

Secondary Stock Market Liquidity and the Cost of Issuing Seasoned Equity – European evidence

Finance

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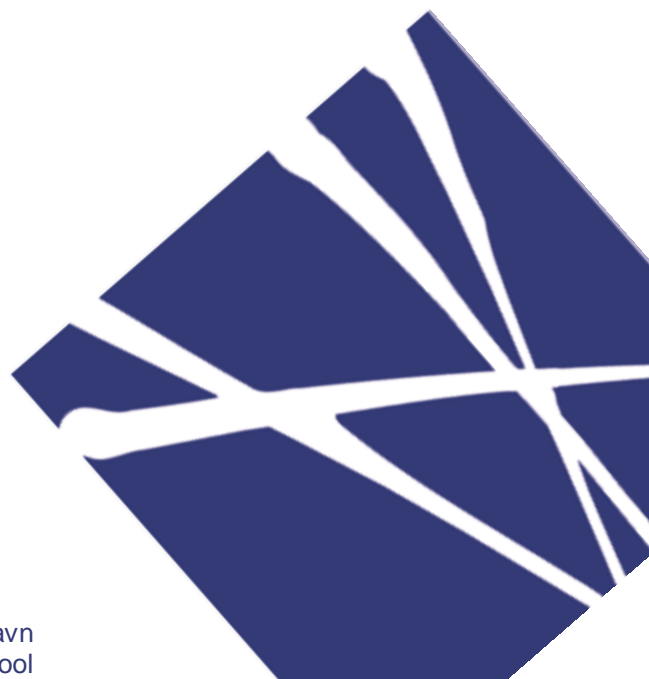
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Executive summary

This thesis finds that secondary market liquidity is an important and significant predictor of the combined cost of issuing seasoned equity. Firms with more liquid shares are on average able to issue new equity at lower costs than their less liquid counterparts. This relation is interpreted as economically meaningful and important.

The intricate and multifaceted concept of market liquidity is explained and discussed along with the wide variety of measures in existence to capture and quantify it. The total costs of a seasoned equity offering (SEO) are argued to consist of direct and indirect costs. The direct cost refers primarily to the gross fees paid to the investment bank which, along the lines of Butler et al. (2005), are argued to be significantly related to the secondary market liquidity of the issuing firm. This insight is confirmed in an empirical analysis of a sample of 145 European SEOs. The analysis finds that gross fees are significantly lower for more liquid issuers, controlling for confounding effects. The indirect costs of an SEO largely derive from the well documented SEO discount. This discount has historically been explained with adverse selection stemming from asymmetric information. Empirically the SEO discount has been found to be positively related to firm risk, as well as the relative size of the offering. These insights are consistently confirmed in this study. Controlling for these and other relevant variables, in the small as well as the large sample (consisting of 2,065 SEOs), the SEO discount is found consistently and significantly negatively related to the secondary market liquidity of the issuing firm. This effect is closely related to the insight of Amihud and Mendelson (1986) that illiquidity is priced in the market, which leads illiquid assets to trade at a discount.

Finally, it is argued that neither direct nor indirect costs should be viewed in isolation when analyzing the decision to issue equity. Rather it is the combined cost that an owner of a firm will incur if he does not subscribe to the issuance on a pro rata basis. These total costs are found to be significantly related to the secondary market liquidity of the issuing firm in an economically important way. Together these findings suggest that secondary market liquidity is a significant and important predictor of the combined cost of issuing seasoned equity and that firms should have a great interest in the market liquidity of their shares, as this may substantially affect the costs at which they can obtain additional equity.

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Abstract

We find that secondary market liquidity is a significant and important predictor of the total cost of issuing seasoned equity. Employing a sample of European seasoned equity offerings we find that *ceteris paribus* both direct costs, in the form of the investment banks' fees, and indirect costs, in the form of the wealth transfer induced by the SEO discount, are significantly negatively associated with levels of secondary market liquidity. Liquidity thus importantly predicts the total cost of an SEO, implying that firms should have a great interest in the liquidity of their shares.

1 Introduction

“Liquidity is the lifeblood of financial markets. Its adequate provision is critical for the smooth operation of an economy. Its sudden erosion in even a single market segment or in an individual instrument can stimulate disruptions that are transmitted through increasingly interdependent and interconnected financial markets worldwide” (Fernandez, 1999, p1).

Liquidity is, unquestionably a central hallmark of any efficient market. It ensures a swift and accurate incorporation of new information into asset prices and allows for a general equilibrium to be reached in a world consisting of heterogeneous investors. Recent years have seen the emergence of vast amounts of literature accounting in various ways for the effects of illiquidity. The dawning acknowledgement of the importance of liquidity is, among other things, reflected in Wyss (2004), who cites Gomber and Schweickert's (2002) observation that various security exchanges plan to introduce public communication of liquidity measures. But while the importance of liquidity for the functioning of financial markets is relatively obvious, it is somewhat more difficult to appreciate its effect on the real economy – on the firms, which are arguably the backbone of any capitalist economy.

Over the years, numerous studies have endorsed the existence of a connection between the liquidity of a share and the cost of capital of that firm. These studies have demonstrated that liquidity is priced in the market implying that investors require a discount when investing in illiquid assets as compensation for the expected transaction cost when selling the asset again at some point. Notably Amihud and Mendelson (1986) deeply impacted the field of asset pricing theory, demonstrating how a rational investor would require a discount when holding an illiquid asset equal to the present value of the entire expected future stream of trading costs. This, as

noted, implies that firms with less liquid stocks face a higher cost of capital *ceteris paribus* than their more liquid counterparts. Liquidity can thus be said to profoundly affect the firms' competitive capabilities providing a real role for liquidity in explaining success or failure of companies. But while this strand of thought has been immensely successful in emphasizing the importance of considering liquidity when determining asset prices, these studies face a common challenge: Any test of the effect of liquidity on required rate of return is invariably a joint test of the capital asset pricing model employed.

An alternative (or supporting) approach to gauging the effect of illiquidity on a company is to adopt an event-study approach, looking to where the cost of capital, likely, has the most discernible impact; the decision to issue new equity. In a seasoned equity offering (SEO) a firm encounters two fundamental types of costs: direct and indirect costs. The *direct* costs relate to the fees to investment banks, lawyers, accountants etc. which the firm will incur when embarking on an SEO. The *indirect* costs refer to the well documented SEO discount; the observed tendency for new equity to be issued at a discount. This discount imposes a cost on the existing owners of the firm in cases where these do not subscribe to the issuance on a pro rata basis, by transferring wealth from old to new shareholders.

In a recent paper Butler et al. (2005) establish that liquidity is an important determinant of the investment banking fee. Studying a large sample of American SEOs from 1993 to 2000, Butler et al. (2005) demonstrate that, all else equal, investment banks' fees are substantially lower for firms with more liquid stocks. Butler et al. (2005) further point to a study by Corwin (2003), who attempts to explain the SEO discount with a variety of factors, noting that Corwin finds the SEO discount to be negatively related to some measures of liquidity. While Corwin's (2003) analysis yielded mixed evidence in this regard, recent studies by Asem et al. (2009) and Stulz et al. (2012), have cemented the existence of a role for liquidity in determining the SEO discount. Liquidity, thus, seems to influence the total cost of raising external equity capital, directly through the investment bankers' fee as well as indirectly through the SEO discount. This in turn provides an important role for liquidity in the management's decision to issue equity.

This paper attempts to gauge the relation between illiquidity and the combined cost of issuing equity. By analyzing a large European dataset, the role of illiquidity in determining investment bankers' fees is analyzed, implicitly testing the insights of Butler et al. (2005) in a European context. The paper will subsequently formalize the analysis by Corwin, scrutinizing the relation between illiquidity and SEO discount. Finally, the paper will discuss any possible relationship

between direct and indirect costs, providing the foundation for an overall assessment of the significance of illiquidity on the combined cost of undertaking an SEO.

1.1 Problem statement

This outline gives rise to the following overall problem statement that this paper will attempt to address:

‘How does secondary market illiquidity predict the combined cost of issuing seasoned equity?’

This question will be approached through the following four sub-questions

- i. What is liquidity and how is it measured?
- ii. What determines the direct costs of an SEO and are they related to liquidity?
- iii. What determines the indirect costs of an SEO and are they related to liquidity?
- iv. How can the combined costs of an SEO be defined and are they related to liquidity?

In attempting to answer these questions the thesis is structured as follows, section 2 sets out with a brief explanation of why liquidity matters in relation to asset prices. This includes a brief overview of some of the main developments within asset pricing theory. Section 3 proceeds by giving an introduction to the concept of liquidity, explaining its elusive nature and the inherent problems in capturing and quantifying it. It provides an overview of commonly used measures of liquidity, discussing the various ‘dimensions’ they capture. Finally, a set of measures to be employed in the subsequent analysis is selected.

Section 4 gives a brief introduction to seasoned equity offerings. This includes an overview of the various methods in existence, with an emphasis on the varying level of involvement from the investment bank and consequently differing fees.

This leads into section 5, which contains a broader discussion, of the existing research on the topic of investment bankers’ fees in relation to equity offerings. Furthermore the hypothesized relation between the investment bankers’ fee and the secondary market liquidity of the stock will be thoroughly explained and discussed.

Addressing the topic of indirect costs, Section 6 sheds light on the fundamental decision to issue equity, including an explanation of the essential link between SEOs and the field of capital structure theory. This emphasizes the crucial importance of certain fundamental capital structure concepts such as ‘adverse selection’ in understanding the dynamics of an SEO. Section 6 further explains the concept of the SEO discount, providing firstly a discussion of various theoretical

explanations, and secondly an overview of previous studies within the field. Finally, the section discusses the hypothesized relation between the SEO discount and the secondary market liquidity.

Section 7 introduces the dataset and explains how it was produced and discusses issues of econometric methodology specific to this paper. With the sample and methodology thus presented, sections 8 carry out a two pronged analysis of the relation between liquidity and the costs associated with an SEO. Firstly, the relation between the direct costs and secondary market liquidity is analyzed, in a univariate as well as a multivariate framework. Secondly, a similar analysis of the indirect costs is performed.

Before venturing into an econometric analysis of the total cost, section 9 discusses the potential relation between direct and indirect costs theoretically. Subsequently continuing with an empirical analysis of how the combined cost of an SEO is related to liquidity.

On a closing note, section 10 reflects on the broader perspectives of the insights from this thesis, discussing potential applications as well as fields of further study. Section 11 concludes.

In doing this we rely on a wide variety of academic theories as well as previous empirical studies. In the subsequent section general methodological considerations underlying the application of these are reflected upon.

1.2 General methodology

This paper makes an attempt to assess to what extent secondary market illiquidity can predict the direct and indirect costs associated with an SEO. This is done by assessing both the direct costs of the offering itself and the less tangible costs of the welfare loss to existing shareholders.

Throughout the discourse, the paper will take a positivist approach to the research question, rather than developing a normative guide. For example, using the positivist approach when analyzing what level of SEO discount would be suitable for a firm with a given level of secondary market illiquidity. Furthermore this paper will employ deductive reasoning drawn from, in this case, a body of theory relating to numerous different fields in an attempt to provide an answer to the research question.

Firstly this paper employs concepts from the field of market liquidity theory and how it may impact the cost of capital for a firm. The latter, in turn, is firmly placed in the realm of asset pricing theory.

Other fields that this paper will draw on include contracting theory and how this affects both the choice of flotation method as well as the direct costs associated with the flotation itself. Finally, the study will also draw on capital structure theory and other proposed explanations to the seasoned equity discounts some of which are intimately linked with game theory. A large body of literature exists in the canon, positing theories that will be deduced and discussed to provide a more complete theoretical framework for the paper.

This paper will also draw heavily on several empirical studies of seasoned equity offerings. These have been selected to add further weight to the discussion by being able to provide real world examples of the direct costs as well as indirect costs, collated over a long period of time. This further facilitates a comparison and a discussion of how the insights from the data analysis of this paper relates to previous findings with varying scopes and samples. Further, research on initial public offerings (IPO) will be applied in providing valuable additional insights. While comparisons across IPOs and SEOs should be done with care, several researchers note that the insights obtained in one area are essentially applicable to the other.

This paper will also rely heavily on publicly available data during the data analysis section of the paper. Well renowned financial databases, such as Dealogic and Bloomberg are relied upon for the data input. While the quality and potential biases of the data employed is discussed at relevant places in the analysis, this paper, by and large, relies on the validity of the data produced by the aforementioned databases. While this may be viewed as a potential weakness, it is a characteristic that pertains to most empirical studies that the authors have come across. When employing samples of the size that this paper (and several others) does, obtaining and collecting data first hand is simply not an option.

Having established the general methodological applied the thesis sets of with a discussion of the importance of liquidity.

2 Why liquidity matters

The direct and indirect costs of an SEO are intimately linked to the cost of capital of a firm an analysis of this relation is, therefore, firmly placed in the realm of asset pricing theory. It is, therefore, relevant to initiate this paper with a brief and non-exhaustive overview of some of the main developments within this field, starting with its beginning and the highly influential papers by Sharp (1964) and Lintner (1965). This brief overview will, naturally, put more emphasis on the

developments that are related to the acknowledgement that liquidity is a significant explanatory variable in explaining the observed prices of assets.

2.1 A brief history of asset pricing theory

The capital asset pricing model (CAPM) as developed by Sharpe (1964) and Lintner (1965) was in many ways the inauguration of asset pricing theory as a field of research and resulted in a Nobel Prize for Sharpe in 1990. It takes its beginning in the model of portfolio choice developed by Harry Markowitz (1952), where investors were assumed risk averse and, when choosing among portfolios, were assumed only to care about the mean and variance of return on their investment. This resulted in the famous ‘Mean-Variance Model’ that predicts an efficient frontier in variance-return space to which every asset must adhere.

Among the attractive features of CAPM is its provision of very powerful and intuitive explanations with a sound theoretical background about risk measurement and the relationship between risk and expected return. In its original form it states, quite simply, that the expected return of any asset is a function of the return of the risk free asset, the expected return on the market portfolio and the correlation between the return of the asset and that of the general market.

$$E(R_i) = R_f + \beta_{iM}(E(R_M) - R_f)$$

Where $E(R_i)$ is the expected return on asset i, R_f is the risk free return, β_{iM} is the sensitivity to the assets return to variations in the market return and $E(R_M)$ is the expected return on the market portfolio.

The CAPM is a one-period model and provides little guidance on its implementation. Where the intuition behind the beta of a stock to the market, the market return, and the risk free rate is fairly clear, these factors are much harder to verify. For example, when calculating the beta of a stock one should ideally construct a market portfolio, calculate its periodical returns, and then regress the periodical return of the stock on that. However, creating a value-weighted portfolio consisting of both traded (stocks, bonds etc.) and non-traded assets (private companies, human capital etc.) is virtually impossible, which is why large diversified indexes are used for practical purposes.

