.55	0.0080	0.0000
0.60	0.0087	0.0000
0.65	0.0085	0.0000
0.70	0.0086	0.0000
0.75	0.0091	0.0000
0.80	0.0088	0.0000
0.85	0.0086	0.0000
0.90	0.0061	0.1789
0.95	0.0052	0.1876
OLS	0.0070	0.0002
	CI: 0.0047, 0.0094	

$CVaR_{0.99}$

τ	Coefficient	p-value
0.05	0.0077	0.0121
0.10	0.0079	0.0001
0.15	0.0061	0.0001
0.20	0.0071	0.0165
0.25	0.0064	0.0000
0.30	0.0055	0.1687
0.35	0.0092	0.0454
0.40	0.0126†	0.0086
0.45	0.0140†	0.0001
0.50	0.0130†	0.0000
0.55	0.0124†	0.0000
0.60	0.0112	0.0000
0.65	0.0101	0.0169
0.70	0.0108	0.0104
0.75	0.0119†	0.0016
0.80	0.0084	0.0151
0.85	0.0031	0.5469
0.90	0.0042	0.6975
0.95	0.0070	0.4482
OLS	0.0068	0.0644
	CI: 0.0016, 0.0119	

$VaR_{0.95}$

τ	Equality	p-value
0.25,0.50	3.8207	0.0000
0.50,0.75	2.6638	0.0000
0.25,0.75	5.7787	0.0000
0.05,0.95	6.4313	0.0000

$VaR_{0.99}$

τ	Equality	p-value
0.25,0.50	3.9688	0.0000
0.50,0.75	2.6849	0.0000
0.25,0.75	4.4999	0.0000
0.05,0.95	5.5466	0.0000

$CVaR_{0.95}$

τ	Equality	p-value
0.25,0.50	3.8378	0.0000
0.50,0.75	3.7200	0.0000
0.25,0.75	7.1980	0.0000
0.05,0.95	4.9773	0.0000

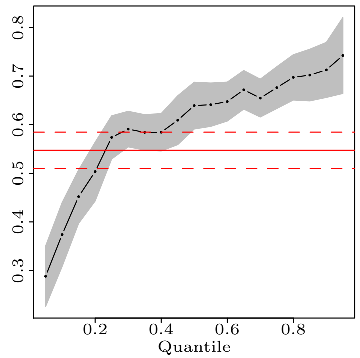
$CVaR_{0.99}$

τ	Equality	p-value
0.25,0.50	3.5381	0.0000
0.50,0.75	1.8621	0.0011
0.25,0.75	4.8047	0.0000
0.05,0.95	7.4484	0.0000

Figure 2: Quantile Regressions for Quoted Spread

Graphs plot Quoted Spread (*QuotedSp*) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ and for conditional value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for Quoted Spread (*QuotedSp*) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.

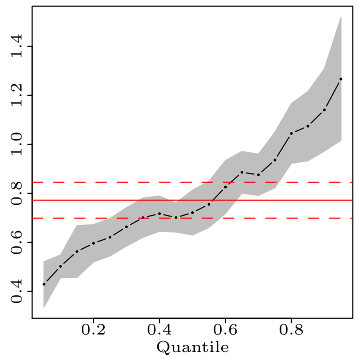
$\text{VaR}_{0.95}$



τ	Coefficient	p-value
0.05	0.2881†	0.0000
0.10	0.3739†	0.0000
0.15	0.4520†	0.0000
0.20	0.5035†	0.0000
0.25	0.5739	0.0000
0.30	0.5910†	0.0000
0.35	0.5842	0.0000
0.40	0.5844	0.0000
0.45	0.6092†	0.0000
0.50	0.6393†	0.0000
0.55	0.6412†	0.0000
0.60	0.6476†	0.0000
0.65	0.6718†	0.0000
0.70	0.6547†	0.0000
0.75	0.6763†	0.0000
0.80	0.6973†	0.0000
0.85	0.7021†	0.0000
0.90	0.7127†	0.0000
0.95	0.7423†	0.0000
OLS	0.5475	0.0000
	CI: 0.5103, 0.5847	

τ	Equality	p-value
0.25,0.50	2.9129	0.0000
0.50,0.75	2.3783	0.0000
0.25,0.75	7.6069	0.0000
0.05,0.95	4.5119	0.0000

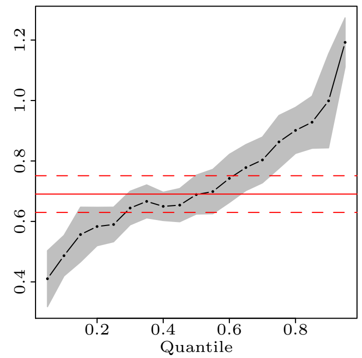
$\text{VaR}_{0.99}$



τ	Coefficient	p-value
0.05	0.4292†	0.0000
0.10	0.5023†	0.0000
0.15	0.5627†	0.0000
0.20	0.5964†	0.0000
0.25	0.6209†	0.0000
0.30	0.6635†	0.0000
0.35	0.7008	0.0000
0.40	0.7172	0.0000
0.45	0.7013	0.0000
0.50	0.7214	0.0000
0.55	0.7553	0.0000
0.60	0.8260	0.0000
0.65	0.8861†	0.0000
0.70	0.8758†	0.0000
0.75	0.9363†	0.0000
0.80	1.0447†	0.0000
0.85	1.0743†	0.0000
0.90	1.1407†	0.0000
0.95	1.2666†	0.0000
OLS	0.7719	0.0000
	CI: 0.6987, 0.8452	

τ	Equality	p-value
0.25,0.50	2.3505	0.0000
0.50,0.75	3.3706	0.0000
0.25,0.75	5.8879	0.0000
0.05,0.95	6.1316	0.0000

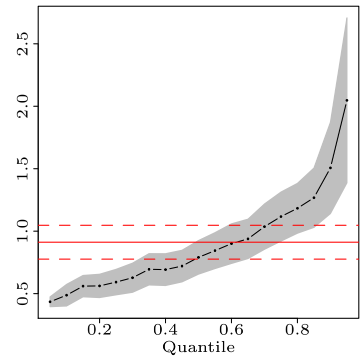
$\text{CVaR}_{0.95}$



τ	Coefficient	p-value
0.05	0.4104†	0.0000
0.10	0.4866†	0.0000
0.15	0.5566†	0.0000
0.20	0.5832†	0.0000
0.25	0.5899†	0.0000
0.30	0.6443	0.0000
0.35	0.6663	0.0000
0.40	0.6498	0.0000
0.45	0.6539	0.0000
0.50	0.6888	0.0000
0.55	0.6988	0.0000
0.60	0.7423	0.0000
0.65	0.7781†	0.0000
0.70	0.8034†	0.0000
0.75	0.8631†	0.0000
0.80	0.9011†	0.0000
0.85	0.9282†	0.0000
0.90	0.9989†	0.0000
0.95	1.1923†	0.0000
OLS	0.6905	0.0000
	CI: 0.6298, 0.7512	

τ	Equality	p-value
0.25,0.50	2.9381	0.0000
0.50,0.75	4.2437	0.0000
0.25,0.75	8.9199	0.0000
0.05,0.95	9.4073	0.0000

$\text{CVaR}_{0.99}$



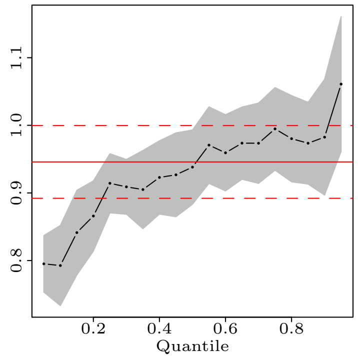
τ	Coefficient	p-value
0.05	0.4348†	0.0000
0.10	0.4875†	0.0000
0.15	0.5601†	0.0000
0.20	0.5619†	0.0000
0.25	0.5923†	0.0000
0.30	0.6274†	0.0000
0.35	0.6949†	0.0000
0.40	0.6923†	0.0000
0.45	0.7206†	0.0000
0.50	0.7904	0.0000
0.55	0.8443	0.0000
0.60	0.9003	0.0000
0.65	0.9383	0.0000
0.70	1.0363	0.0000
0.75	1.1167†	0.0000
0.80	1.1832†	0.0000
0.85	1.2678†	0.0000
0.90	1.5067†	0.0000
0.95	2.0473†	0.0000
OLS	0.9117	0.0000
	CI: 0.7762, 1.0473	

τ	Equality	p-value
0.25,0.50	3.0361	0.0000
0.50,0.75	2.8770	0.0000
0.25,0.75	4.7749	0.0000
0.05,0.95	5.8681	0.0000

Figure 3: Quantile Regressions for Realised Spread

Graphs plot Realised Spread (*RealSp*) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ and for conditional value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for Realised Spread (*RealSp*) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.

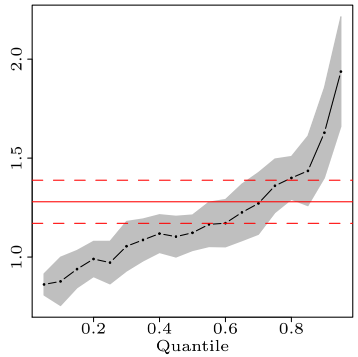
$\mathrm{VaR}_{0.95}$



τ	Coefficient	p-value
0.05	0.7951†	0.0000
0.10	0.7926†	0.0000
0.15	0.8413†	0.0000
0.20	0.8659†	0.0000
0.25	0.9143	0.0000
0.30	0.9090	0.0000
0.35	0.9050	0.0000
0.40	0.9229	0.0000
0.45	0.9268	0.0000
0.50	0.9382	0.0000
0.55	0.9707	0.0000
0.60	0.9593	0.0000
0.65	0.9736	0.0000
0.70	0.9735	0.0000
0.75	0.9947	0.0000
0.80	0.9802†	0.0000
0.85	0.9736†	0.0000
0.90	0.9825†	0.0000
0.95	1.0610†	0.0000
OLS	0.9458	0.0000
	CI: 0.8920, 0.9996	

τ	Equality	p-value
0.25,0.50	3.3506	0.0000
0.50,0.75	2.1280	0.0000
0.25,0.75	6.5552	0.0000
0.05,0.95	4.1599	0.0000

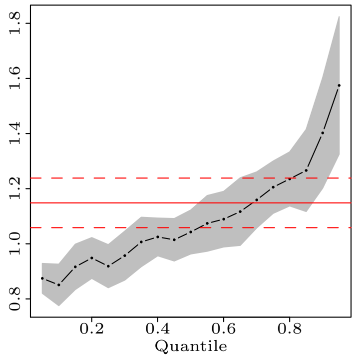
$\mathrm{VaR}_{0.99}$



τ	Coefficient	p-value
0.05	0.8617†	0.0000
0.10	0.8771†	0.0000
0.15	0.9390†	0.0000
0.20	0.9903†	0.0000
0.25	0.9720†	0.0000
0.30	1.0546†	0.0000
0.35	1.0865†	0.0000
0.40	1.1185†	0.0000
0.45	1.1032†	0.0000
0.50	1.1227†	0.0000
0.55	1.1652†	0.0000
0.60	1.1712	0.0000
0.65	1.2258	0.0000
0.70	1.2710	0.0000
0.75	1.3601	0.0000
0.80	1.3999†	0.0000
0.85	1.4356†	0.0000
0.90	1.6283†	0.0000
0.95	1.9371†	0.0000
OLS	1.2794	0.0000
	CI: 1.1704, 1.3883	

τ	Equality	p-value
0.25,0.50	2.6010	0.0000
0.50,0.75	3.1299	0.0000
0.25,0.75	5.1969	0.0000
0.05,0.95	7.3503	0.0000

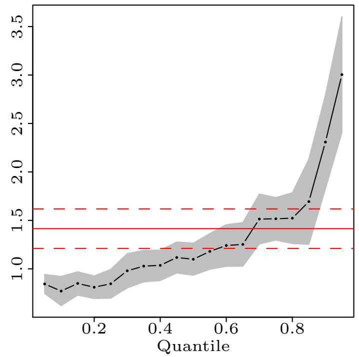
$\mathrm{CVaR}_{0.95}$



τ	Coefficient	p-value
0.05	0.8745†	0.0000
0.10	0.8508†	0.0000
0.15	0.9163†	0.0000
0.20	0.9485†	0.0000
0.25	0.9188†	0.0000
0.30	0.9571†	0.0000
0.35	1.0067†	0.0000
0.40	1.0249†	0.0000
0.45	1.0146†	0.0000
0.50	1.0428†	0.0000
0.55	1.0741	0.0000
0.60	1.0895	0.0000
0.65	1.1168	0.0000
0.70	1.1592	0.0000
0.75	1.2054	0.0000
0.80	1.2354	0.0000
0.85	1.2662†	0.0000
0.90	1.4023†	0.0000
0.95	1.5746†	0.0000
OLS	1.1485	0.0000
	CI: 1.0585, 1.2385	

τ	Equality	p-value
0.25,0.50	2.8892	0.0000
0.50,0.75	3.8214	0.0000
0.25,0.75	5.7045	0.0000
0.05,0.95	9.3159	0.0000

$\mathrm{CVaR}_{0.99}$



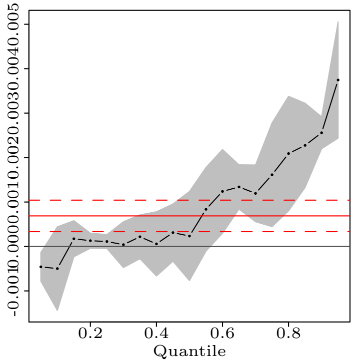
τ	Coefficient	p-value
0.05	0.8438†	0.0000
0.10	0.7709†	0.0000
0.15	0.8492†	0.0000
0.20	0.8102†	0.0000
0.25	0.8461†	0.0000
0.30	0.9797†	0.0000
0.35	1.0281†	0.0000
0.40	1.0361†	0.0000
0.45	1.1171†	0.0000
0.50	1.0989†	0.0000
0.55	1.1800†	0.0000
0.60	1.2410	0.0000
0.65	1.2523	0.0000
0.70	1.5140	0.0000
0.75	1.5167	0.0000
0.80	1.5228	0.0000
0.85	1.6939†	0.0000
0.90	2.3079†	0.0000
0.95	3.0040†	0.0000
OLS	1.4148	0.0000
	CI: 1.2108, 1.6189	

τ	Equality	p-value
0.25,0.50	2.6926	0.0000
0.50,0.75	3.1249	0.0000
0.25,0.75	4.8078	0.0000
0.05,0.95	6.5701	0.0000

Figure 4: Quantile Regressions for Kyle's λ

Graphs plot Kyle's (1985) λ ($Kyle\ \lambda$) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ and for conditional value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for Kyle's (1985) λ ($Kyle\ \lambda$) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.

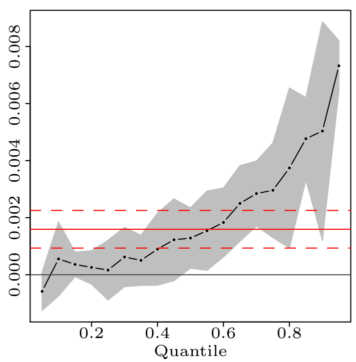
$\text{VaR}_{0.95}$



τ	Coefficient	p-value
0.05	−0.0005†	0.0195
0.10	−0.0005†	0.3840
0.15	0.0002†	0.4828
0.20	0.0001†	0.2114
0.25	0.0001†	0.2416
0.30	0.0001†	0.8983
0.35	0.0002†	0.4671
0.40	0.0001†	0.8954
0.45	0.0003	0.4263
0.50	0.0002†	0.7004
0.55	0.0008	0.1442
0.60	0.0012†	0.0308
0.65	0.0013†	0.0000
0.70	0.0012†	0.0021
0.75	0.0016†	0.0231
0.80	0.0021†	0.0077
0.85	0.0023†	0.0001
0.90	0.0026†	0.0000
0.95	0.0038†	0.0000
OLS	0.0007	0.0777
	CI: 0.0003, 0.0010	