In spite of such issues, this comparatively simple model has had a tremendous impact, and retains a significant place today where, *“It is the centerpiece of MBA investment courses. Indeed, it is often the only asset pricing model taught in these courses”* (Fama and French, 2004, p25). And certainly any business school student cannot fail to come across the CAPM at some point.

However in spite of an ‘improvement’ by Fischer Black (1972) among other things, relaxing the assumption of the ability to lend and borrow unlimited at the risk free rate, CAPM has taken several blows in subsequent empirical studies.

One of the first studies to notably shake the foundation of the CAPM was that of Basu (1977) who set out to determine, empirically, to what extent the investment performance of stocks could be shown to be related to their P/E ratios. Proving that low P/E stocks tend to have higher returns, than justified by their underlying risk, would indeed be inconsistent with the predictions of CAPM. Basu (1977) concluded that, “*These results suggest a violation in the joint hypothesis that (i) the asset pricing models employed in this paper have descriptive validity and (ii) security price behavior is consistent with the efficient market hypothesis*” (Basu, 1977, p680). This frontal attack on the very foundation of the CAPM initiated a multitude of attempts to explain this apparent inconsistency.

A broad field of study, subsequently, focused on enhancing the understanding of the cross-sectional characteristics of stock-returns. This field largely produced two significant insights: a tendency for firms with relatively small market capitalizations to perform better than those with a larger market cap, and equivalently for high market-to-book ratio stocks to outperform their low market to book counterparts. These insights were elegantly summarized in the ‘Three factor model’ of Fama and French (1992), which adds to the traditional Sharp, Lintner and Black versions of the CAPM two factors: the ‘Small Minus Big’ (SMB) factor and the ‘High Minus Low’ (HML) factor, where SMB captures the small cap discount and HML captures high market-to-book ratio effect (Fama and French, 1992).

In addition to the scrutiny of cross-sectional explanations for stock-return anomalies, another line of thought took its departure in the inspired works of Tversky and Kahneman – their introduction of the concept of ‘heuristics’ in decision making (1974) and their highly influential ‘Prospect Theory’ (1979), which was a stark critique of the traditional expected utility theory. These articles strongly contributed to the founding of the field of ‘Behavioral Finance’, which was arguably inaugurated by De Bondt and Thaler’s (1985) article, ‘Does the Stock Market Overreact?’. In the article, De Bondt and Thaler (1985) found indications of inconsistencies with the predictions of CAPM in the time-series of returns.

De Bondt and Thaler (1985) found evidence of a momentum effect, based on research within experimental psychology, indicating that people tend to ‘overreact’ to recent and unexpected information. Empirically, this finding was strongly supported by Jegadeesh and Titman (1993)

who concluded that: *“Trading strategies that buy past winners and sell past losers realize significant abnormal returns over the 1965 to 1989 period.”* (Jegadeesh and Titman, 1993, p89). This finding ultimately lead to Carhart’s (1997) addition of a fourth factor to the aforementioned Fama and French three factor model, the momentum factor.

Only a year after the De Bondt and Thaler (1985) article introduced psychology into the realm of finance, a completely different, but arguably even more influential strand of thought took its beginning. In the landmark article, ‘Asset Pricing and the Bid-Ask Spread’ Amihud and Mendelson (1986) demonstrated that a rational investor should price illiquidity as measured by the bid-ask spread into the asset price.

In a traditional sense, it could be argued that if such frictions really lead to substantial costs to market participants, the efficient market hypothesis would predict an institutional response profiting from easing these frictions. However, as noted by Amihud, Mendelson and Pedersen (2005), alleviating frictions comes at a cost. If frictions did not affect prices, the institutions alleviating these frictions would not be compensated for doing so, in which case one would not have an incentive to alleviate the frictions in the first place. The authors thus conclude that: *“There must be an ‘equilibrium level of disequilibrium,’ that is, an equilibrium level of illiquidity: The market must be illiquid enough to compensate liquidity providers (or information gatherers), and not so illiquid that it is profitable for new liquidity providers to enter.”* (Amihud et al., 2005, p275).

Amihud and Mendelson (1986) define illiquidity as *“...the cost of immediate execution.”* (Amihud and Mendelson, 1986, p223) and note that quoted ask prices contain a premium for immediate buying and that the bid price in the same fashion contains a concession for immediate sale. This lead them to conclude that the bid-ask spread is a natural measure of illiquidity, as this is effectively the sum of this buying premium and selling concession.

The very essence of Amihud and Mendeson’s (1986) argument is that an agent, when buying an asset, anticipates a cost when eventually selling it again. The agent, subsequently buying the asset, too foresees this transaction cost and as does the next buyer and so on. This affects the value of the asset as: *“Consequently, the investor will have to consider, in her valuation, the entire future stream of transaction costs that will be paid on her security. Then, the price discount due to illiquidity is the present value of the expected stream of transaction costs through its lifetime.”* (Amihud et al., 2005, p279). In a very simple model with risk neutral investors with a discount

rate of $\frac{1}{1+r^f}$, where in each period the investor receives a dividend d_t^i , which is independently and identically distributed with mean \bar{d}^i and where the investor upon each trade incurs a transaction cost of C^i the stationary equilibrium price P^i is expressed by

$$P^i = \frac{(\bar{d}^i + P^i - C^i)}{1 + r^f}$$

which implies that

$$P^i = \frac{(\bar{d}^i - C^i)}{r^f}$$

In this simple model, it is obvious that the price of an asset is simply the present value of all future expected dividends minus the present value of all future transaction costs. Expressed in a somewhat more general fashion, where agents need not exit the market in each period, but rather at any point in time must exit with probability μ , the price is expressed by

$$P^i = \frac{(\bar{d}^i - \mu C^i)}{r^f}$$

This expression essentially calculates the future transaction costs taking the expected trading frequency into account. Alternatively the expression can be rearranged to express the required return $E(r^i)$

$$E(r^i) = r^f + \mu \frac{C^i}{P^i}$$

In simple terms, this implies that the required rate of return on an illiquid asset is the risk free rate plus the transaction costs relative to the price, weighted by the trading frequency. The discount on illiquidity is, thus, driven by two factors: the per-trade cost as well as the intensity with which trading occurs. Realizing the importance of the latter factor yields another important insight from Amihud and Mendelson's (1986) theory; if investors fundamentally differ in their expected trading intensity or holding period, illiquidity will matter more to some than others.

Thus, in addition to predicting that assets with higher spreads will yield higher expected returns, they predict that; *"...there is a clientele effect whereby investors with longer holding periods select assets with higher spreads"* (Amihud and Mendelson, 1986, p224). While both long and short holding investors strictly prefer more liquid assets, investors with longer holding periods

have a comparative advantage in illiquid assets as, “...an investor expecting a long holding period can gain by holding high-spread assets” (Amihud and Mendelson, 1986, p224).

Amihud et al. (2005) emphasize that this rests on an important assumption that agents are not able to borrow unlimited amounts. Firstly absent of any borrowing constraints, all the illiquid assets would be bought by the investors with the longest holding periods, and in turn imply that there is, in essence, only one type of investors active in the market. Secondly, “...without borrowing constraints, investors could achieve a long holding period by postponing liquidation of assets when facing a cash need and instead financing consumption by borrowing. Hence, borrowing frictions are important for market liquidity to affect prices” (Amihud et al., 2005, p283). This interaction between market liquidity and funding liquidity (as measured by borrowing frictions) is highly interesting, and will be touched upon below.

Under the, somewhat extreme, assumption of no borrowing at all, Amihud and Mendelson (1986) derive an equilibrium condition where the agents with the shortest expected holding period, termed ‘type 1’ investors (to whom liquidity matters the most) will hold a combination of the riskless assets and the illiquid securities with the lowest trading cost. Agents with the second shortest holding period, ‘type 2’ investors, hold the second most liquid assets etc.

Amihud et al. (2005) show that when type j investors (the investors with the longest holding period) are marginal investors, for security i , the expected gross return of security i is given by

$$E(r^i) = r^f + (r^{*j} - r^f) + \mu^j \frac{C^i}{p^i}$$

where r^{*j} is the liquidity adjusted required return of investor type j given by

$$r^{*j} = \frac{\bar{d}^{ij-1} - \mu^j C^{ij-1}}{p^{ij-1}}$$

The required rate of return is thus “...the sum of the risk free rate r^f , investor j ’s “rent” ($r^{*j} - r^f$), and his amortized relative trading cost $\mu^j \frac{C^i}{p^i}$.” (Amihud et al., 2005, p285). The clientele effect thus according to Amihud and Mendelson (1986) gives rise to a concave function by which required returns are affected by illiquidity.

Amihud and Mendelson (1986) treat illiquidity very much as a stable phenomenon; a constant factor in the marketplace. But what if the level of liquidity is not constant but fluctuates over time? In that case, investors face an additional risk that liquidity ‘may not be there’ when they

need it. Put differently, contrary to the assumption in Amihud and Mendelson (1986), investors may not exactly know what the future transaction cost will be when they sell the asset at some point in the future. This risk should be priced in addition to the fundamental friction caused by the prevailing level of liquidity.

One notable attempt to account for this effect is a recent article by Acharya and Pedersen (2005), who cite among other Chordia et al. (2000) in providing evidence that liquidity does indeed fluctuate over time. Acharya and Pedersen (2005) argue that, as it has been demonstrated that liquidity affects asset prices, alterations in liquidity must also affect fundamental price volatility. Thus, *“For both of these reasons, liquidity fluctuations constitute a new type of risk that augments the fundamental cash-flow risk.”* (Amihud et al. 2005, p286). Acharya and Pedersen (2005) set out to develop a model of the effect of a security’s liquidity risk (i.e. the risk of changing liquidity over time) on required return. Acharya and Pedersen (2005) foster a model which is essentially a liquidity augmented CAPM introducing three liquidity betas termed β^{L1} , β^{L2} and β^{L3} complementing the traditional β , which as the reader will recall is defined as

$$\beta_t = \frac{\text{cov}_t(r_{t+1}^i, r_{t+1}^M)}{\text{var}_t(r_{t+1}^M - c_{t+1}^M)}$$

The additional three betas are defined as follows

$$\beta_t^{L1} = \frac{\text{cov}_t(c_{t+1}^i, c_{t+1}^M)}{\text{var}_t(r_{t+1}^M - c_{t+1}^M)}$$

$$\beta_t^{L2} = \frac{\text{cov}_t(r_{t+1}^i, c_{t+1}^M)}{\text{var}_t(r_{t+1}^M - c_{t+1}^M)}$$

$$\beta_t^{L3} = \frac{\text{cov}_t(c_{t+1}^i, r_{t+1}^M)}{\text{var}_t(r_{t+1}^M - c_{t+1}^M)}$$

These betas combine into the following liquidity augmented condition for the expected return

$$E_t(r_{t+1}^i) = r^f + E_t(c_{t+1}^i) + \lambda_t(\beta_t + \beta_t^{L1} - \beta_t^{L2} - \beta_t^{L3})$$

In simple terms this model predicts that the required return, in excess of the risk free rate, is the expected relative cost of illiquidity $E_t(c_{t+1}^i)$ as per Amihud and Mendelson (1986), plus the above defined four betas times the risk premium. In the same way as the traditional CAPM of Sharpe et al. expected return increases in the market beta.

The first liquidity beta β_t^{L1} implies that the expected return is higher for assets with a higher covariance between the liquidity of the asset and that of the general market. Acharya and Pedersen (2005) note that: *“This is because investors want to be compensated for holding a security that becomes illiquid when the market in general becomes illiquid”* (Acharya and Pedersen, 2005, p382).

The second liquidity beta β_t^{L2} considers the covariance between the return of the asset and the liquidity of the general market. The required rate of return is affected negatively by β_t^{L2} as investors ceteris paribus prefer securities which yields a high return during periods of waning market liquidity.

The third liquidity beta β_t^{L3} accounts for the covariance between the liquidity of the asset in question and the return on the general market. This effect again is negative, as investors prefer holding an asset that is also liquid in negative markets. Acharya and Pedersen (2005) explain that: *“When the market declines, investors are poor and the ability to sell easily is especially valuable. Hence, an investor is willing to accept a discounted return on stocks with low illiquidity costs in states of poor market return”* (Acharya and Pedersen, 2005, p382).

Both Amihud and Mendelson (1986) and Acharya and Pedersen (2005) as well as a multitude of other articles, in the field of asset pricing and liquidity, perform empirical studies in addition to their theoretical work. Amihud and Mendelson (1986) tested their hypothesis by employing bid-ask spread data from 1960-1979 as well as stock returns in the following year – that is from 1961 through 1980. They formed portfolios of stocks in each year that were based on relative spread and then sorted on estimated beta, so as to account for the predictions of CAPM. Subsequently monthly returns were calculated for each portfolio. The illiquidity effect was then estimated with dummy variables for each of the ‘illiquidity portfolios’ giving rise to a piece-wise linear curve. Amihud and Mendelson (1986) found strong support that the average return of the portfolio did increase in the bid-ask spread as hypothesized. Secondly, the finding that this ‘slope’ decreased in the bid-ask spread, confirmed that this relation, indeed, seemed concave. Amihud et al. (2005) note that this finding can be summarized in the following model

$$R_j = 0.0065 + 0.0010\beta_j + 0.0021\ln(S_j)$$

where R_j is the monthly stock portfolio return over and above the 90-day treasury bill rate, β_j is the systematic risk as defined in the CAPM, and S_j is the relative bid-ask spread in the previous 12 months.

Acharya and Pedersen (2005) employ a somewhat more sophisticated measure of illiquidity in empirically testing their theoretical predictions. Rather than the simple relative bid-ask spread they employ a liquidity measure developed by Amihud (2002) called ILLIQ. This measure they calculate from daily stock returns of NYSE/AMEX stocks from 1964 through 1999. Upon estimating the above model, consisting of the traditional CAPM, the Amihud and Mendelson (1986) illiquidity premium as well as the three additional liquidity betas, the authors find that the model has a higher explanatory power in the cross section than the standard CAPM. Finally, Amihud et al. (2005) find a substantial economic impact from the least to the most liquid securities, noting that; “...the total annual liquidity risk premium is estimated to 1.1% while the premium for liquidity level is 3.5%” (Amihud et al., 2005, p325).

In summary asset pricing theory has developed significantly from its beginning in the mid 60's even with various attacks on its validity. While there are still competing explanations of its various shortcomings, one field, addressing the role of illiquidity in explaining asset prices has been immensely successful. One would, therefore, naturally look to other fields of research to explore the potential for liquidity to account for other observed phenomena. In this context the attempt of this paper to explore the effect of illiquidity on the costs of issuing seasoned equity and can be viewed as a small contribution to this vast field of study.