τ	Equality	p-value
0.25,0.50	3.5413	0.0000
0.50,0.75	2.7852	0.0000
0.25,0.75	5.5015	0.0000
0.05,0.95	7.3749	0.0000

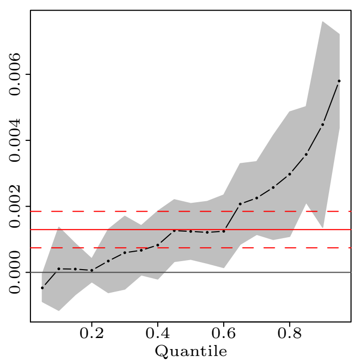
$\text{VaR}_{0.99}$



τ	Coefficient	p-value
0.05	−0.0006†	0.1527
0.10	0.0006†	0.4844
0.15	0.0004†	0.1642
0.20	0.0003†	0.4704
0.25	0.0002†	0.7974
0.30	0.0006†	0.3256
0.35	0.0005†	0.3439
0.40	0.0009	0.2427
0.45	0.0012	0.1597
0.50	0.0013	0.0454
0.55	0.0015	0.0679
0.60	0.0018	0.0127
0.65	0.0025†	0.0020
0.70	0.0029†	0.0000
0.75	0.0030†	0.0033
0.80	0.0037†	0.0282
0.85	0.0048†	0.0000
0.90	0.0050†	0.0306
0.95	0.0073†	0.0000
OLS	0.0016	0.0172
	CI: 0.0009, 0.0023	

τ	Equality	p-value
0.25,0.50	3.6110	0.0000
0.50,0.75	1.7768	0.0023
0.25,0.75	4.2689	0.0000
0.05,0.95	5.5658	0.0000

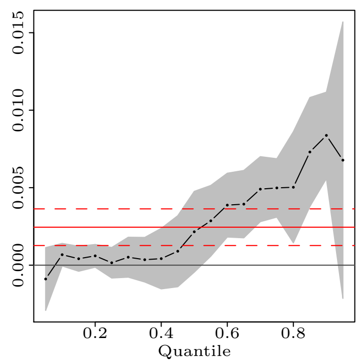
$\text{CVaR}_{0.95}$



τ	Coefficient	p-value
0.05	−0.0005†	0.0643
0.10	0.0001†	0.8888
0.15	0.0001†	0.8331
0.20	0.0001†	0.7706
0.25	0.0003†	0.5556
0.30	0.0006†	0.3746
0.35	0.0007	0.1408
0.40	0.0008	0.1865
0.45	0.0013	0.0265
0.50	0.0012	0.0157
0.55	0.0012	0.0332
0.60	0.0012	0.0628
0.65	0.0021†	0.0053
0.70	0.0023†	0.0008
0.75	0.0026†	0.0073
0.80	0.0030†	0.0095
0.85	0.0036†	0.0001
0.90	0.0045†	0.0181
0.95	0.0058†	0.0000
OLS	0.0013	0.0217
	CI: 0.0007, 0.0018	

τ	Equality	p-value
0.25,0.50	3.6687	0.0000
0.50,0.75	2.2002	0.0000
0.25,0.75	4.2396	0.0000
0.05,0.95	5.9464	0.0000

$\text{CVaR}_{0.99}$



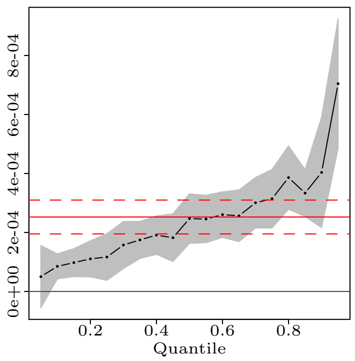
τ	Coefficient	p-value
0.05	−0.0009†	0.4686
0.10	0.0007†	0.1279
0.15	0.0004†	0.3998
0.20	0.0006†	0.1781
0.25	0.0002†	0.7961
0.30	0.0005†	0.5123
0.35	0.0004†	0.6876
0.40	0.0004†	0.7226
0.45	0.0009†	0.5189
0.50	0.0022	0.1745
0.55	0.0029	0.0395
0.60	0.0039†	0.0020
0.65	0.0039†	0.0029
0.70	0.0049†	0.0001
0.75	0.0050†	0.0000
0.80	0.0050†	0.0212
0.85	0.0073†	0.0007
0.90	0.0084†	0.0000
0.95	0.0068†	0.2118
OLS	0.0024	0.0290
	CI: 0.0013, 0.0036	

τ	Equality	p-value
0.25,0.50	3.3859	0.0000
0.50,0.75	1.9582	0.0004
0.25,0.75	5.1465	0.0000
0.05,0.95	4.5259	0.0000

Figure 5: Quantile Regressions for Kyle's λ CN

Graphs plot Kyle's (1985) λ CN ($Kyle\ \lambda\ CN$) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ and for conditional value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for Kyle's (1985) λ CN ($Kyle\ \lambda\ CN$) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.

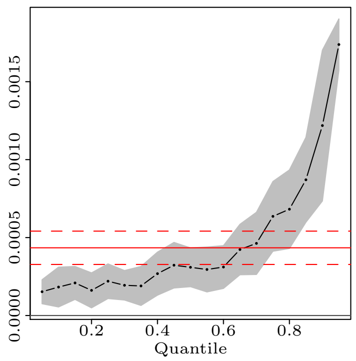
$VaR_{0.95}$



τ	Coefficient	p-value
0.05	0.00005†	0.4351
0.10	0.00009†	0.0009
0.15	0.00010†	0.0007
0.20	0.00011†	0.0030
0.25	0.00012†	0.0148
0.30	0.00016†	0.0012
0.35	0.00017†	0.0000
0.40	0.00019†	0.0000
0.45	0.00018†	0.0002
0.50	0.00025	0.0000
0.55	0.00025	0.0000
0.60	0.00026	0.0000
0.65	0.00026	0.0000
0.70	0.00030	0.0000
0.75	0.00031	0.0000
0.80	0.00039†	0.0000
0.85	0.00033†	0.0000
0.90	0.00040†	0.0004
0.95	0.00070†	0.0000
OLS	0.00025	0.0000
	CI: 0.00020, 0.00031	

τ	Equality	p-value
0.25,0.50	3.6275	0.0000
0.50,0.75	2.4130	0.0000
0.25,0.75	4.3872	0.0000
0.05,0.95	8.0672	0.0000

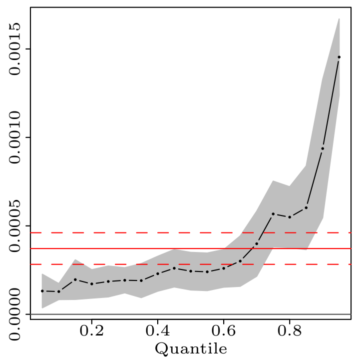
$VaR_{0.99}$



τ	Coefficient	p-value
0.05	0.00015†	0.0011
0.10	0.00018†	0.0189
0.15	0.00021†	0.0012
0.20	0.00016†	0.0181
0.25	0.00022†	0.0012
0.30	0.00019†	0.0008
0.35	0.00019†	0.0127
0.40	0.00027†	0.0014
0.45	0.00032†	0.0003
0.50	0.00031†	0.0000
0.55	0.00030†	0.0008
0.60	0.00031†	0.0002
0.65	0.00042	0.0000
0.70	0.00046	0.0001
0.75	0.00064†	0.0000
0.80	0.00068†	0.0000
0.85	0.00087†	0.0000
0.90	0.00122†	0.0000
0.95	0.00174†	0.0000
OLS	0.00043	0.0000
	CI: 0.00033, 0.00054	

τ	Equality	p-value
0.25,0.50	3.4612	0.0000
0.50,0.75	2.2673	0.0000
0.25,0.75	5.1236	0.0000
0.05,0.95	8.1406	0.0000

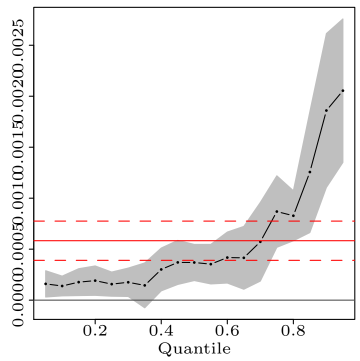
$CVaR_{0.95}$



τ	Coefficient	p-value
0.05	0.00013†	0.0228
0.10	0.00013†	0.0000
0.15	0.00020†	0.0040
0.20	0.00017†	0.0005
0.25	0.00019†	0.0005
0.30	0.00019†	0.0000
0.35	0.00019†	0.0011
0.40	0.00023†	0.0001
0.45	0.00026†	0.0001
0.50	0.00024†	0.0002
0.55	0.00024†	0.0002
0.60	0.00026†	0.0001
0.65	0.00030	0.0005
0.70	0.00040	0.0004
0.75	0.00057†	0.0000
0.80	0.00055†	0.0000
0.85	0.00060†	0.0000
0.90	0.00094†	0.0001
0.95	0.00145†	0.0000
OLS	0.00037	0.0000
	CI: 0.00028, 0.00046	

τ	Equality	p-value
0.25,0.50	3.5764	0.0000
0.50,0.75	2.2889	0.0000
0.25,0.75	4.5159	0.0000
0.05,0.95	6.8916	0.0000

$CVaR_{0.99}$

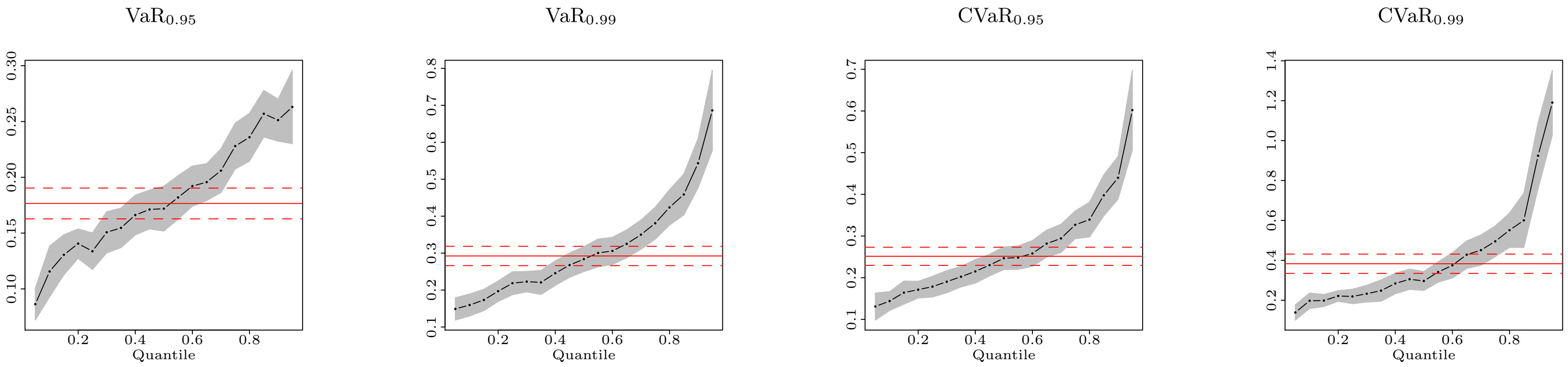


τ	Coefficient	p-value
0.05	0.00016†	0.0422
0.10	0.00014†	0.0187
0.15	0.00018†	0.0277
0.20	0.00019†	0.0294
0.25	0.00016†	0.0297
0.30	0.00018†	0.0386
0.35	0.00014†	0.2795
0.40	0.00030†	0.0185
0.45	0.00037†	0.0049
0.50	0.00037†	0.0006
0.55	0.00035†	0.0028
0.60	0.00042	0.0061
0.65	0.00042	0.0269
0.70	0.00057	0.0147
0.75	0.00087†	0.0001
0.80	0.00083†	0.0000
0.85	0.00126†	0.0005
0.90	0.00186†	0.0000
0.95	0.00205†	0.0000
OLS	0.00058	0.0001
	CI: 0.00039, 0.00078	

τ	Equality	p-value
0.25,0.50	3.4143	0.0000
0.50,0.75	2.1345	0.0000
0.25,0.75	5.9673	0.0000
0.05,0.95	4.3911	0.0000

Figure 6: Quantile Regressions for Kyle's λ CQ

Graphs plot Kyle's (1985) λ CQ ($Kyle\ \lambda\ CQ$) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ and for conditional value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for Kyle's (1985) λ CQ ($Kyle\ \lambda\ CQ$) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.



$VaR_{0.95}$

τ	Coefficient	p-value
0.05	0.0863†	0.0000
0.10	0.1156†	0.0000
0.15	0.1305†	0.0000
0.20	0.1406†	0.0000
0.25	0.1338†	0.0000
0.30	0.1507†	0.0000
0.35	0.1547†	0.0000
0.40	0.1662	0.0000
0.45	0.1712	0.0000
0.50	0.1719	0.0000
0.55	0.1820	0.0000
0.60	0.1921†	0.0000
0.65	0.1957†	0.0000
0.70	0.2060†	0.0000
0.75	0.2280†	0.0000
0.80	0.2359†	0.0000
0.85	0.2570†	0.0000
0.90	0.2513†	0.0000
0.95	0.2630†	0.0000
OLS	0.1766	0.0000
	CI: 0.1628, 0.1904	

$VaR_{0.99}$

τ	Coefficient	p-value
0.05	0.1489†	0.0000
0.10	0.1595†	0.0000
0.15	0.1732†	0.0000
0.20	0.1970†	0.0000
0.25	0.2185†	0.0000
0.30	0.2228†	0.0000
0.35	0.2208†	0.0000
0.40	0.2456†	0.0000
0.45	0.2676	0.0000
0.50	0.2837	0.0000
0.55	0.3004	0.0000
0.60	0.3059	0.0000
0.65	0.3251†	0.0000
0.70	0.3499†	0.0000
0.75	0.3809†	0.0000
0.80	0.4237†	0.0000
0.85	0.4587†	0.0000
0.90	0.5433†	0.0000
0.95	0.6863†	0.0000
OLS	0.2923	0.0000
	CI: 0.2661, 0.3185	

$CVaR_{0.95}$

τ	Coefficient	p-value
0.05	0.1309†	0.0000
0.10	0.1440†	0.0000
0.15	0.1642†	0.0000
0.20	0.1713†	0.0000
0.25	0.1786†	0.0000
0.30	0.1904†	0.0000
0.35	0.2024†	0.0000
0.40	0.2151†	0.0000
0.45	0.2302	0.0000
0.50	0.2467	0.0000
0.55	0.2483	0.0000
0.60	0.2582	0.0000
0.65	0.2818†	0.0000
0.70	0.2942†	0.0000
0.75	0.3269†	0.0000
0.80	0.3394†	0.0000
0.85	0.3976†	0.0000
0.90	0.4397†	0.0000
0.95	0.6020†	0.0000
OLS	0.2514	0.0000
	CI: 0.2296, 0.2732	

$CVaR_{0.99}$

τ	Coefficient	p-value
0.05	0.1388†	0.0000
0.10	0.1974†	0.0000
0.15	0.1985†	0.0000
0.20	0.2214†	0.0000
0.25	0.2190†	0.0000
0.30	0.2329†	0.0000
0.35	0.2484†	0.0000
0.40	0.2841†	0.0000
0.45	0.3054†	0.0000
0.50	0.2966†	0.0000
0.55	0.3414	0.0000
0.60	0.3750	0.0000
0.65	0.4284	0.0000
0.70	0.4512†	0.0000
0.75	0.4953†	0.0000
0.80	0.5511†	0.0000
0.85	0.6004†	0.0000
0.90	0.9243†	0.0000
0.95	1.1905†	0.0000
OLS	0.3830	0.0000
	CI: 0.3346, 0.4314	

$VaR_{0.95}$

τ	Equality	p-value
0.25,0.50	3.3151	0.0000
0.50,0.75	2.5914	0.0000
0.25,0.75	5.9958	0.0000
0.05,0.95	8.0735	0.0000

$VaR_{0.99}$

τ	Equality	p-value
0.25,0.50	3.0328	0.0000
0.50,0.75	2.9283	0.0000
0.25,0.75	4.8907	0.0000
0.05,0.95	5.4719	0.0000