In addition, a common criticism of most studies exploring the relation between asset prices and liquidity is, as noted, that any such test also implicitly tests the capital asset pricing model employed – that is, it assumes that returns are actually priced in accordance with the capital asset pricing model in use. The research design employed in this study circumvents this problem as it adopts an event-study based approach, not attempting to account for the stock returns, but rather to study the predictive power of secondary market liquidity on asset prices at a particular point in time. While in no way a substitute for the aforementioned studies, this study can also be seen as a contribution to accentuating the validity of their common insight; that liquidity matters.

In exploring whether liquidity matters, also in the context of SEOs, a thorough discussion and exposition of what liquidity is, and how it may be quantified is a logical place to start. The following section, therefore, is dedicated to that particular purpose.

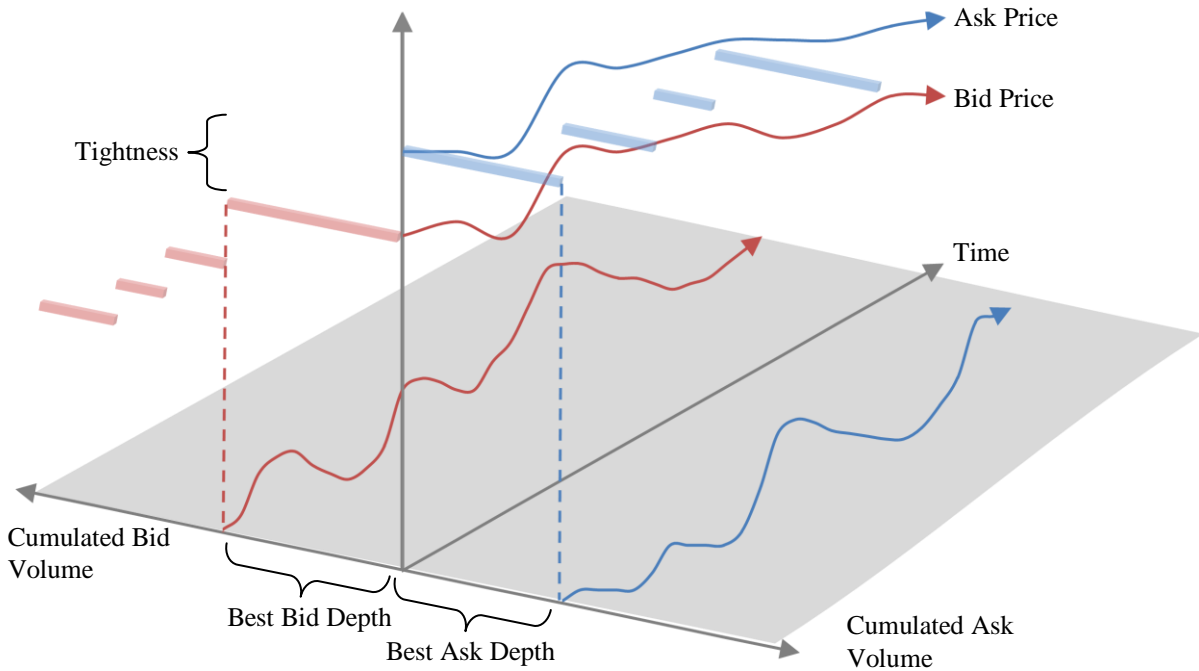
3 Liquidity

3.1 Introduction

Liquidity is a highly complex and elusive concept that can be defined in a multitude of ways. The liquidity of an asset can be described as the ease with which the asset can be converted into cash. Liquid assets are assets that can be easily converted into cash with little reduction in value – i.e. at a low cost and/or in a short time – i.e. very swiftly. Accountants make a similar distinction when presenting the financial statements in the annual report. If one read an annual report, using the requirement of International Financial Accounting Standards (IFRS), it will be noticeable how the assets are presented with respect to how liquid the assets are. For example, intangible assets are listed in the top of the statement (the most illiquid), and cash holdings are found in the bottom (the most liquid).

Marketable securities are also found as one of the bottom balance sheet items, hereby considering these as one of the most liquid types of assets. Whereas the distinction between top and bottom of the balance sheet comes somewhat naturally, it is more difficult to distinguish securities from each other in terms of how liquid they are. Usually, when trying to define what liquidity is, one will come across simple one sentence definitions like the one presented above – “The liquidity of an asset describes the ease with which the asset can be converted into cash.” One reason why these definitions come out somewhat vague is that liquidity, in its essence, cannot be simply captured because liquidity is a highly complex and multidimensional concept. This complexity for instance, is evident from the four general aspects of liquidity as presented by Wyss (2004). The four general aspects are trading time, tightness, depth and resiliency (Wyss, 2004, p5). The intuition behind some of these aspects is visible when illustrating the limit order book as in the figure below.

Figure 1



Trading time: measures the ‘flow’ or waiting time between subsequent trades and can be used to describe how frequently a stock is traded. Another possible and more intuitive way to capture trading time is the reciprocal of waiting time, namely the number of trades per time unit.

Tightness: sheds light on the heterogeneity of the two essential components of any marketplace: the buyer and the seller. This is contrary to trading time, which focuses solely on the frequency of trades. Tightness is generally captured through the use of various measures employing the bid-ask spread. A review and discussion of numerous variations over the bid-ask spread based measures shall be provided later, but generally stated, they proxy the trading costs that investors will incur when trading, as well as convey something about the level of disagreement between buyers and sellers in the marketplace. This, in turn, is closely linked to the notion of asymmetric information between agents in the market.

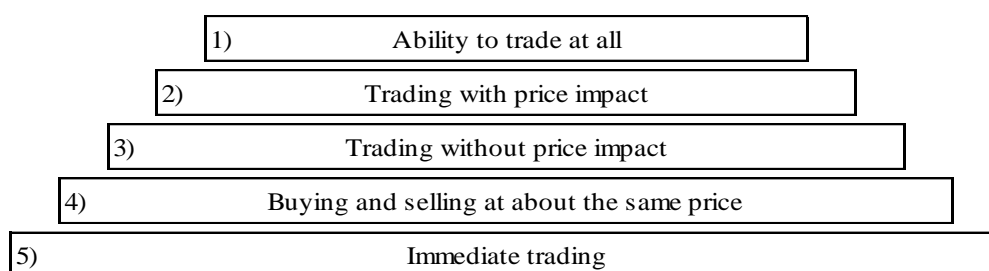
Depth: puts emphasis on the size of the indicated willingness to buy and sell at the current price levels, typically looking at the total buy and ask volume at the best bid and offer prices. Apart from the order depth itself, depth related measures include the order ratio and the flow ratio. Finally, underscoring the difficulty of distinguishing between various aspects of liquidity, one could very well argue that volume also captures elements of the depth-dimension. It too essentially holds information about the “...ability to buy or to sell a certain amount of an asset

without influence on the quoted price” (Wyss, 2004, p5), even though volume is backward looking, realized liquidity, and depth is unrealized liquidity.

Resiliency: depth is closely linked to Wyss’ (2004) final aspect of liquidity, namely that of resiliency, as the limit order book also contains information about the extent to which prices would be affected by a certain amount of shares traded or again inversely how many shares that would have to be traded in order to shift the price by a given amount. Considering resiliency, one would typically look further into the order book (i.e. not only analyzing at the best bid and offer-level) and attempt to estimate the actual elasticity of supply and demand. In addition to scrutinizing the order book, resiliency may be assessed from an empirical point of view, through an analysis of how much prices have been affected by a given number of shares traded.

Wyss uses the abovementioned aspect of liquidity to define five levels of liquidity (Wyss, 2004, p8). Where level one is the least liquid and level five is the most liquid level.

Figure 2



The first level of liquidity is rather obvious; if the market is completely illiquid, no trades will take place. Thus, the very first prerequisite of any market is that there is at least one bid and one ask quote thus, making a trade possible. But provided the ability to trade, the subsequent question is what impact trading will have on the price. The second level of liquidity thus, describes markets where trades can take place but will have a discernible impact on the price. Thirdly, as markets become more liquid (at least when viewed in the depth perspective of liquidity) the impact of trading on quoted prices will diminish, as one will be able to buy and sell ‘any’ position if the debt in that particular security is large enough. While the ranking of liquidity level one through three is relatively obvious, Wyss’ (2004) fourth and fifth level of liquidity captures other fundamental aspects of liquidity. The fourth level essentially, encompasses a relatively tight spread, enabling round-trips at a reasonable cost, and the fifth level incorporates the time aspect of liquidity, calling for the ability to trade immediately. But as Wyss notes, one could imagine a

market where instant trading was possible, but with a severe impact on the price, in which case; “...level five should be regrouped at the position of level two” (Wyss, 2004, p8).

This part of the thesis serves to describe how liquidity can be measured, and hereby, excluding a discussion of the vast field of research around market microstructure. However, market microstructure’s focus on price formation and price discovery, market structure and design, information and transparency, and the interface of market microstructure with corporate finance, asset pricing, and international finance, could help to explain the origins of illiquidity (Madhavan, 2002, pp28-29). So while this thesis relates a certain level of liquidity to the costs of issuing seasoned equity, it does not try to explain how companies can improve liquidity in their stock.

From this it follows clearly that none of these aspects succeed alone in quantifying liquidity in its full scope and compass, but all capture various manifestations of liquidity or lack thereof. In the following section there will be an overview and discussion of the various liquidity measures that are commonly applied in research with an emphasis not only on practical issues of computation, but also on wider considerations of application and interpretation. The section will initially address the ‘basic’ measures that take only one variable into account, but will subsequently argue that combining variables into more complex multidimensional measures enables one to capture other aspects of liquidity and provides one with a more holistic assessment of the liquidity of the asset in question.

3.2 Grouping of liquidity measures

As presented above Wyss (2004) shows that liquidity measures can be grouped in terms of trading time, tightness, depth, and resiliency. We argue that this way of grouping liquidity measures is not quite comprehensive. The following section will provide examples, supplementing Wyss (2004), of alternative, relevant ways to group and analyze liquidity measures.

3.2.1 Backward versus forward looking liquidity measures

All liquidity measures are based on historic events from which proxies or indications of future trading patterns can be calculated. All of the described measures below come from data, which by definition are historic. There is a fundamental difference between measures that assess the potential for trades to occur without a trade necessarily occurring and those capturing trades that actually occurred. The former could be termed ex-ante measures of liquidity and the latter ex-post measures. Ex-ante measures thus, quantify ‘potential’ liquidity, while ex-post measures captures ‘realized’ liquidity.

For example, a security with low trading volume does not constitute low liquidity per se. One could imagine a hypothetical situation where a tight spread and a substantial depth does not result in a trade. A trade however, could easily (and at low price concession) have occurred, had someone wished to execute the trade i.e. making the ‘last’ price concession. In the same fashion one could imagine a stock with a wide spread, but where trades frequently occur inside the spread. This stock would be illiquid in terms of its absolute bid-ask spread measure, but relatively more liquid when measured in terms of the ‘effective bid-ask spread’ and turnover. These examples illustrate the potential benefit from using different measures to gauge the liquidity of a particular security.

3.2.2 *High-frequency versus low-frequency liquidity measures*

When computing liquidity measures one faces the choice of whether to use high-frequency data, which could often imply intraday data that contain information about each and every trade, or low-frequency data, which often implies the use of end of day data. Essentially the question is whether end of day observations hold the same information as intraday observations, or in other words: how much information is ‘lost’ when using low frequency data as compared to high frequency data. This potential ‘loss’ should obviously be compared to the benefit of having substantially less data to sift through. Considering using end of day data one could fear that the nature of this data will bias the liquidity measures in one direction or the other. For example, one could argue that end of day spreads might act somewhat differently since day-traders will be out of the market at this point and as they realize their positions turning into cash overnight. Hence, the supply and demand by the end of the day might be different from the rest of the day for some stocks.

Recently, Fong et al. (2011) has done extensive research to answer the question of whether low-frequency data can be applied as proxy for high frequency data. They compare liquidity proxies constructed from low-frequency stock data to liquidity benchmarks computed from high-frequency data. Their research is carried out across 18,472 firms and over 43 exchanges around the world from January 1996 to December 2007, and they conclude firmly that; “...*Intraday liquidity benchmarks can be effectively captured by proxies based on daily data*” (Fong et al., 2011, p24).

3.2.3 *Percent-cost measures versus cost per-volume*

As presented by Fong et al. (2011), another way to group liquidity measures is to distinguish between whether they measure/proxy the cost (what price concession is required to execute the

trade) or cost per quantity (what price concession per unit of quantity is required). Accordingly, they differentiate between *percent-cost measures* that estimate the cost of trading as a percentage of the price and *cost per-volume measures* that capture the marginal transaction cost per unit of volume as measured in local currency (Fong et al., 2011, p4).

3.2.4 One-dimensional versus multi-dimensional measures

Yet another meaningful way of grouping liquidity measures is according to whether they describe only a single dimension or aspect of liquidity, or capture two or more. While some measures solely focus on one parameter of liquidity, other account for several aspects in the same measure by including various dimensions of liquidity. This distinction can be useful as one could argue that one may sometimes prefer the more transparent nature of a single-dimension liquidity measure over a more complex measure as this may tie in with ones hypothesis. Such an example is the previously discussed and much cited paper by Amihud and Mendelson (1986) where the expected return is mathematically expressed as a function of the bid-ask spread.

3.3 Liquidity measures

In the following section, a thorough analysis of various liquidity measures is made in order to establish the best foundation of which measures to base the subsequent empirical analysis on. The measures are overall grouped along the distinction of whether the measure is one- or multi-dimensional. However the other characteristics that the measures can hold, is also used. It shall be noted that the following section will employ the same notation as used by Wyss (2004) in his dissertation titled *“Measuring and Predicting Liquidity in the Stock Market.”* Here he thoroughly reviews ways to measure liquidity. The section moreover, is inspired by the way Wyss (2004) choose to group the liquidity measures. The decisive factor when deciding what measures to include in this section has been whether the particular measure helps to explain how liquidity can be quantified.

The paramount importance of assessing what measures to apply is well stated by Amihud et al. (2005), as they note that; *“Any liquidity measure used clearly measures liquidity with an error”*. This error is argued to exist because of three main reasons: first *“...a single measure cannot capture all the different dimensions of liquidity”*; second *“...the empirically-derived measure is a noisy estimate of the true parameter”*; and third *“...the use of low-frequency data to create the estimates increases the measurement noise”* (Amihud et al., 2005, p305).