$CVaR_{0.95}$

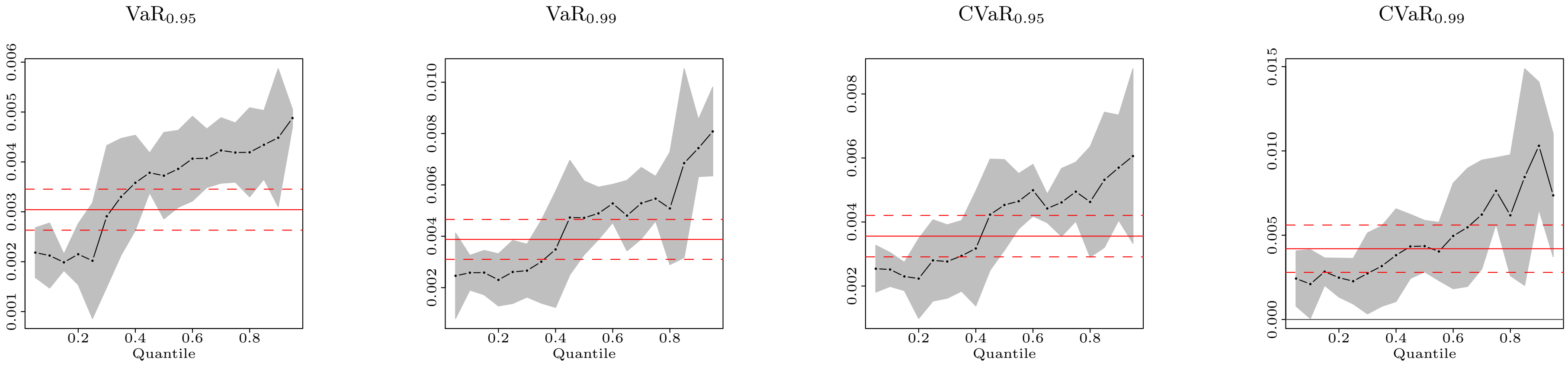
τ	Equality	p-value
0.25,0.50	3.1805	0.0000
0.50,0.75	2.6599	0.0000
0.25,0.75	5.1068	0.0000
0.05,0.95	7.3840	0.0000

$CVaR_{0.99}$

τ	Equality	p-value
0.25,0.50	3.9446	0.0000
0.50,0.75	2.7568	0.0000
0.25,0.75	5.5210	0.0000
0.05,0.95	6.1367	0.0000

Figure 7: Quantile Regressions for Illiquidity

Graphs plot Illiquidity (*Illiquidity*) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ and for conditional value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for Illiquidity (*Illiquidity*) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.



VaR$_{0.95}$

τ	Coefficient	p-value
0.05	0.0022†	0.0000
0.10	0.0021†	0.0000
0.15	0.0020†	0.0000
0.20	0.0022†	0.0000
0.25	0.0020†	0.0042
0.30	0.0029	0.0007
0.35	0.0033	0.0000
0.40	0.0036†	0.0000
0.45	0.0038†	0.0000
0.50	0.0037†	0.0000
0.55	0.0039†	0.0000
0.60	0.0041†	0.0000
0.65	0.0041†	0.0000
0.70	0.0042†	0.0000
0.75	0.0042†	0.0000
0.80	0.0042†	0.0000
0.85	0.0043†	0.0000
0.90	0.0045†	0.0000
0.95	0.0049†	0.0000
OLS	0.0030	0.0000
	CI: 0.0026, 0.0035	

τ	Equality	p-value
0.25,0.50	4.1068	0.0000
0.50,0.75	2.2288	0.0000
0.25,0.75	5.0778	0.0000
0.05,0.95	21.8090	0.0000

VaR$_{0.99}$

τ	Coefficient	p-value
0.05	0.0025†	0.0150
0.10	0.0026†	0.0000
0.15	0.0026†	0.0000
0.20	0.0023†	0.0002
0.25	0.0026†	0.0005
0.30	0.0027†	0.0000
0.35	0.0030†	0.0022
0.40	0.0035	0.0112
0.45	0.0047	0.0005
0.50	0.0047	0.0000
0.55	0.0049†	0.0000
0.60	0.0053†	0.0000
0.65	0.0048†	0.0000
0.70	0.0053†	0.0000
0.75	0.0055†	0.0000
0.80	0.0051†	0.0001
0.85	0.0069†	0.0022
0.90	0.0074†	0.0000
0.95	0.0081†	0.0000
OLS	0.0039	0.0000
	CI: 0.0031, 0.0047	

τ	Equality	p-value
0.25,0.50	3.8276	0.0000
0.50,0.75	2.5187	0.0000
0.25,0.75	5.1942	0.0000
0.05,0.95	7.1394	0.0000

CVaR$_{0.95}$

τ	Coefficient	p-value
0.05	0.0025†	0.0000
0.10	0.0025†	0.0000
0.15	0.0023†	0.0000
0.20	0.0022†	0.0033
0.25	0.0028†	0.0003
0.30	0.0028†	0.0001
0.35	0.0029	0.0000
0.40	0.0032	0.0037
0.45	0.0042	0.0001
0.50	0.0045†	0.0000
0.55	0.0047†	0.0000
0.60	0.0050†	0.0000
0.65	0.0044†	0.0000
0.70	0.0046†	0.0000
0.75	0.0050†	0.0000
0.80	0.0046†	0.0000
0.85	0.0053†	0.0000
0.90	0.0057†	0.0000
0.95	0.0061†	0.0003
OLS	0.0036	0.0000
	CI: 0.0029, 0.0042	

τ	Equality	p-value
0.25,0.50	3.2047	0.0000
0.50,0.75	2.2005	0.0000
0.25,0.75	5.2843	0.0000
0.05,0.95	9.8499	0.0000

CVaR$_{0.99}$

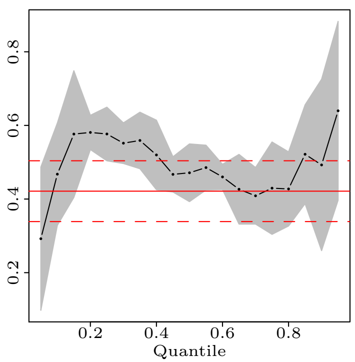
τ	Coefficient	p-value
0.05	0.0024†	0.0151
0.10	0.0021†	0.0911
0.15	0.0028	0.0000
0.20	0.0025†	0.0004
0.25	0.0023†	0.0057
0.30	0.0027†	0.0615
0.35	0.0032	0.0293
0.40	0.0038	0.0227
0.45	0.0043	0.0002
0.50	0.0044	0.0000
0.55	0.0040	0.0001
0.60	0.0050	0.0093
0.65	0.0055	0.0104
0.70	0.0062†	0.0016
0.75	0.0076†	0.0000
0.80	0.0062†	0.0046
0.85	0.0085†	0.0307
0.90	0.0103†	0.0000
0.95	0.0074†	0.0009
OLS	0.0042	0.0004
	CI: 0.0028, 0.0056	

τ	Equality	p-value
0.25,0.50	3.1198	0.0000
0.50,0.75	2.2446	0.0000
0.25,0.75	5.4576	0.0000
0.05,0.95	4.4860	0.0000

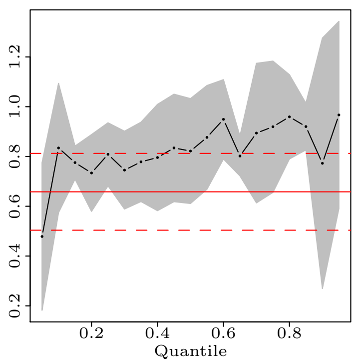
Figure 8: Quantile Regressions for Turnover

Graphs plot Turnover (*Turnover*) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ and for conditional value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for turnover (*Turnover*) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.