3.3.1 One-dimensional liquidity measures

3.3.1.1 Volume related measures

Trading volume

The volume (Q_t) measures the number of shares traded in a given time interval. The volume is calculated from $t - 1$ to time t . q_i represents each observed transaction in the market.

$$Q_t = \sum_{i=1}^{N_t} q_i$$

Volume is a widely used measure to estimate the liquidity of a particular stock. It is typically readily available, and very easy to interpret. However, volume in itself might be a poor proxy when used for comparison across securities, as share prices can vary substantially across different stocks. Comparing the volume of a stock with a price of 10 EUR to that of one priced at 100 EUR is clearly not meaningful. Also one could argue that variations in opening time across exchanges could bias the measure, as some stocks would potentially face trading longer than others. Volume as a liquidity measure is not all bad though; the measure can be good for comparing the liquidity in a single stock over time assuming the price has not changed much in the same period.

Turnover

Turnover (V_t) aggregates the value (price (p_i) multiplied by the volume (q_i) of each trade) of all trades in a given time interval. More simply stated turnover is the volume multiplied by the volume weighted average price (VWAP).

$$V_t = \sum_{i=1}^{N_t} p_i \cdot q_i$$

When stated in the same currency turnover is a better measure for comparison across stocks than volume. As a rule of thumb, one could thus argue that while the volume may be best suited for analysis in the time series, turnover should be preferred in cross sectional analysis. As with volume, one could argue that variations in opening hours across exchanges could bias the measure.

Depth

Depth (D_t) measured in its simplest form is the sum of the best ask depth (q_t^A) and the best bid depth (q_t^B). This is also referred to as the BBO (best bid and offer) depth.

$$D_t = q_t^A + q_t^B$$

While the aforementioned measures (volume and turnover) ‘require’ a trade to occur and as argued, could be considered ex-post measures of liquidity, depth, and the following two variations of depth, do not. These measures could be considered ex-ante measures of liquidity, as they assess the ‘potential’ for a trade to happen. The depth may be divided by two to create a proxy for the average bid or ask depth. However, this may bias the measure if the depth is highly skewed either to the bid or the ask side. This could be the case in a generally rising or falling market, respectively.

Log depth

As stated below, the log depth ($Dlog_t$) is simply the logarithmized depth.

$$Dlog_t = \ln(q_t^A) + \ln(q_t^B) = \ln(q_t^A \cdot q_t^B)$$

As in other geometrical matters, the log is taken in order to enhance the distributional properties of the variable. As was the case with volume, depth and log depth it can be hard to compare across stocks because of variations in stock prices. In a fashion similar to turnover this can be solved by the following measure.

Dollar depth

Overcoming the problem of comparing the depth across stocks, the aggregated ‘depth value’ i.e. the dollar depth ($D\$_t$) is calculated. P_t^A and P_t^B denote the best ask and bid prices respectively.

$$D\$_t = \frac{q_t^A \cdot p_t^A + q_t^B \cdot p_t^B}{2}$$

While the above, mentioned depth measures only focus on the depth at the best bid and ask prices, when placing larger orders one might have to ‘walk the book’ (Wyss, 2004). Walking the book entails that the order exceeds the quoted depth at the best bid or ask price, implying that one will incur an extra price concession when executing the trade. To account for this price concession, further dimensions of liquidity have to be assessed, which will be presented below.

3.3.1.2 Time-related liquidity measures

Number of transactions

Number of transactions (N_t) is, like volume, a fundamental measure to describe liquidity, as it focuses on the frequency by which trades occur.

$$N_t$$

The measure can be reversed in order to express the average waiting time between trades (Wyss, 2004, p12). Note that the issue of comparing stocks with different prices persists when using the number of trades or related measures to this.

Number of orders

In the same category, numbers of orders (NO_t) is found. This measure refers to the number of orders placed for a particular security in a given time interval.

$$NO_t$$

As opposed to number of transactions, the number of orders does not have to be executed. One could therefore say that it represents an ex-ante as well as an ex-post measure. Using the number of orders one can account for the possibility that only a few or no trades have been executed, which would return erroneous proxies of liquidity if only the realized transactions were reported.

Before touching upon multi-dimensional liquidity measures, the spread related measures are to be presented. The direct economic impact from the above mentioned measures can be hard to quantify but the spread related measures hold exactly this information by looking at the difference between the prices at which investors are willing to sell (the ask price) and the price at which investors are prepared to buy (the bid price). The common denominator for the following spread-related measures is that they all in some way quantify the cost incurred when making a ‘round trip’ – that is to buy and subsequently sell a share. However, these measures do not contain information on how many shares can be traded at this cost.

3.3.1.3 Spread-related liquidity measures

Absolute spread

The absolute spread ($Sabs_t$) measures the absolute difference between the best bid and offer price.

$$Sabs_t = P_t^A - P_t^B$$

Note that the absolute spread does not compare across stocks traded in different currencies. In that case, a dollar spread (or any currency of choice) could be applied. In addition to the former, one should again be careful when comparing absolute spreads over securities trading at substantially different prices.

Log absolute spread

While the absolute spread is widely used it, like the depth measure, imposes a challenge as its distribution may well be skewed. In order to address this issue one can take the logarithm, obtaining the log absolute spread (*LogSabs*).

$$LogSabs = \ln(Sabs_t) = \ln(p_t^A - p_t^B)$$

Relative spread

Relative spread (*SrelM_t*) addresses the problem of comparing the spread across different securities. This is done by scaling the spread with the mid-price (P_t^M) of the bid and ask price.

Calculating the relative spread makes it comparable across different stocks. However, one has to remember that the relative spread is based on the best bid and ask quotes which, “...does not necessarily measure well the cost of selling many shares” (Acharya and Pedersen, 2005, pp385-386).

$$SrelM_t = \frac{p_t^A - p_t^B}{p_t^M}$$

In addition to the mid-price, the last traded price (p_t) can be used to calculate the relative spread (*Srelp_t*). However, as noted by Wyss (2004), using the last traded price holds the advantage of accounting for upwards and downwards moving markets. In an upward moving market, trades tend to occur at the ask price and vice versa in a downwards moving market (Wyss, 2004, p15).

$$Srelp_t = \frac{p_t^A - p_t^B}{p_t}$$

While the property of accounting for moving markets is certainly desirable, the case of mixing of ex-ante and ex-post observation may prove problematic. If a trade has not occurred within a

reasonable time span then the use of last trade prices may yield erroneous results (Wyss, 2004, p15).

Relative spread of log prices

Simply the logarithmized relative spread.

$$Srellog_t = \ln(p_t^A) - \ln(p_t^B) = \ln\left(\frac{p_t^A}{p_t^B}\right)$$

Following the prior argumentation the relative spread can be calculated using log prices.

Effective spread

As pointed out with $Srelp_t$ trades may, in fact, occur inside the spread. The effective spread ($Seff_t$) accounts for this by measuring the absolute difference between the mid-price and the most recent trade.

$$Seff_t = |p_t - p_t^M|$$

Even though the intuition is better than $Srelp_t$, the problem, in cases where the ‘timing’ of observations differs substantially, still persists. Note that the effective spread can be multiplied by two, creating a proxy, which is comparable to the quoted spread.

Relative effective spread

Consistent with the relative spread, the effective spread can be scaled by either the price of the last trade or by the mid-price obtaining a relative effective spread ($Seffrelp_t$).

$$Seffrelp_t = \frac{|p_t - p_t^M|}{p_t}$$

This transformation to a relative measure is along with the aforementioned argument, done to make the measure comparable across stocks – for use in the cross section. Shown below is the formula for scaling the effective spread by the mid-price ($SeffrelM_t$).

$$SeffrelM_t = \frac{|p_t - p_t^M|}{p_t^M}$$

The spread related measures presented here only incorporate the best bid and ask data, these measures, as pointed out, fail to account for the cost incurred when trading larger quantities. This

may cause one, as mentioned, to have to ‘walk the book’. When analyzing the impact of trading larger orders one can, for example, construct aggregate supply and demand curves of the market for the stock in question, enabling one to account for the price impact occurring when trading across ticks. While it may seem one is solving many of the above mentioned problems, deriving aggregate supply and demand curves may not convey a perfect picture since traders and market makers, using modern trading platforms, are able to ‘hide’ parts of an order. For example, if a trader wants to realize a position of 10,000 shares he may offer them in the market at once but set up his system in a way that the order is only ‘revealed’ in portions of say, 1,000 at the time. This implies that he does not have to disclose the amount he is actually willing to sell at the given price.

Even though this kind of ‘hidden’ demand and supply exists, interesting insights can certainly still be drawn from assessing the order book in its entirety. Obtaining this insight essentially requires that the different one-dimensional measures are combined into multi-dimensional measures of liquidity. The following section presents examples of such multi-dimensional measures.

3.3.2 Multi-dimensional liquidity measures

Quote slope

The quote slope (QS_t), as used by Hasbrouck and Seppi (2001), is calculated by dividing the absolute spread by the logarithm to the best bid and ask depth.

$$QS_t = \frac{Sabs_t}{Dlog_t} = \frac{p_t^A - p_t^B}{\ln(q_t^A) + \ln(q_t^B)}$$

The following figure is a visualization of the quoted spread, and shows the relation between a deeper order book at the best bid and ask and the liquidity. A low quote slope logically denotes high liquidity.

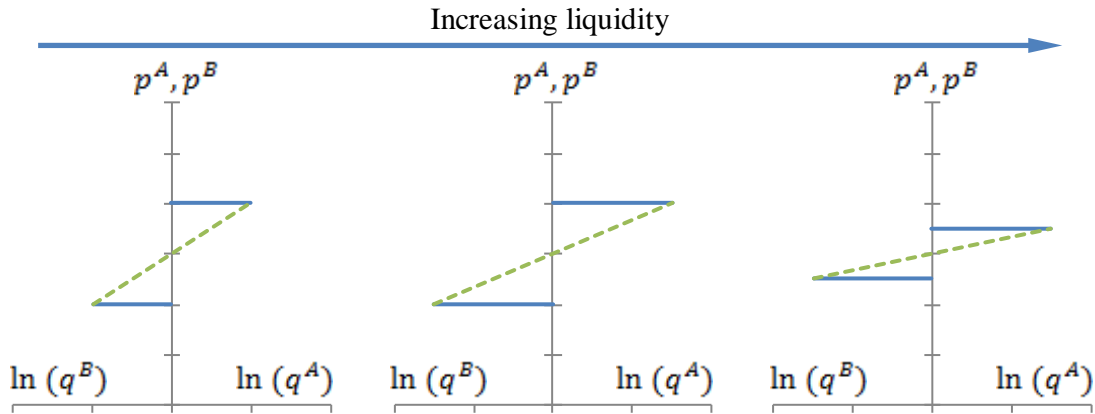


Figure 3

From the first to the second graph, the spread is constant but the order depth at the best bid and ask price increases. From the second to the third graph, the spread additionally narrows. Both steps could be said to enhance liquidity.

The quote slope is a comparatively intuitive measure, yet it faces some challenges when compared across stocks, because of its use of the absolute spread.

Log quote slope

If multiple stocks are compared the log quote slope (LogQS_t) solves the problem of comparing absolute spreads across stocks by using the logarithmized relative spread in the numerator.

$$\text{LogQS}_t = \frac{S_{\text{rellog}}}{D_{\text{log}}} = \frac{\ln\left(\frac{p_t^A}{p_t^B}\right)}{\ln(q_t^A \cdot q_t^B)} = \frac{\ln(p_t^A) - \ln(p_t^B)}{\ln(q_t^A) + \ln(q_t^B)}$$

Hasbrouck and Seppi see the two aforementioned measures “...as summary measures of the liquidity supply curve” (Hasbrouck and Seppi, 2001, p9), since they combine both price and quantity information. However, looking into the log quote slope, one might question the intuition if there is a significant difference in the best bid and ask depth. This is typically the case in a strongly upward or downward moving market.

Adjusted log quote slope

If the best bid and ask depth is substantially asymmetric the adjusted log quote slope ($\text{LogQS}_{\text{adj}_t}$) may be preferred, as it accounts for this asymmetry by adding a correction term.

$$LogQSadj_t = \frac{Srellog_t}{Dlog_t} + \frac{\left| \ln\left(\frac{q_t^B}{q_t^A}\right) \right|}{\ln(q_t^A \cdot q_t^B)} \cdot \ln\left(\frac{p_t^A}{p_t^B}\right)$$

The equation is more intuitive when rewritten as follows:

$$LogQSadj_t = \frac{Srellog_t}{Dlog_t} + \frac{|\ln(q_t^B) - \ln(q_t^A)|}{\ln(q_t^A) + \ln(q_t^B)} \cdot (\ln(p_t^A) - \ln(p_t^B))$$

The intuition behind the log quote slope is shown in the figure below. The red hatched area relates to the parts of the equation with the red font. The correction term basically scale the degree of upward- or downward movement by the aggregated bid and ask depth and multiply it by the spread.

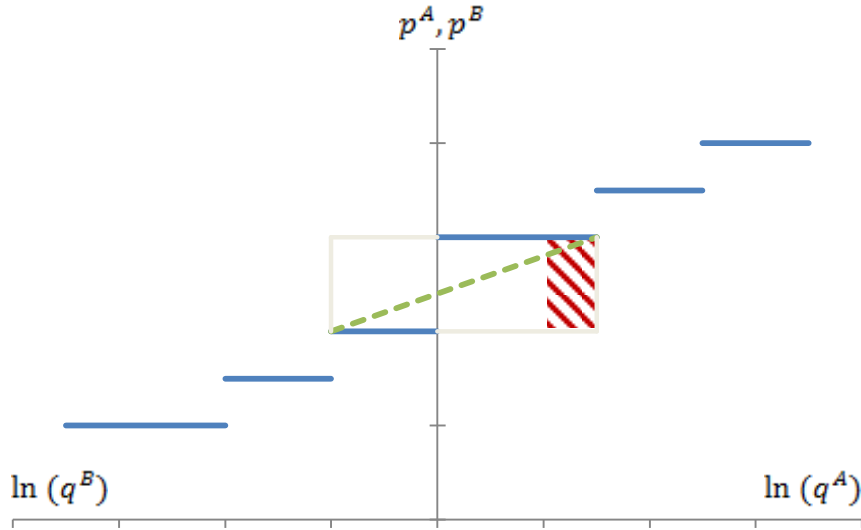


Figure 4

The extra term, therefore, increases the liquidity measure (implying reduced liquidity) if there is asymmetry between the best bid and ask depth. Note that if the best bid and ask depths are the same, the correction term will be zero. Even though this correction intuitively makes sense, one should remember that when comparing securities across different periods, the correction term will be affected by general upward or downward moving markets.

While these measures are essentially ex-ante measures of liquidity (i.e. anticipating what can happen) similar effects could be captured analyzing realized transactions.