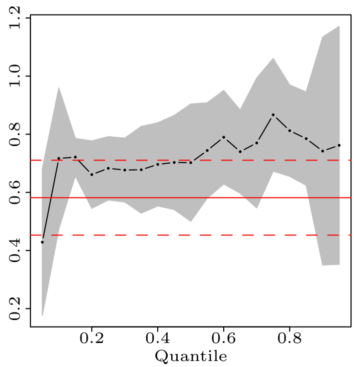
$\mathrm{VaR}_{0.95}$



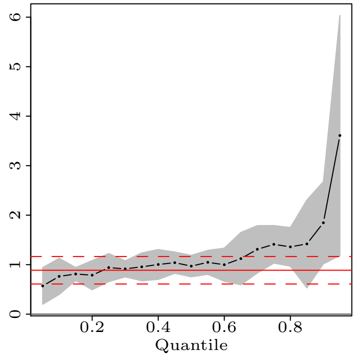
$\mathrm{VaR}_{0.99}$



$\mathrm{CVaR}_{0.95}$



$\mathrm{CVaR}_{0.99}$



$\mathrm{VaR}_{0.95}$

τ	Coefficient	p-value
0.05	0.2922†	0.0135
0.10	0.4676	0.0000
0.15	0.5765†	0.0000
0.20	0.5809†	0.0000
0.25	0.5767†	0.0000
0.30	0.5517†	0.0000
0.35	0.5591†	0.0000
0.40	0.5198†	0.0000
0.45	0.4670	0.0000
0.50	0.4713	0.0000
0.55	0.4854	0.0000
0.60	0.4601	0.0000
0.65	0.4266	0.0000
0.70	0.4088	0.0000
0.75	0.4295	0.0000
0.80	0.4274	0.0000
0.85	0.5216†	0.0000
0.90	0.4926	0.0005
0.95	0.6397†	0.0000
OLS	0.4214	0.0000
	CI: 0.3388, 0.5040	

$\mathrm{VaR}_{0.99}$

τ	Coefficient	p-value
0.05	0.4786†	0.0080
0.10	0.8342†	0.0000
0.15	0.7755	0.0000
0.20	0.7338	0.0000
0.25	0.8087	0.0000
0.30	0.7452	0.0000
0.35	0.7784	0.0000
0.40	0.7958	0.0000
0.45	0.8343†	0.0000
0.50	0.8218†	0.0000
0.55	0.8767†	0.0000
0.60	0.9492†	0.0000
0.65	0.8019	0.0000
0.70	0.8940†	0.0000
0.75	0.9194†	0.0000
0.80	0.9593†	0.0000
0.85	0.9202†	0.0000
0.90	0.7726	0.0116
0.95	0.9668†	0.0000
OLS	0.6581	0.0000
	CI: 0.5038, 0.8124	

$\mathrm{CVaR}_{0.95}$

τ	Coefficient	p-value
0.05	0.4286†	0.0051
0.10	0.7168†	0.0000
0.15	0.7214†	0.0000
0.20	0.6612	0.0000
0.25	0.6828	0.0000
0.30	0.6768	0.0000
0.35	0.6778	0.0000
0.40	0.6963	0.0000
0.45	0.7029	0.0000
0.50	0.7022	0.0000
0.55	0.7440†	0.0000
0.60	0.7898†	0.0000
0.65	0.7400†	0.0000
0.70	0.7700†	0.0000
0.75	0.8668†	0.0000
0.80	0.8124†	0.0000
0.85	0.7849†	0.0000
0.90	0.7422†	0.0019
0.95	0.7619†	0.0022
OLS	0.5817	0.0000
	CI: 0.4528, 0.7106	

$\mathrm{CVaR}_{0.99}$

τ	Coefficient	p-value
0.05	0.5701†	0.0116
0.10	0.7631	0.0006
0.15	0.8111	0.0000
0.20	0.7872	0.0000
0.25	0.9405	0.0000
0.30	0.9156	0.0000
0.35	0.9559	0.0000
0.40	1.0038	0.0000
0.45	1.0402	0.0000
0.50	0.9707	0.0000
0.55	1.0472	0.0000
0.60	0.9994	0.0000
0.65	1.1219	0.0005
0.70	1.3103†	0.0000
0.75	1.4107†	0.0000
0.80	1.3596†	0.0000
0.85	1.4192†	0.0087
0.90	1.8467†	0.0003
0.95	3.6097†	0.0145
OLS	0.8871	0.0005
	CI: 0.6094, 1.1648	

$\mathrm{VaR}_{0.95}$

τ	Equality	p-value
0.25,0.50	3.8551	0.0000
0.50,0.75	2.3366	0.0000
0.25,0.75	5.1229	0.0000
0.05,0.95	6.9752	0.0000

$\mathrm{VaR}_{0.99}$

τ	Equality	p-value
0.25,0.50	3.0193	0.0000
0.50,0.75	2.6164	0.0000
0.25,0.75	4.6236	0.0000
0.05,0.95	6.3958	0.0000

$\mathrm{CVaR}_{0.95}$

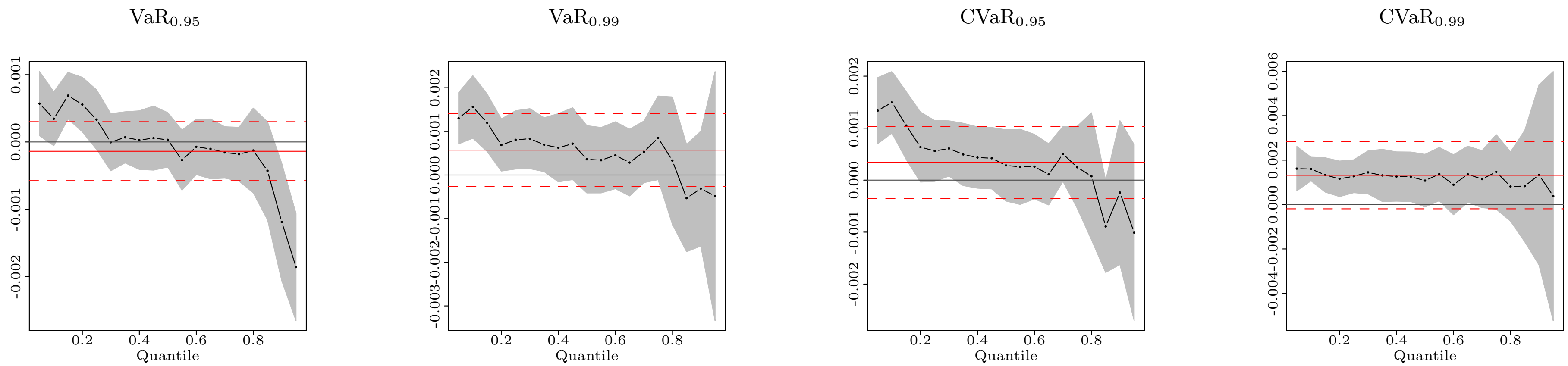
τ	Equality	p-value
0.25,0.50	3.3829	0.0000
0.50,0.75	3.6867	0.0000
0.25,0.75	5.5387	0.0000
0.05,0.95	8.6424	0.0000

$\mathrm{CVaR}_{0.99}$

τ	Equality	p-value
0.25,0.50	3.0092	0.0000
0.50,0.75	2.2394	0.0000
0.25,0.75	5.0469	0.0000
0.05,0.95	4.2645	0.0000

Figure 9: Quantile Regressions for Underwriter Reputation

Graphs plot underwriter reputation ($UwRank$) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for underwriter reputation ($UwRank$) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.