Liquidity ratio 1

Liquidity ratio 1 ($LR1_t$) is unlike the quote slope measure based on ex-post data, thus giving another dimension to liquidity.

$$LR1_t = \frac{V_t}{|r_t|} = \frac{\sum_{i=1}^N p_i \cdot q_i}{|r_t|}$$

Liquidity ratio 1 divides the turnover (V_t) by the absolute price change $|r_t|$ for a certain period. ($LR1_t$) is also known as the Amivest liquidity ratio. With the absolute price change placed in the denominator, the measure describes how much turnover that corresponds to a one unit change in the price. A high ($LR1_t$) thus denotes high liquidity as it means that it has historically been possible to trade large quantities without significantly affecting the price. When comparing liquidity measures over time, one may argue that ($LR1_t$) could be biased by variations in the market return, since the market return is expected to have a higher correlation with the return of an individual stock than with the volume of that particular stock. A variant of ($LR1_t$) is the return per turnover (A_t), which is used by Amihud (2002), the measure is shown below.

$$A_t = \frac{1}{LR1_t} = \frac{|r_t|}{V_t}$$

The intuition behind the reciprocal of liquidity ratio 1 is to calculate what price impact one unit of turnover has on the price when analyzing a specific time interval. Clearly, as opposed to $LR1_t$ a low Amihud measure denote high liquidity. As with liquidity ratio 1, the Amihud measure is a rather ingenious way of estimating the cost per volume traded.

Liquidity ratio 2

Building on ($LR1_t$), liquidity ratio 2 ($LR2_t$) divides ($LR1_t$) by the term $(N_e - N_o)$ which denotes the difference between the total number of shares (N_e) and the number of shares owned by the company (N_o), hereby applying an ‘easy to calculate’ estimation of the free float.

$$LR2 = \frac{LR1_t}{(N_e - N_o)} = \frac{\frac{V_t}{|r_t|}}{(N_e - N_o)} = \frac{V_t}{(N_e - N_o) \cdot |r_t|}$$

Liquidity ratio 2 expresses how much turnover is needed to change the value of the free floated shares by one unit, over a given time interval. Hence, a high measure again indicates high liquidity.

Liquidity ratio 3

Along the idea of liquidity ratio 1 and 2, liquidity ratio 3 ($LR3_t$) measures the average price impact per trade (N_t).

$$LR3_t = \frac{\sum_{i=0}^N |r_t|}{N_t}$$

This measure assumes that each trade has the same impact on the price, hereby implying that each trade is equally sized, which is presumably a rough approximation. Similar criticism could however be stated in relation to the other measures.

Flow ratio

The flow ratio (FR_t) measures the ratio between the turnover and average waiting time between trades, over a given time interval. The average waiting time is calculated by adding all time intervals between trades and averaging it over the number of trades (N).

$$FR_t = \frac{V_t}{WT_t} = \frac{\sum_{i=1}^{N_t} p_i \cdot q_i}{\frac{1}{N-1} \cdot \sum_{i=2}^{N_t} tr_i - tr_{i-1}}$$

The higher frequency of trades the lower the denominator, and hence, a high flow ratio indicates high liquidity. As Wyss (2004) notes, the flow ratio can, for most practical purposes (when analyzing the same time interval across different securities), be restated as follows (Wyss, 2004, p20).

$$FR_t = N_t \cdot V_t = N_t \cdot \sum_{i=1}^N p_i \cdot q_i$$

However, the term N_t should be replaced with $N_t - 1$ in order to get the same result as returned by the ‘original’ flow ratio.

Order ratio

In relation to the depth measures described earlier, the order ratio (OR_t) focuses on the likely asymmetry in the depths at the best bid and ask quotes, measured as the absolute difference between the best bid and ask depth ($|q_t^B - q_t^A|$) scaled by the turnover (V_t).

$$OR_t = \frac{|q_t^B - q_t^A|}{V_t} = \frac{|q_t^B - q_t^A|}{p_t \cdot q_t}$$

Note that a low order ratio denotes high liquidity, as for example, a substantial difference in the best bid and ask depth, accompanied with a low turnover, would be a sign of an imbalance in the supply and demand of the stock.

Market impact

At this point, the former measures have focused on either the best bid and ask prices, the best bid and ask depth, various time related measures or the combinations of these. While the Amivest and Amihud measure are both impact measures, the market impact ($MI_t^{V^*}$), looks beyond the actual number of shares traded, and measures the price impact incurred when trading a certain amount of money e.g. one million Euros. This is done by subtracting the average price paid (p_t^{A,V^*}) (if buying for a certain amount of money) by the average price achieved (p_t^{B,V^*}) (if selling for a certain amount of money). The market impact measure, thereby takes into account if one has to trade over several ticks by enlarging the quoted spread.

$$MI_t^{V^*} = p_t^{A,V^*} - p_t^{B,V^*}$$

A high market impact denotes low liquidity, as it essentially tries to describe the round trip cost of trading a certain amount of money.

Depth for price impact

Associated with the market impact is the depth for price impact ($DI_t^A(k)$). It measures how many shares have to be traded in order to move the price k ticks away from the quote mid-price.

$$DI_t^A(k) = Q_k^A$$

The measure can be calculated from the bid-side of the market too.

$$DI_t^B(k) = Q_k^B$$

The depth for price impact measure is faced with a lack of comparability across stocks as it does not account for the relative ownership differences across shares, i.e. it does not account for the aggregated turnover that has to be traded. A high measure denotes high liquidity.

3.3.3 Other measures of liquidity

Zeros measures and FHT

Quite a different approach to measuring liquidity is the group of liquidity measures based on ‘zeros’. The various zeros-based measures utilize the observed number of zero return days in a given time series in estimating the level of illiquidity. In its simplest form, the zeros measure implies that a high relative frequency of zero returns in a given time series effectively reveals that the market for the share is illiquid. Lesmond et al. (1999) combine the proportion of zero returns with the return volatility and combine it into their LOT (Lesmond, Ogden and Trzcinka) measure. They model the likelihood of a return occurring in any of three regions (negative return, zero return and positive return) based on the volatility of the time series. *“The premise of this model is that if the value of the information signal is insufficient to exceed the cost of trading, then the marginal investor will either reduce trading or not trade, causing a zero return.”* (Lesmond et al., 1999, p1115). The estimate from the model by Lesmond et al. (1999) is in essence the effective transaction costs of the marginal investor, as the cost of transacting constitutes a threshold that must be exceeded before an asset price will reflect new information accumulated in the market. It follows that an asset with large effective transaction costs ceteris paribus will have more zero returns events in a given time series than an asset with lower effective transaction costs (Lesmond et al., 1999). This is easily confirmed when casually observing various segments of the stock market.

While the LOT measure estimates the effective transaction costs via a rather intricate and tedious likelihood function, Fong et al. (2011) in a working paper simplifies the LOT measure substantially, deriving instead their FHT (Fong, Holden and Trzcinka) measure. FHT initially makes the simplifying assumption that transaction costs are symmetric, meaning that the percent transaction cost incurred when buying ($\frac{S}{2}$) or selling ($-\frac{S}{2}$) a stock is symmetric, where S is the round-trip percent transaction cost.

The FHT measure describes the observed return (R) of an individual stock as a function of the unobserved ‘true’ return (R*) and the percent transaction cost (S). The true return results from the individual stock’s sensitivity to the market, multiplied by the market return, plus a variable representing public information shock (Fong et al., 2011).

The observed return in the market is now categorized in three intervals based on the abovementioned view of when a trade occurs.

$$R = R^* + \frac{S}{2} \quad \text{when } R^* < -\frac{S}{2}$$

$$R = 0 \quad \text{when } -\frac{S}{2} < R^* < \frac{S}{2}$$

$$R = R^* - \frac{S}{2} \quad \text{when } \frac{S}{2} < R^*$$

This view on the observed return is fundamentally based on the limited dependent variable (LDV) model of Tobin (1958) and Rosett (1959) and can be graphically illustrated as follows.

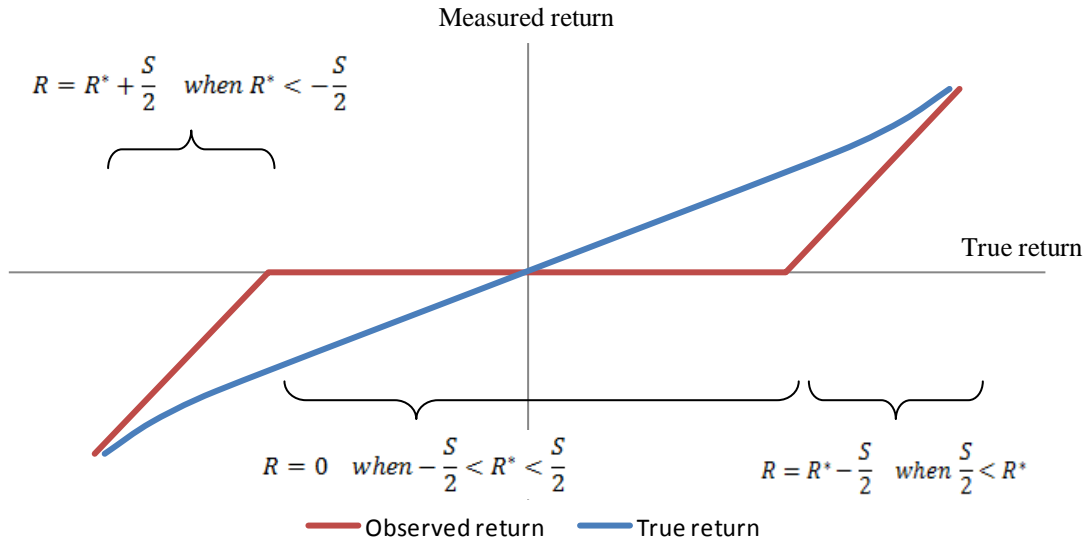


Figure 5

The ‘middle’ part of the observed returns, where the observed return is 0, is called liquidity trading- or the zero return region, implying that the only reason why one would trade here would be because of liquidity trading. The empirically observed frequency of days with zero return (z) is calculated by the following formula.

$$z = \text{Zeros} = \frac{\text{ZRD}}{\text{TD} + \text{NTD}}$$

The number of observed zero return days (ZRD) is divided by the sum of the trading days (TD) (non-zero return days) and no-trade days (NTD) (zero return days).

As seen from the three abovementioned intervals, the FHT measures focus on the return distribution of an individual stock with no role for the market portfolio. Further, it is assumed that the unobserved ‘true’ return (R^*) of an individual stock on a single day is normally distributed with a mean zero and variance σ^2 . Thus, the theoretical probability of a zero return is the

probability of being in the middle region of the LDV model, which is given by (Fong et al., 2011, p8)

$$N\left(\frac{S}{2\sigma}\right) - N\left(\frac{-S}{2\sigma}\right)$$

The empirical observed frequency of zeros is then set equal to the theoretical probability of a zero return. This equation is then solved for (S), the round-trip percent transaction cost.

$$\begin{aligned} z &= N\left(\frac{S}{2\sigma}\right) - N\left(\frac{-S}{2\sigma}\right) \\ \Downarrow \\ z &= N\left(\frac{S}{2\sigma}\right) - \left(1 - N\left(\frac{S}{2}\right)\right) \\ \Downarrow \\ z &= N\left(\frac{S}{2\sigma}\right) - 1 + N\left(\frac{S}{2}\right) \\ \Downarrow \\ \frac{1+z}{2} &= N\left(\frac{S}{2\sigma}\right) \\ \Downarrow \\ FHT = S &= 2 \cdot \sigma \cdot N^{-1}\left(\frac{1+z}{2}\right) \end{aligned}$$

The FHT measure is based on the relatively straight forward idea that a zero return is the result of the true return being in between the transactions cost ‘bounds’ given by the transaction cost for selling respectively buying a stock. Analyzing this mathematical expression of FHT reveals that a larger fraction of zeros implies wider bounds and thus a larger spread, holding the volatility of the true return constant. Holding the proportion of zeros constant, an increase in volatility of the true return will in turn imply that the ‘bounds’ have to be further apart in order return the same proportion of zero returns thus a yielding a larger spread. Fong et al. (2011) conclude that: “...*the percent spread is an increasing function of both the proportion of zero returns and the volatility of the return distribution*” (Fong et al., 2011, p9).

The liquidity measures listed in this section provide an overview of the breadth of measures in existence for capturing different aspects of liquidity. And while these measures cover the fundamental views of liquidity it is not a comprehensive list of measures. It should be obvious from this discussion that liquidity, as stated in the introduction, is a highly complex and intangible concept, which is difficult to capture. And while all presented measures convey some dimension of liquidity, no single measure presents a holistic view. In the following section a selected group

of liquidity measures are included in a liquidity index, which will be used to determine the level of liquidity for the observations analyzed in this thesis.

3.4 Liquidity index

When deciding what measure to include in an empirical study, it is of utmost importance to assess what data is available. This section discusses that, and subsequently demonstrates how the optimal selection of liquidity measures can be elegantly combined into a single liquidity index.

3.4.1 Data availability for liquidity measures

The data to compute the liquidity measures is sourced from Bloomberg. While Bloomberg stores an enormous variety of financial figures it still has its limitations. Firstly Bloomberg only carries 2 years of historical intraday data. Given the relatively long time horizon of this study, this rules out measures based on high frequency data, in turn limiting the study to rely on end of day data. However, as noted earlier Fong et al. (2011) argue that intraday liquidity benchmarks can be effectively captured by proxies based on daily data (Fong et al., 2011, p24). Secondly, Bloomberg does not store data on historic bid and ask depth, therefore practically excluding the use of depths based measures.

3.4.2 Measures included in the liquidity index

Based on the previous discussion of the various dimensions of liquidity, and bearing in mind the data constraints that this present study face, the following four measures have been selected. As noted these will be combined into a single liquidity index.

3.4.2.1 Turnover

The first measure to be included in the index is the volume-related measure; turnover¹ (V_t). In this particular study the measure was calculated as the average daily turnover over the preceding 12 months before the SEO. It is then converted into EURm using historic exchange quotes, making the measure comparable across shares quoted in different currencies. Note that turnover and the following three liquidity measures have also been calculated using 3 and 6 months of data respectively. The differences in these estimates will be discussed in section 7. By including turnover, the depth dimension of liquidity is not completely overlooked, as the turnover could be argued to hold information about ‘realized depth’. One might argue that it is an ex-post measure of depth.

¹ Turnover is calculated with the function TURNOVER in Bloomberg

3.4.2.2 *Relative spread*

The second measure in the index is the spread-related measure of ‘relative spread’ scaled with the mid-price² ($SrelM_t$). The measure is calculated as an average of the daily observations over the last 12 months before the SEO. The relative spread captures the percent cost incurred when trading, and is one of the most widely used liquidity measures.