VaR$_{0.95}$

τ	Coefficient	p-value
0.05	0.0006†	0.0494
0.10	0.0004†	0.1572
0.15	0.0007†	0.0011
0.20	0.0006†	0.0239
0.25	0.0003	0.2169
0.30	0.0001	0.9878
0.35	0.0001	0.7663
0.40	0.0001	0.9162
0.45	0.0001	0.8424
0.50	0.0001	0.8976
0.55	−0.0003	0.3205
0.60	−0.0001	0.7736
0.65	−0.0001	0.7029
0.70	−0.0002	0.5037
0.75	−0.0002	0.4530
0.80	−0.0001	0.7416
0.85	−0.0004	0.3324
0.90	−0.0012†	0.0249
0.95	−0.0019†	0.0001
OLS	−0.0001	0.6330
	CI: -0.0006, 0.0003	

τ	Equality	p-value
0.25,0.50	4.3689	0.0000
0.50,0.75	3.7052	0.0000
0.25,0.75	7.0511	0.0000
0.05,0.95	11.3880	0.0000

VaR$_{0.99}$

τ	Coefficient	p-value
0.05	0.0013	0.0003
0.10	0.0016†	0.0004
0.15	0.0012	0.0028
0.20	0.0007	0.0583
0.25	0.0008	0.0474
0.30	0.0008	0.0464
0.35	0.0007	0.0642
0.40	0.0006	0.1888
0.45	0.0007	0.1517
0.50	0.0004	0.4424
0.55	0.0003	0.4569
0.60	0.0005	0.3313
0.65	0.0003	0.5393
0.70	0.0005	0.2162
0.75	0.0009	0.1440
0.80	0.0003	0.7086
0.85	−0.0005†	0.4782
0.90	−0.0003†	0.6976
0.95	−0.0005†	0.7809
OLS	0.0006	0.2849
	CI: -0.0002, 0.0014	

τ	Equality	p-value
0.25,0.50	4.2490	0.0000
0.50,0.75	2.5652	0.0000
0.25,0.75	5.2978	0.0000
0.05,0.95	5.4521	0.0000

CVaR$_{0.95}$

τ	Coefficient	p-value
0.05	0.0013†	0.0006
0.10	0.0015†	0.0000
0.15	0.0011†	0.0081
0.20	0.0006	0.1204
0.25	0.0006	0.1151
0.30	0.0006	0.0602
0.35	0.0005	0.1753
0.40	0.0004	0.2258
0.45	0.0004	0.2409
0.50	0.0003	0.4975
0.55	0.0003	0.5619
0.60	0.0003	0.4929
0.65	0.0001	0.7565
0.70	0.0005	0.1164
0.75	0.0003	0.6044
0.80	0.0001	0.9197
0.85	−0.0009†	0.0980
0.90	−0.0002	0.7762
0.95	−0.0010	0.3266
OLS	0.0003	0.4448
	CI: -0.0004, 0.0010	

τ	Equality	p-value
0.25,0.50	3.3105	0.0000
0.50,0.75	2.8976	0.0000
0.25,0.75	6.2452	0.0000
0.05,0.95	5.7522	0.0000

CVaR$_{0.99}$

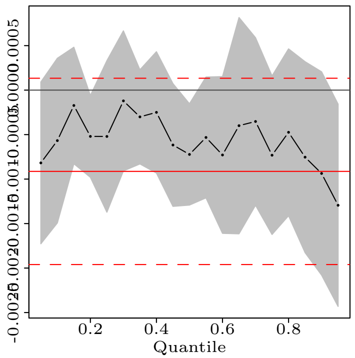
τ	Coefficient	p-value
0.05	0.0016	0.0078
0.10	0.0016	0.0000
0.15	0.0013	0.0047
0.20	0.0012	0.0176
0.25	0.0013	0.0047
0.30	0.0015	0.0142
0.35	0.0013	0.0666
0.40	0.0013	0.0618
0.45	0.0013	0.0653
0.50	0.0011	0.1361
0.55	0.0014	0.0605
0.60	0.0009	0.2785
0.65	0.0014	0.0763
0.70	0.0011	0.1427
0.75	0.0015	0.1499
0.80	0.0008	0.3924
0.85	0.0008	0.5865
0.90	0.0013	0.5884
0.95	0.0004	0.9115
OLS	0.0013	0.1699
	CI: -0.0002, 0.0028	

τ	Equality	p-value
0.25,0.50	3.2375	0.0000
0.50,0.75	2.4037	0.0000
0.25,0.75	5.4369	0.0000
0.05,0.95	6.8706	0.0000

Figure 10: Quantile Regressions for Number of Underwriters in Syndicate

Graphs plot the number of underwriters in a syndicate ($NumUW$) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for number of underwriters in a syndicate ($NumUW$) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.

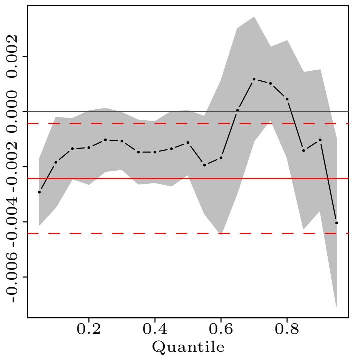
$\text{VaR}_{0.95}$



τ	Coefficient	p-value
0.05	−0.0008	0.1391
0.10	−0.0006	0.3133
0.15	−0.0002	0.6643
0.20	−0.0005	0.0629
0.25	−0.0005	0.3146
0.30	−0.0001	0.8005
0.35	−0.0003	0.3500
0.40	−0.0003	0.5464
0.45	−0.0006	0.1414
0.50	−0.0007	0.0369
0.55	−0.0005	0.1976
0.60	−0.0007	0.1735
0.65	−0.0004	0.5887
0.70	−0.0003	0.5382
0.75	−0.0007	0.1770
0.80	−0.0005	0.4058
0.85	−0.0008	0.2482
0.90	−0.0009	0.1777
0.95	−0.0013	0.0613
OLS	−0.0009	0.1397
	CI: -0.0020, 0.0001	

τ	Equality	p-value
0.25,0.50	4.3689	0.0000
0.50,0.75	3.7052	0.0000
0.25,0.75	7.0511	0.0000
0.05,0.95	11.3880	0.0000

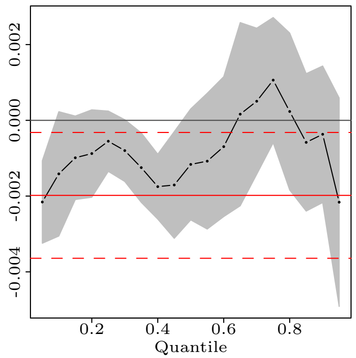
$\text{VaR}_{0.99}$



τ	Coefficient	p-value
0.05	−0.0029	0.0001
0.10	−0.0018	0.0629
0.15	−0.0013	0.0425
0.20	−0.0013	0.1059
0.25	−0.0010	0.1403
0.30	−0.0011	0.0878
0.35	−0.0015	0.0369
0.40	−0.0015	0.0289
0.45	−0.0014	0.1009
0.50	−0.0011	0.1088
0.55	−0.0019	0.0709
0.60	−0.0017	0.3231
0.65	0.0001†	0.9796
0.70	0.0012†	0.3874
0.75	0.0010†	0.1991
0.80	0.0005†	0.7222
0.85	−0.0014	0.4120
0.90	−0.0010	0.5061
0.95	−0.0040	0.0281
OLS	−0.0024	0.0367
	CI: -0.0044, -0.0004	

τ	Equality	p-value
0.25,0.50	4.2490	0.0000
0.50,0.75	2.5652	0.0000
0.25,0.75	5.2978	0.0000
0.05,0.95	5.4521	0.0000

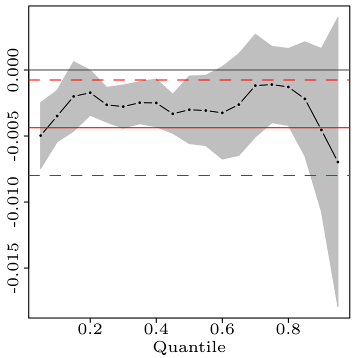
$\text{CVaR}_{0.95}$



τ	Coefficient	p-value
0.05	−0.0022	0.0012
0.10	−0.0014	0.1569
0.15	−0.0010	0.1402
0.20	−0.0009	0.2117
0.25	−0.0006	0.2547
0.30	−0.0008	0.1074
0.35	−0.0013	0.0253
0.40	−0.0018	0.0008
0.45	−0.0017	0.0464
0.50	−0.0012	0.1917
0.55	−0.0011	0.3228
0.60	−0.0007	0.5363
0.65	0.0002†	0.9121
0.70	0.0005†	0.6676
0.75	0.0011†	0.2901
0.80	0.0002†	0.8530
0.85	−0.0006	0.5978
0.90	−0.0004	0.7369
0.95	−0.0022	0.1966
OLS	−0.0020	0.0419
	CI: -0.0036, -0.0003	

τ	Equality	p-value
0.25,0.50	3.3105	0.0000
0.50,0.75	2.8976	0.0000
0.25,0.75	6.2452	0.0000
0.05,0.95	5.7522	0.0000