3.4.2.3 *Amihud*

The third measure in the index is the multi-dimensional cost per volume measure, Amihud³ (A_t). The measure is calculated as an average of the daily observation over the last 12 months before the SEO. The measure is only calculated on days where there is an actual price movement and it is required that there is a minimum of 5 days with return information. This is done to enhance the robustness of the measure. A low Amihud measure, as noted, indicates high liquidity, and implies that each unit of currency traded made little impact on the price change.

3.4.2.4 *FHT*

The fourth measure in the index is the implied spread related measure FHT⁴ (FHT). The measure is calculated as an average of the daily measures over the last 12 months before the SEO. Along the same criteria as in the paper by Fong et al. (2011), it is required that a stock have a least five positive-volume days on average per month, as it is also required that a stock have at least five non-zero return days on average per month (Fong et al., 2011, p10). While the relative spread measures the observed, ex-ante trading costs, FHT implicitly estimates the effective trading costs based on realized trades.

The authors argue that these measures complement each other in capturing the liquidity of a stock in its many different manifestations.

3.4.3 *Liquidity index description*

The idea of combining the four measures of liquidity into an index is derived from the approach used by Butler et al. (2005), and is calculated consistently with their approach⁵. The liquidity index (L_i) is calculated for each observation ($i = 1, \dots, N$), first by ranking each of the four liquidity measures relative to the other observations, where the k^{th} measure of liquidity for firm i

² Relative spread scaled with the mid-price is calculated using the functions PX_ASK and PX_BID in Bloomberg

³ Amihud is calculated using the functions CHG_NET_1D and TURNOVER in Bloomberg

⁴ FHT is calculated using the functions CHG_PCT_1D and PX_VOLUME

⁵ The liquidity index is applied in accordance with the approach presented in Butler et al., 2005, p337

is given by $(X_{i,k})$. The four liquidity measures are ranked from least to most liquid, where the most liquid observation receives the value N , and the least liquid receives the value 1. Turnover is ranked in an ascending order (the observation with the highest turnover gets the highest rank) and the Relative spread, Amihud, and FHT are ranked in a descending order (the observation with the lowest measure gets the highest rank). Hypothetically, if one observation has the most liquid measures across all four liquidity measures, that observation would have a liquidity index of 1. The liquidity index is calculated as follows.

$$L_i = \frac{1}{N} \cdot \frac{1}{K} \cdot \sum_{k=1}^K Rank_k(X_{i,k})$$

When applying this formula each of the four liquidity measures is given equal weight, implying that each of them is regarded equally important in determining the ‘true’ liquidity of a particular stock. In addition, an index has the desirable property of being relatively robust to outliers, since the rank of the observation rather than its actual value is applied. Moreover, the nature of an index implies that few assumptions about the underlying distribution of the data are made – it is thus non-parametric in its nature. Finally as noted, employing an index of liquidity measures is in line with the attempt of Butler et al. (2005) to demonstrate the importance of liquidity in the gross fee of an SEO.

While it should be obvious that no ‘perfect’ liquidity measure exists, it seems justified that this approach should produce the most robust and consistent results when investigating how secondary market liquidity may predict the direct and indirect costs of an SEO. However, before venturing into this discussion it is of interest to understand how an SEO actually takes place. The next section is devoted to explaining and discussing the process of an SEO.

4 Seasoned equity offerings

4.1 What is a seasoned equity offering

This section provides a brief description of what an SEO fundamentally is, the different costs incurred when undertaking an SEO, and what issuance methods an issuer can choose from.

A seasoned equity offering is a placement of shares in the marketplace of an already listed company, as opposed to an initial public offering (IPO), which is defined as the event where the company is floated for the first time.

SEOs can be carried out in two fundamentally different ways, namely through a seasoned public offering (SPO) or as rights offers. While an SPO is an issuance of shares to the public, a rights offer is an issuance made for existing shareholders who receive an option to subscribe to new shares. It could, therefore, be viewed as a non-public issuance. However, regardless of the method chosen, the issuer will incur a variety of costs when embarking on an equity offering. These costs can roughly be categorized in two: direct costs and indirect costs. Summarized by Eckbo et al. (2007), the direct and indirect costs grasp at least the following costs (Eckbo et al., 2007, p24):

Direct cost:

- Underwriting fee – also known as the gross fee.
- Other ‘out of the pocket expenses’, which cover fees to accountants, law firms, listing fees, registration fees, printing, advertising, road show expenses as well as the cost of management time.

Indirect cost:

- SEO discount, i.e. the indirect wealth transfer from old to new shareholders as a consequence of the typical discount seen on seasoned offerings.
- Stock price reaction to the offering announcement, and the follow up announcement about the issue.
- Costs incurred if the offer is delayed or cancelled.

Throughout this thesis the terms direct cost and indirect are used interchangeably to describe the gross fee and the SEO discount respectively, unless stated otherwise. The total cost, or as stated in the problem statement, ‘*the combined cost*’ of raising seasoned equity, is the combination of the gross fee and the SEO discount. It is obvious based on the short review of the various costs above that the gross fee and SEO discount is an approximation of the ‘actual’ combined cost, however, due to data availability this computation serves as the best proxy for the total costs. Further, it is reasonable to assume that the relationship that this paper analyzes will not affect the costs above and beyond the gross fee and the SEO discount in a meaningful way, as these costs can essentially be viewed as ‘fixed’.

One will find that there are certain nontrivial problems in comparing the indirect cost across the two fundamental variations of seasoned equity offerings. In the subsections below, the difference on how to the indirect cost of an SPO and a rights offer affects the wealth transfer from old to new shareholders will be discussed.

4.1.1 Seasoned public offerings

SPOs are used to float existing or new shares, or any combination thereof to the public. As seen in section 4.3 the process of undertaking an SPO range roughly from 1-14 days depending on the specific issuance method chosen by the issuer and the investment bank. However, regardless of the issuance method chosen, the investment bank conducts research in the market about what price concession will likely be ‘needed’ for the issuance to be successful, see section 4.2.1. This often results in shares being offered at a discount in the market – the so called SEO discount. The discount affects existing shareholders who do not subscribe to the issuance on pro rata basis, as their stake will be diluted. This dilution effect constitutes an indirect cost resulting from the wealth transfer from existing to new shareholders when outside investors subscribe to the discounted offering. The dilution effect is explained through a simple example below.

Table 1

Example of the dilution effect in SPOs	
Input	EUR ¹
# of outstanding shares - ex ante SPO	100,000
Market cap. - ex ante SPO	10,000,000
Price per share - ex ante SPO	100.00
Theoretical issue value	2,685,285
Indirect cost - SEO discount (%)	5.00%
Indirect cost (EUR)	134,264
Gross proceeds per share	95.00
Gross proceeds from issuance	2,551,020
# of shares issued	26,853
Direct cost - Gross fee (%)	2.00%
Direct cost (EUR)	51,020
Net proceeds from issuance	2,500,000
# of outstanding shares - ex post SPO	126,853
Market cap. - ex post SPO	12,500,000
Price per share - ex post SPO	98.54
Note 1: except # of outstanding shares and SEO discount	

If an existing shareholder with say, 1,000 shares before the issuance (implying a relative ownership of 1 percent of the company), decides not to subscribe to the offering, the value of his holdings will be reduced from 100,000 EUR (ex ante SPO price of 100 EUR multiplied by 1,000 shares) to ~98,540 EUR (ex post SPO price of ~98.54 multiplied by 1,000 shares) implying a total

reduction of his wealth of 1,460.6 EUR or a relative loss of 1.46 percent of the total holdings. On the other hand, if he decides to subscribe pro rata to the issuance, he has to buy 1 percent of the newly issued shares (~269 shares) at an offer price of 95 EUR per share. The combined wealth effect when subscribing pro rata is shown below.

Table 2

Example of effect of buying pro rata	
Input	EUR ¹
# of shares owned	1,000
Ownership (%)	1.00%
Pro rata subscription - # of new shares	268.53
Cost of new shares	25,510
Value of new shares - ex post SPO	26,461
Price change on new shares	950.4
Loss on old shares	-1,460.6
Total wealth effect of SEO	-510.2
Wealth effect of new shares (%)	-2.00%
Note 1: except # of shares, ownership, and relative wealth effect	

The shareholder then pays 25,510 EUR (~269 shares at an offer price of 95 EUR per share) for the pro rata subscription, but the market price of his new shares is ~98.54, giving him a wealth effect on the new shares of 950.4 EUR. Totaling the wealth effect from his existing shares (-1,460.6 EUR) and his new shares (950.4), the shareholder ends up with a total loss of 510.2 EUR when subscribing pro rata. The wealth reduction of 510.2 EUR corresponds exactly to the shareholders relative share of the direct costs, hereby illustrating that if existing shareholders buy new shares in a pro rata ratio to their holdings, they will not be affected by the SEO discount. However, as shall be discussed later, under a more thorough discussion of the indirect costs, the existing shareholders cannot control exactly how many shares they are allocated when subscribing to the issuance. Moreover, this relation implies that if all existing shareholders buy new shares on a pro rata basis there will not be any transfer of wealth from existing to new shareholders. This, in turn, implies that the reported SEO discount of a particular issuance *ceteris paribus* will overestimate the average indirect cost incurred by excising shareholders. However, in the absence of a readily available measure of the ‘effective’ SEO discount, the ‘observed’ SEO discount can be used to describe the indirect cost incurred for a shareholder who does not subscribe to the issuance at all.

4.1.2 Rights offers

While this paper, as noted, is concerned with public offering it is relevant to elaborate briefly on the topic of rights offers. This is done to highlight the problems that arise from directly comparing the two – something which not all previous studies seem to acknowledge.

As noted, in a rights offer, the new shares are initially only offered to existing shareholders. Moreover, the offering is arranged in a fundamentally different way than an SPO. In a rights offering, existing shareholders are offered a right to buy new shares on a pro rata basis at a discount relative to the current market price (see e.g. Bøhren et al., 1997, p223). This essentially implies that existing shareholders are offered an in the money call option on new shares. The shareholders are typically allowed to sell the option, should they not wish to participate in the offering. The idea behind the rights offer is that the value of the right should financially offset the non-subscribing shareholders for the fall in the share price ex-post issuance. This ex-post share price is more commonly known as the Theoretical Ex-Rights Price (TERP), which is calculated as the weighted average of the price of new and existing shares.

$$TERP = \frac{(Market\ value\ of\ old\ shares\ before\ issuance) + (proceeds\ from\ issuance)}{Number\ of\ shares\ ex - rights\ offer}$$
$$\Downarrow$$
$$TERP = \frac{(N_{existing\ shares} \cdot P_{ex-ante\ issuance} + N_{new\ shares} \cdot P_{net\ proceeds\ per\ newly\ issued\ share})}{(N_{existing\ share} + N_{new\ shares})}$$

Whereas the execution of an SPO is rather swift (see section 4.3), the process of a rights offer is somewhat more time-consuming. According to, for instance, German law, the offer period has to be a minimum of 2 weeks for rights issues (Bühner and Kaserer, 2002, p323). Another example is in the United Kingdom, where the offer period has to be at least 3 weeks (Armitage, 2000, p58). These offer periods affect the TERP, as it is exposed to changes in the share price, which in turn influences the value of the right. If the price of the underlying stock falls below the sum of, the cost of buying a right and the cost of subsequently subscribing to the new share at the offer price, no rational investor would exercise his right. This would be equal to exercising a call option which is out of the money. This risk can be mitigated through underwriting. It is, thus common to distinguish between two types of rights offerings: uninsured rights and rights with standby underwriting. Issuers who use rights with standby underwriting are guaranteed that the underwriter will exercise the rights if the issuance is not subscribed in full by the end of the offer

period. On the contrary, an uninsured right is solely dependent on the subscription of existing shareholders and is as such comparable to the best efforts type of public offering.

As noted, the right can be seen as a call option on additional shares at a given price. In addition the option is only exercisable at maturity and the right, thus, specifically compares to a European call option. The intuition is that the value of the right is approximately equal to the difference between the TERP and the price at which the new shares are offered, i.e. the offer price.

If the shareholder receiving this right does not want to participate in the offering, he incurs on dilution as he should be able to sell the right at a price equal to the TERP and the offer price. However, if the right trades this price, the non-subscribing investor would incur an indirect cost from a wealth transfer much like the case of an SPO. One may expect that the right would trade below its theoretical value for three main reasons; firstly, for several of the same reasons that the SPO is offered at a discount, see section 6. This is supported by Eckbo and Masulis (1992) who note that from an outside investor's view, a rights issue, to which current shareholders decide not to subscribe, is informationally equivalent to a direct sale of shares to the public, i.e. as SPOs. Secondly, the right will likely be less liquid than the underlying asset in the offer period, which should lead investors to require a discount. Thirdly, depending on the particular regulatory system, the investor may incur a period of non-tradability in the time span between buying the right, and until the shares are allocated. Somewhat surprisingly, it has not been possible to find papers that try to determine the 'actual' incurred rights offer discount. The insight from this discussion is that as long as the right has a value, the discount on the rights offer is not comparable with the SEO discount on the SPO.

While as noted, indirect costs between public offerings and rights offerings are at best difficult to compare, the direct costs are quite comparable. Empirical evidence suggests that the direct costs associated with a rights offer are generally lower than those of an SPO. This is a long time well documented fact and as noted by Smith (1977) "*...the subscription price for a rights offer can be set low enough so that the probability of failure of the rights offering becomes arbitrarily close to zero*" (Smith, 1977, p289). From this he reasons that the 'insurance policy' associated with underwritten issue must be of small value.

This lower direct cost should intuitively encourage an issuer to choose rights offers when issuing seasoned equity. However, empirical evidence shows that issuers, in particular US issuers, favor underwritten SPOs when making an SEO. This favoring of underwritten SPOs over rights issues, despite its higher direct cost has received much attention in academia and is known as 'the rights

offer paradox'. Ursel (2006a) summarizes the rights offer paradox as the paradox that *"...American firms raise seasoned equity via underwritten public offerings despite the lower cost alternatives of non-underwritten or underwritten rights issues"* (Ursel, 2006a, p31).

However, as noted by Eckbo and Masulis (1992) this paradox is not seen across all markets. Eckbo and Masulis (1992) note that *"...the rarity of rights issues in the U.S. contrasts with the situation in Canada, where in recent years almost half of all equity issues have been sold through rights offers, and in Europe and the Pacific Basin, where the majority of equity issues are sold through rights, though a trend toward a greater use of underwritten offers is evident in a number of countries"* (Eckbo and Masulis, 1992, p294). Bøhren et al. (1997) generalize this by linking smaller capital markets with a higher frequency of rights offers and vice versa for larger capital markets and SPOs.

As the rights offer paradox has received a significant amount of attention within academia, many possible explanations on its existence have been proposed. While this is not directly the topic for this present study, a very brief and non-exhaustive overview of the findings is relevant. This is in order to access the different motives for choosing between rights offers and SPOs, which in turn sheds light on the decision itself to issue equity via an underwritten public offering. Hansen (1989) finds that *"...firms making underwritten rights offerings paid lower underwriting fees but incurred significantly larger price drops just prior to the offering than did firms making underwritten public offerings"* (Hansen, 1989, p291). Hansen's (1989) findings suggest that if shareholders are expected to resell their new shares, after subscribing to the proposed rights offer, an SPO may be a preferred flotation method, even if it entails larger underwriting fees.

Moreover, Hansen (1989) argues that underwriters are able to place new common stock at a higher price than the existing shareholders. This partly follows on from the argument made by Smith (1977), that shareholders not subscribing to the issue must sell their rights (or subscribe and sell the new shares) to avoid losing and foregoing the value of the right. These transactions will then create profits that are subject to capital gain tax, which increases with the subscription-price discount, hereby discouraging large discounts (Smith, 1977, p279).

Solely focusing on rights offers on the Oslo Stock Exchange, Bøhren et al. (1997), find that *"...the probability that a rights offer is underwritten is negatively related to expected shareholder take-up"* (Bøhren et al., 1997, p258). Gajewski and Ginglinger (2002) add to this relation in their French study as they find *"...that the percentage of shares held by the main shareholder in France is significantly greater for rights offers."* This indicates that rights offers are used by

companies with high shareholder concentration and high expected shareholders take-up. Bøhren et al. (1997) further note that “...an analysis based on direct flotation costs alone, which underlines the so-called ‘rights offer paradox’, misses important indirect costs of uninsured rights” (Bøhren et al., 1997, p259), hereby building on Hansen’s (1989) abovementioned findings.

The above arguments may indicate that the apparent, clever idea of issuing new capital via rights offerings may not be favorable for the existing shareholders as they, rather than the investment bank, carry much of the risk. In practice they may do so less efficiently than the investment bank. In addition, after controlling for endogeneity in the choice of flotation method, Ginglinger et al. (2010) find that “...public offerings are less expensive and improve liquidity more than standby rights whereas uninsured rights are still the best choice for low liquidity, closely held firms.” (Ginglinger et al., 2010, p2). This suggests a bias in terms of which companies choose to undertake a public offering, namely that stock liquidity seems to be an important determinant in the choice of issuance method. Ginglinger et al. (2010), base their findings on a French dataset consisting of 178 SEOs, including public offerings, uninsured rights offerings and standby right offerings, during the period of 1995 to 2006.

Based on the discussion in the two prior subsections, it should be clear that comparing the cost, of issuing capital in the form of an SPO or as rights, is not simple. The direct cost (i.e. the gross fee) paid to the investment bank is not directly comparable, as the investment bank is faced with profoundly different risks and responsibilities under the two issuance types. What is furthermore important to note is that the SEO discount associated with public offerings and that of rights offers are fundamentally different in nature, and as such incomparable when assessing the indirect cost incurred when issuing equity. Finally, the two types of issuance seem to be incomparable in the sense that there is a bias in the nature of companies that choose to make an SPO and a rights offer respectively.

Knowing the fundamental difference of how SPOs and rights offers are organized, and why they cannot be directly compared in a meaningful way, the paper will continue with a discussion of the direct cost associated with underwritten public offerings in the next section. It should be noted that only the above section differentiates between SEOs and SPOs, henceforth the term SEO is used to describe the event of an SPO. The term rights offering will be applied specifically when relevant.

4.2 The process of a seasoned equity offering

This section describes the process taking place around an SEO. Firstly, a description of the role of investment banks in SEOs is provided. Discussed next are the various issuance methods that the issuer and the investment banks can choose when making an SEO. Finally, this section will review empirical findings of the direct cost and discuss the factors that serve to explain the gross fee, including recent research indicating an important role for secondary market liquidity.

The direct costs of an SEO can be categorized in two: costs where the service provider is exposed to a financial risk and costs where the provider bears no such risks. In an SEO with any form of underwriting agreement, it is obvious that the investment bank bears financial risk. However, it seems hard to argue that the other direct cost, the so called out of the pocket expenses to attorneys, accountants etc. are exposed to any such risk as these fees are typically calculated on a per hour basis. One could argue that such service providers also face certain reputational risks in association with an equity offering. In turn, this could lead to their fees varying somewhat from case to case. But this variation is expected to be insignificant – after all it is a relatively standardized service that is provided. The idea that investment banks are exposed to a fundamentally different type of risk, than the other service providers making up the total direct costs, is founded in the way the investment bank is compensated through the gross fee. The gross fee is simply calculated as the difference between the price at which the investment bank buys the shares from the issuer, and the price at which the investment bank floats the shares in the market – the offer price. Hence, there is a direct link between the success of the offering and the compensation received by the investment bank. Before venturing into establishing a link between the risk incurred by the investment bank and the gross fee they receive, it is of great interest to understand the role of the investment bank.

4.2.1 The role of the investment bank

The investment bank is sometimes referred to as the bookrunner, book manager, lead manager or underwriter. These names refer to the order book, often built by the underwriting investment bank when undertaking IPOs as well as SEOs. The underwriting investment bank gathers information about the market demand for the equity offering and creates a ‘book’ of interested investors in order to gauge the demand for the new shares and price the issuance efficiently. Cornelli and Goldreich (2003) summarize the role of underwriting investment banks as follows: *“Investment banks acting as underwriters in securities offerings conduct the preliminary analysis, choose the offer price, allocate the shares, and stabilize the aftermarket price”* (Cornelli and Goldreich, 2003, p1415).

Specifically, as noted by Hansen (1989); “...*the issuer sells all the new shares directly to the underwriter, who, in turn, resells them to investors*” (Hansen, 1989, p290).

Underwriters of equity typically perform at least three roles in a deal; first they advise the issuer on how to structure the transaction, second, they buy the securities from the issuer, and third resell the shares to the public. The risk incurred by the investment bank, when taking the new shares on their own books is a risk that Butler et al. (2005) compare to the risk incurred by a market maker when they take shares on their books, before selling the shares again. This intermediary service encompasses that “...*the market maker faces a risk of fundamental price change in the mean time and must be compensated for this risk*” (Amihud et al., 2005, p298). In addition to the role as underwriter, the investment bank is typically involved in writing a prospectus, marketing the issuance, as well as various other advisory services.

As anecdotal evidence of the risk faced by an underwriting investment bank, Geddes (2003) recalls an SEO by British Petroleum (BP). Right before the stock market crashed in 1987, the syndicate had underwritten the issuance at a price of 330p per share, the following stock market crash saw the share price drop from a level around 345-355p to under 300p. This fall in the stock price, implied a loss of hundreds of millions of pounds for the underwriters (Geddes, 2003, p212).

While the costs associated with underwriting of the offering are likely to vary with issue size, Altinkiliç and Hansen (2000) argue that this is not necessarily the case for several of the additional ‘out of the pocket’ expenses. Altinkiliç and Hansen (2000) note that: “*The syndicate’s costs contain a fixed cost that is the same for each offering. It concludes state and federal taxes and fees, expert fees, SEC registration fees, and other setup expenses that are independent of issue size.*” (Altinkiliç and Hansen, 2000, p195).

In larger deals the underwriting is often done in cooperation between the leading investment bank (the lead book runner) and several other investment banks, the so called sub-underwriters, which together form the underwriting syndicate. If the issuance is underwritten, it is sometimes referred to as a ‘firm commitment’ offering, a ‘firm undertaking’ or ‘hard underwriting’. If the issuance is not underwritten it is referred to as a ‘best efforts’ offering, implying that the investment bank is only ‘obliged’ to do its best, and in this case the investment bank simply acts as a marketing and distribution agent. In best efforts deals, the investment bank obviously carries no risk, should the issuance fail to be subscribed in full. However, one might argue the bank still bears certain, reputational risk if the offering fails. Best effort offerings rely on the market appetite of the investment bank, rather than with a firm commitments where is contractually bound to subscribe.

In addition to the various levels of underwriting, the issuing firm and its investment bank has a palette of flotation methods to choose from. These also influence the risk and workload faced by the investment bank and are therefore, also important when assessing the level of the direct costs. The following section looks into these issuance methods.

4.3 Flotation methods for a seasoned equity offering

The following section will look into some of the major issuance methods that can be used to exercise a seasoned equity offering. As described, SEOs can be split into two major categories, SPOs and rights offers, and depending on the type of SEO, the offering can be floated in a variety of ways. Smith (1977), and Eckbo and Masulis (1992) distinguish between three general issuance methods, namely uninsured rights, rights with standby underwriting, and firm commitments. A firm commitment underwriting can be organized in different ways, as to be seen in the following section. Compared in the table below are some of the different ways to issue equity.

Table 3

Selected issuance methods for SEOs			
Offer type	Target market	SEO type	Execution time
Fully marketed	Public	SPO	~14 days
Accelerated Bookbuild	Public	SPO	~2 days
Bought Deal	Public	SPO	~1 day
Cash Placing	Public	SPO	~1 day
Guaranteed preferential allocation	Public	SPO	Case specific
Rights Issue	Existing shareholders	Rights offering	~14-21 days

Building on the view of Smith (1977) and Eckbo and Masulis (1992), there are various views on how to categorize issuance methods. As noted by Geddes (2003) four main methods exist to raise new capital; marketed secondary offerings (henceforth fully marketed offerings), rights issues, bought deals and accelerated bookbuilds. Gao and Ritter (2010) argue that one should discriminate between three general offer methods: fully marketed offers, accelerated offers (covering accelerated bookbuilt offers and bought deals), and rights offers. As noted this paper focuses on public offerings and hence, rights offers will not be discussed. In the following sections the structure used by Gao and Ritter (2010) is applied. Note that the following section is non-exhaustive review and primarily focuses on some of the common issuance methods. Some issues are made as a combination of several issuance methods. These so called hybrid approaches (or mixed issues) are typically used to make sure that shares are being allocated appropriately to different investor groups; these will not be examined further in this thesis.

4.3.1 Fully marketed offerings

A fully marketed offering is organized in much the same way as an IPO. The issuer negotiates the underwriting terms with the investment bank, which then floats the shares in the market. According to Gao and Ritter (2010), the underwriter performs a due diligence to certify the quality of the issuing company. After having agreed on the terms of the underwriting, the so called road show is carried out. During the road show, the investment bank and managers from the issuing company visits selected institutional investors as well as analyst and securities sales personnel (Gao and Ritter, 2010, p34). Throughout the road show, the bookrunner builds the order book, based on submitted indicative offers received from investors, which, in addition to general investor feedback, is used to set an offer price.

The process of a fully marketed offering gives the investment bank the advantage of gradually sensing investor considerations and reservations. According to Bortolotti et al. (2008) the investment bank typically postpones the final decision whether to underwrite the offering or not, until the road show has ended (Bortolotti et al., 2008, p36). Regarding the execution time of the offering, Iannotta (2010) note that a fully marketed offering takes on average a couple of weeks (Iannotta, 2010, p51). This is in line with the empirical findings of Gao and Ritter (2010) who report that, “...fully marketed offers, on average take 31 calendar days to complete...”⁶ (Gao and Ritter, 2010, p49).

Gao and Ritter (2010) argue that the rationale of making a fully marketed offering, among other things, is to affect (improve) the short-run demand elasticity⁷ hereby, achieving a higher offer price and post-issue market price. Moreover, they show that “...firms that face a relatively inelastic demand curve prior to the offer, raise a large amount of capital, or offer a large number of shares compared to number of shares outstanding before the offer, are more likely to conduct a fully marketed SEO.” (Gao and Ritter, 2010, p34). Furthermore they find that issuers with a smaller market capitalization and less analyst coverage tend to use fully marketed offers.

Interestingly Gao and Ritter (2010) find that fully marketed offerings and accelerated offerings differ in the sense that “...fully marketed deals tend to have a larger relative size, which would

⁶ They note that there is considerable dispersion in these durations. They find that the “time to market” of a fully marketed offer has gone from a median time of 31 days in 1996 to 7 days in 2007. (Gao and Ritter, 2010, p45)

⁷ Gao and Ritter (2010) use the following four measures to proxy for the demand elasticity. “The first measure is an order flow inverse demand elasticity, the average daily ratio of the absolute value of returns to turnover. The second measure is an arbitrage risk measure, the variance of daily market model return residuals. The third measure is the stock’s non-institutional ownership fraction. The fourth measure is the stock’s average price impact using Trade and Quote (TAQ) data.” (Gao and Ritter, 2010, p34)

everything else the same, result in a more negative average market reaction” (Gao and Ritter, 2010, pp49-50). This leads to a discussion of the accelerated offerings in the following section.

4.3.2 Accelerated offerings

As noted, the term accelerated offerings includes the issuance methods accelerated bookbuilt offers and bought deals. Gao and Ritter (2010) analyze accelerated offerings, relative to fully marketed offerings, and finds that accelerated offerings pay a gross fee which is, on average, 3.3 percentage points less than that of fully marketed offerings. Geddes (2003), studying the US and UK market, notes that a disadvantage for both the accelerated bookbuilt offerings and the bought deals is “...*the bank’s inability to access retail demand*” (Geddes, 2003, p228). This disadvantage arises because these issuance methods, unlike the fully marketed offering, do not entail writing a prospectus. The nature of accelerated bookbuilt offerings and bought deals are presented separately and in more depth in the following subsections.

4.3.3 Accelerated bookbuilt offerings

Accelerated bookbuild offerings (ABOs) are, according to Bortolotti et al. (2008) the most popular type of accelerated underwriting in their global study. However, the empirical study by Gao and Ritter (2010) on the US market, finds a more equal distribution between the use of accelerated bookbuilding and bought deals. When signing up for an ABO the investment bank does not have time collect the same level of information, as when making a fully market offering, this means that the underwriter must quickly asses the market demand before committing to an offer price. Bortolotti et al. (2008) note that issuers using ABOs “...*choose the lead underwriter based on the “backstop clause” (which includes the minimum price guaranteed the issuer), the underwriting spread, and other profit sharing agreements.*” (Bortolotti et al., 2008, p56). The process of an accelerated bookbuild is typically completed within 48 hours, according to Gao and Ritter (2010).

In terms of empirical findings, Gao and Ritter (2010) note that “...*in accelerated bookbuilt offers and fully marketed offers, the offer price is not set until after the market knows about the issue and has reset the stock price.*” (Gao and Ritter, 2010, p49). This entails that the underwriter ceteris paribus is faced with less risk than opposed to the process of a bought deal, which will be discussed in the next section.