$\text{CVaR}_{0.99}$



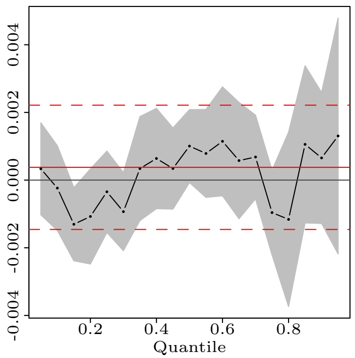
τ	Coefficient	p-value
0.05	−0.0050	0.0010
0.10	−0.0035	0.0033
0.15	−0.0020	0.2098
0.20	−0.0017	0.0969
0.25	−0.0026	0.0010
0.30	−0.0028	0.0053
0.35	−0.0025	0.0105
0.40	−0.0025	0.0234
0.45	−0.0033	0.0002
0.50	−0.0030	0.0525
0.55	−0.0031	0.0570
0.60	−0.0033	0.1270
0.65	−0.0026	0.2626
0.70	−0.0012	0.6161
0.75	−0.0011	0.5299
0.80	−0.0013	0.4680
0.85	−0.0022	0.4045
0.90	−0.0045	0.2258
0.95	−0.0070	0.2950
OLS	−0.0044	0.0281
	CI: -0.0080, -0.0008	

τ	Equality	p-value
0.25,0.50	3.2375	0.0000
0.50,0.75	2.4037	0.0000
0.25,0.75	5.4369	0.0000
0.05,0.95	6.8706	0.0000

Figure 11: Quantile Regressions for Venture Capital Backed IPOs

Graphs plot venture capital-backed ($VC - backed$) slope coefficients of estimated linear quantile regressions for value-at-risk confidence levels $c = \{0.95, 0.99\}$ as a function of τ. Quantile regressions have τ values from 0.05 to 0.95 with step size 0.05. Continuous black lines represent values of quantile regression coefficients at different levels of τ. Grey areas indicate 90% confidence intervals of quantile regression coefficients. Continuous red lines represent values of least squares regression coefficients. Dashed red lines represent 90% confidence intervals of least squares regression coefficients. Tables across the middle row of the figure show coefficient values for venture capital-backed IPOs ($VC - backed$) at each level of τ and their corresponding significance values. Significance levels are adjusted for robust standard errors. Coefficient values for all remaining variables reported in Table V to Table VIII are omitted for brevity reasons. † indicates that a coefficient in relation to the τ^{th} quantile is outside the 90% confidence interval (CI) of the least squares regression coefficients. Tables across the bottom row of the figure report tests of equality of quantile regression coefficients across different levels of τ. F-statistics test for pairwise equality of slope coefficients across different quantiles of τ. p-values report the corresponding confidence levels of F-tests.

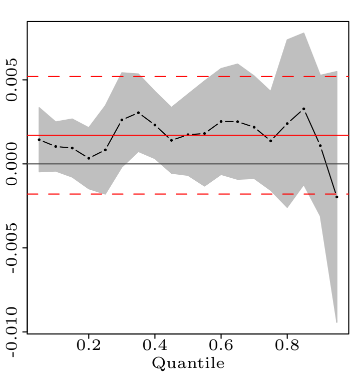
$\text{VaR}_{0.95}$



τ	Coefficient	p-value
0.05	0.0003	0.6860
0.10	−0.0002	0.7560
0.15	−0.0013	0.0469
0.20	−0.0011	0.2074
0.25	−0.0004	0.6365
0.30	−0.0009	0.1837
0.35	0.0003	0.7158
0.40	0.0006	0.4785
0.45	0.0003	0.6387
0.50	0.0010	0.1249
0.55	0.0008	0.3188
0.60	0.0012	0.2418
0.65	0.0006	0.5810
0.70	0.0007	0.3644
0.75	−0.0010	0.2069
0.80	−0.0012	0.4585
0.85	0.0011	0.4545
0.90	0.0007	0.5778
0.95	0.0013	0.5384
OLS	0.0004	0.7224
	CI: -0.0015, 0.0022	

τ	Equality	p-value
0.25,0.50	4.3689	0.0000
0.50,0.75	3.7052	0.0000
0.25,0.75	7.0511	0.0000
0.05,0.95	11.3880	0.0000

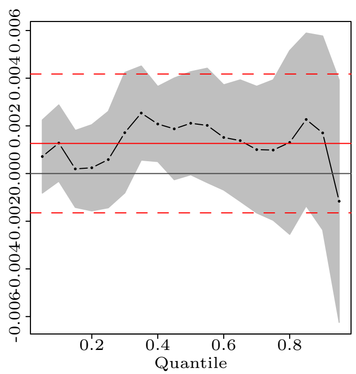
$\text{VaR}_{0.99}$



τ	Coefficient	p-value
0.05	0.0014	0.2155
0.10	0.0010	0.2449
0.15	0.0009	0.3693
0.20	0.0003	0.7612
0.25	0.0008	0.6027
0.30	0.0026	0.1255
0.35	0.0030	0.0301
0.40	0.0023	0.0572
0.45	0.0014	0.2389
0.50	0.0017	0.2378
0.55	0.0018	0.3417
0.60	0.0025	0.1880
0.65	0.0025	0.2285
0.70	0.0022	0.2390
0.75	0.0014	0.4444
0.80	0.0024	0.4292
0.85	0.0033	0.2323
0.90	0.0011	0.6701
0.95	−0.0020†	0.6645
OLS	0.0017	0.3777
	CI: -0.0018, 0.0052	

τ	Equality	p-value
0.25,0.50	4.2490	0.0000
0.50,0.75	2.5652	0.0000
0.25,0.75	5.2978	0.0000
0.05,0.95	5.4521	0.0000

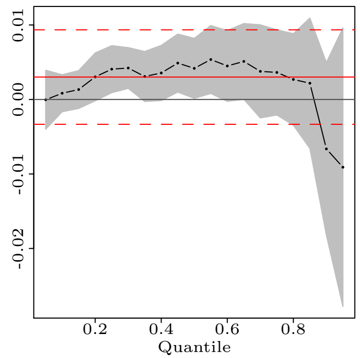
$\text{CVaR}_{0.95}$



τ	Coefficient	p-value
0.05	0.0007	0.4440
0.10	0.0013	0.1890
0.15	0.0002	0.8429
0.20	0.0002	0.8255
0.25	0.0006	0.6334
0.30	0.0017	0.2647
0.35	0.0025	0.0345
0.40	0.0021	0.0300
0.45	0.0019	0.1485
0.50	0.0021	0.1086
0.55	0.0020	0.1664
0.60	0.0015	0.2590
0.65	0.0014	0.3730
0.70	0.0010	0.5342
0.75	0.0010	0.5824
0.80	0.0013	0.5778
0.85	0.0023	0.3037
0.90	0.0017	0.4908
0.95	−0.0012	0.7067
OLS	0.0013	0.4355
	CI: -0.0017, 0.0042	

τ	Equality	p-value
0.25,0.50	3.3105	0.0000
0.50,0.75	2.8976	0.0000
0.25,0.75	6.2452	0.0000
0.05,0.95	5.7522	0.0000

$\text{CVaR}_{0.99}$



τ	Coefficient	p-value
0.05	−0.0001	0.9865
0.10	0.0008	0.5811
0.15	0.0013	0.3881
0.20	0.0030	0.1213
0.25	0.0041	0.0345
0.30	0.0042	0.0113
0.35	0.0031	0.1311
0.40	0.0036	0.1143
0.45	0.0049	0.0394
0.50	0.0042	0.0883
0.55	0.0054	0.0533
0.60	0.0045	0.1199
0.65	0.0051	0.0990
0.70	0.0038	0.3213
0.75	0.0036	0.2962
0.80	0.0027	0.4727
0.85	0.0022	0.6822
0.90	−0.0066†	0.3470
0.95	−0.0091†	0.4239
OLS	0.0030	0.3799
	CI: -0.0033, 0.0094	

τ	Equality	p-value
0.25,0.50	3.2375	0.0000
0.50,0.75	2.4037	0.0000
0.25,0.75	5.4369	0.0000
0.05,0.95	6.8706	0.0000