4.3.4 Bought deal

A bought deal, involves the investment bank buying the issued shares and then selling these shares as quickly as possible to institutional investors. The issuer typically makes different investment banks bid on the issue and the winning investment bank is then responsible for reselling the shares, see Bortolotti et al. (2008). This auction-based setting, where banks bid for shares, is made to increase the competition between investment banks and ultimately increase the proceeds to the issuer. According to Gao and Ritter (2010) the process of a bought deal is typically completed within 24 hours and is sometimes referred to as an overnight deal. Since the investment bank buys the shares without knowing how the market will react to the issue, it entails a greater risk than both the fully marketed offerings and the accelerated bookbuilt offerings. This ties perfectly with the insight from Ianotta (2010) who notes that investment banks carry a greater risk in a bought deal, than in a fully marketed offering (Ianotta, 2010, p55). Ursel (2006b) notes that *“the bought deal method was suited to the market turbulence that began in the 1980s, when markets could move substantially in the weeks necessary to complete fully marketed deals”* (Ursel, 2006b, pp6-7). These potential market movements add another facet to why the issuer should choose a bought deal.

Another deal type that one may come across is block trades. These too, are essentially a type of accelerated offerings, and work much like a bought deal. The block trade however, consists solely of existing shares and therefore, firms do not raise new equity through them. Block trades are also known as ‘pure secondary offerings’.

4.3.5 Other flotation methods

4.3.5.1 Cash placing

A cash placing is an issue of shares for cash on a non-preemptive basis. In other words an issuance targeted to a specific group of investors, rather than for general shareholders, which would be a preemptive issue. As noted by Wagstaff et al. (2011), a cash placing constitutes a quick way of issuing capital because it does not require a prospectus or shareholder approval. Moreover, they note that a cash placing is restricted to small equity raisings (maximum 5 percent of the existing share capital), as well as the discount⁸ being restricted to a maximum of 5 percent. Note that the article by Wagstaff et al. (2011) only confirms these properties for the UK market. Finally, Geddes (2003) notes that *“...in the UK, an accelerated bookbuilding that raises funds for*

⁸ Measured as the discount to the middle of the best bid and offer price just before the announcement

the issuer is often called a placing” (Geddes, 2003, p227). However, while a cash placing may have the same propositions as an accelerated bookbuilding, the 5 percent restriction on the relative issue size, will ceteris paribus make the direct cost of a cash placing less comparable with those of an accelerated bookbuilding, where there is no such limitation.

4.3.5.2 *Guaranteed preferential allocation*

A guaranteed preferential allocation also known as preferential allocation, preferential allotment or private placement is where the shares are issued to a specific investor (for example, venture capital, private equity, mutual funds, banks etc.) or investor category (for example, foreign investors, private investors etc.). However, this issuance method is not in itself, linked to a specific level of risk that the investment bank is subject to when underwriting the issue. One may hypothesize these deals to be associated with less risk than the abovementioned issuance methods because the investment bank knows what investor group the issuance is targeted for. On the other hand, it could be argued that this somewhat more narrow buyer-field limits the placing opportunities for the investment bank and in turn increase the risk associated with placing the issuance.

Now that we have presented the concept of underwriting and how it can be carried out, the next section will proceed with a review of empirical findings of the gross fee, and present factors that has been found to explain variations in the gross fee.

5 The direct cost of issuing equity – the Gross fee

5.1 Empirical findings of the Gross fee

As pointed out by Eckbo et al. (2007) in their thorough review article of security offerings; “... *most studies of underwriter spreads, researchers take a particular focus, usually investigating an economic determinant of spreads that is not well documented in the literature, while controlling for other offering characteristics previously shown to affect spreads.*” (Eckbo et al., 2007, p28). This leads to the following section, which describes some empirical findings of the gross fee (i.e. spreads) and presents what explanatory variables these papers find to explain the gross fee.

Smith (1977), who is frequently cited as the first to analyze the gross fee in an empirical context, studied 578 US offerings in the period of January 1971 to December 1975. Among other things, Smith (1977) revealed the apparent paradox of significantly varying costs to underwriters across the offer methods firm commitments, uninsured rights offers, and standby rights offers. Smith

(1977) found that the gross fee averaged 5.02 percent of the offer price for firm commitments⁹ (underwritten public offerings), ranging from around 10 percent for small issues to less than 4 percent for very large issues.

Following Smith (1977), Eckbo and Masulis (1992) studied the underwriter spread and floatation methods too. Their study analyzed 1,249 US offerings in the period of 1963-1981. They distinguished between industrial issuers and utility issuers, and found a total cost (sum of underwriting compensation and other direct costs¹⁰) measured relative to gross proceeds of 6.09 percent for industrial issues and 4.23 percent for utility issues. With underwriting fees making up approximately 90 percent of total the total direct costs.

Eckbo and Masulis (1992) found, in their multivariate analysis, that the direct flotation costs for industrial issues were negatively related to the gross proceeds and average shareholding value and positively related to the relative issue size and standard deviation¹¹. Utility issues were negatively related to gross proceeds, average shareholding value and relative issue size (note that this relation is opposite to that found for industrial issues however, it is not significant for utility issues) and positively related to standard deviation (Eckbo and Masulis, 1992, p305). Their multivariate analysis was performed across three issuance methods, namely firm commitments, standby rights offers and uninsured rights offers. However, they controlled for the issuance method chosen by applying an indicator variable and found that firm commitment offers increased the gross fee compared to standby rights offers.

As discussed Gao and Ritter (2010) and Bortolotti et al. (2008) distinguish between different types of underwritten issues. The table below summarizes their empirical findings of the gross fee (noted gross spread) for different flotation methods. Note that medians are shown in brackets. Gao and Ritter (2010) analyze US issues in the period from January 1st, 1996 to December 31st, 2007 using the Dealogic Equity Capital Markets (ECM) Analytics Database. Gao and Ritter (2010) find that the difference in gross spread across accelerated and fully marked offerings are statistically significant, tested on average and median.

⁹ Smith (1977) reports 4.32 percent average gross fee for rights with standby underwriting and 2.45 percent for uninsured rights

¹⁰ Other direct expenses include fees for legal and accounting services, trustees' fees, listing fees, printing and engraving expenses, SEC registrations fees, Federal Revenue Stamps, and state taxes, (Eckbo and Masulis, 1992, p304)

¹¹ Measured over 450 trading days starting 60 days before the announcement of the offering

Table 4

Summary statistics of offer characteristics - Gao & Ritter (2010)					
	All SEOs	Bought deals	Accelerated bookbuilt SEOs	Fully marketed SEOs	Difference between accelerated and fully marketed offerings
Gross spread (%)	4.82 (5.00)	2.28 (1.70)	4.23 (4.20)	5.10 (5.15)	-1.77 (-1.63)
Observations	3,276	290	276	2,710	-

Bortolotti et al. (2008) analyze global issues in the period from January 1st, 1991 to December 31st, 2004 using the Securities Data Corporation's (SDC) New Issues Database. Note that Bortolotti et al. (2008) include rights offers in their group of fully marketed offers. As discussed earlier, there is a significant difference between the gross fee paid for SPOs and rights offers, thus this way of categorizing the data may bias the results downwards as rights offers generally have lower fees. Pure accelerated offerings cover either pure primary offers or pure secondary offers whereas mixed accelerated offers are a combination of a primary and secondary offer. They find statistical significance across both categories of accelerated offers relative to fully marketed offers, tested against the average.

Table 5

Summary statistics of offer characteristics - Bortolotti et al. (2008)				
	Pure accelerated offerings	Mixed accelerated offerings	Fully marketed SEOs	Difference between pure accelerated and fully marketed offerings
European seasoned equity offerings				
Gross spread (%)	3.46 (3.12)	3.30 (2.94)	7.07 (6.45)	3.61 (4.44)
Observations	2,119	35	3,160	-

As evident from the study by Gao and Ritter (2010) and that of Bortolotti et al. (2008), the gross fee varies depending on the issuance method chosen, though only substantially so for fully marketed offerings.

Lee et al. (1996) further contributed to the empirical research of the direct cost of raising capital. Their study was conducted on 1,593 US SEOs (excluding rights offers) over the period of 1990-1994, and found an average gross spread of 5.44 percent for SEOs. Their main finding was that of substantial economies of scale in the gross spread for SEOs as well as IPOs. Further, they explained the lack of any diseconomies of scale in their results as an effect of "...the market's

greater experience with absorbing large numbers of big offerings” (Lee et al., 1996, p63). They inferred that there had been a structural change in the market up to the time of their study, as they note that earlier studies have found signs of diseconomies of scale for large offers. While the notion of economies of scale in equity offerings (seasoned as well as initial) has in many ways become conventional wisdom, it has been criticized by subsequent scholars.

Altinkiliç and Hansen (2000), who study 1,325 US SEOs from 1990-1997, fundamentally challenge the conclusion of economies of scale in the relation between proceeds raised and the gross fee. Altinkiliç and Hansen (2000) acknowledge that, when companies choose to issue new equity, fixed costs will initially imply economies of scale “...but as issue size increases diseconomies of scale emerge in the spread due to rising placement cost. Placement cost increases because adverse selection problems expand and so do potential agency problems, and because finding more buyers willing to buy the offer at the offer price becomes more difficult” (Altinkiliç and Hansen, 2000, p193). They sort their observations in high and low quality offerings, and they find evidence which indicates that the actual cost curve is a U-shaped function of the proceeds raised, when looking at the respective quality groups. Interestingly, they discover that 40 to 50 percent of the issues are made in the diseconomies region.

This U-shaped relation has later been confirmed on a German dataset by Bühner and Kaserer (2002), analyzing 120 SEOs (predominantly standby rights offers) in the period of 1993-1998 (Bühner and Kaserer, 2002, p334).

Among other things Altinkiliç and Hansen (2000) conclude that “*larger offerings tend to be issued by larger firms whose issues are of higher quality, and thus have lower placement cost per dollar proceeds than issues by smaller firms require*” (Altinkiliç and Hansen, 2000, p199). In addition to the general higher level of placement cost, they note that smaller firms face steeper marginal spreads per dollar of proceeds raised. Moreover, their research suggests that 10.4 percent of the gross fee is fixed costs on average indicating that the underwriting cost is mostly variable. This substantial variable cost in the gross fee leaves substantial room for speculations about what factors may drive these particular costs.

The findings of Altinkiliç and Hansen (2000), that company size and quality seems to be a strong explanatory variable of the gross fee, is closely linked to the focus of another influential paper, namely the recent study by Butler et al. (2005). They argue that the gross fee, to a significant extent, is explained by the level of market liquidity of the issuing firm, and “...hypothesize that when firms access the external equity capital markets the liquidity of their stock affects the

transactions costs – specifically the investment banking fees – associated with floating new equity” (Butler et al., 2005, pp331-332).

Employing a sample of 2,387 US underwritten seasoned equity offerings (excluding rights offers) in the period of 1993-2000 they seek to establish this relationship between firm liquidity and direct cost. Along with the findings in section 3.3, Butler et al. (2005) note that “...*there is no unanimously accepted measure of market liquidity, frequently used proxies are measures that gauge the transaction costs and ease of executing orders*” (Butler et al., 2005, p335). Butler et al. (2005) include the liquidity measures quoted spread, effective spreads, relative effective spreads, quoted depth, average traded size, volume, and turnover and combine these measures into a liquidity index as described in section 3.4.3. Their sample returns an average (median) gross fee of 4.8 percent (5.0 percent).

Acknowledging the potential or likely existence of certain confounding effects, they proceed, testing their results across offer size quintiles and find that the effect of liquidity on the gross fee is higher for large equity issues than for small issues (Butler et al., 2005, p333). They also find that large equity issues (largest issue size quintile) have an average difference in gross fee of 134 basis points compared to small equity issues (lowest issue size quintile) that have an average difference from the least to the most liquid quintile of 44 basis points. Butler et al. (2005), argue that larger issues are more difficult to float in an illiquid stock than a small issue, and interpret this; “...*as evidence that the marginal cost of illiquidity is higher for large issues*” (Butler et al., 2005, p333). Generally stated Butler et al. (2005) argue that; “...*ceteris paribus, investment banks’ fees are substantially lower for firms with more liquid stock*” (Butler et al., 2005, p332).

The multivariate regression analysis that Butler et al. (2005) subsequently perform, supports the univariate result, and thus, emphasizes that fees are strongly related to secondary market illiquidity. Their multivariate regressions show that the gross fee is positively related to the liquidity measures quoted spread, effective spread and relative effective bid-ask spreads, and negatively related to depth, average trade size, average volume, turnover and the aggregated liquidity index. Moreover they find that the gross fee is negatively related to gross proceeds, firms size, share price, and the presence of multiple bookrunners, and positively related to return volatility, as measured by the average daily standard deviation (Butler et al., 2005, p341).

This relation between liquidity and the gross fee is intimately linked to the well-established insight from asset pricing theory, which emphasizes the role of liquidity in explaining expected returns, see section 2.1. Butler et al. (2005) speculate that the gross fee should be related to the

level of liquidity, because “...the cost faced by the investment banking group are similar in spirit to those of other market makers such as dealers, specialists or block traders who line up buyers and sellers to facilitate the intermediation process” (Butler et al., 2005, p332).

While it thus, seems justified by Butler et al. (2005) that secondary market illiquidity helps explaining the direct costs of an SEO, this paper has argued that the direct costs are only a part of the total primary market ‘friction’ that the issuing firm must overcome. Another substantial part of this ‘illiquidity’ in the primary market is the indirect costs that the owners of an issuing firm face, namely the SEO discount. This paper will now proceed with an exposition and discussion of the current theory and research concerned with the existence of an SEO discount. The section will explore to what extent one should expect to find the indirect costs of an SEO to be explained by the secondary market liquidity of the issuer.

6 The indirect cost of issuing equity – the SEO discount

6.1 Introduction

In addition to the direct costs associated with an SEO, owners may as noted incur an additional cost in terms of the implicit potential wealth transfer from old to new shareholders if the issuance is priced at a discount to the ‘real’ value of the asset. In a theoretical situation where all issued shares were subsequently taken up by existing shareholders on a pro rata basis, this would not constitute a welfare loss. However, since this is almost certainly not the case in reality, existing shareholders will therefore incur a dilution of personal wealth. This transfer of wealth may potentially represent a significant indirect cost of using share offerings as a way of raising equity.

Fundamentally, in a classical efficient market hypothesis sense, one should not expect to see equity issuances priced at a discount, as one would expect an efficient market to prevent such ‘leaving money on the table’ – alternatively one could earn rents by participating in SEOs.

One of the early investigations into the dynamics of an efficient market around selling large quantities of common stock is that of Scholes (1972), who developed a number of testable hypotheses about the price behavior surrounding a sale of a major block of shares. Among these was the notion of a downward sloping demand curve for a particular share. This would result in a temporary price pressure upon the sale of the shares. An alternative hypothesis that Scholes (1972) proposed was the ‘information hypothesis’ which states that a sale of a major block may signal to the market that the share is overpriced. The information hypothesis, if true, would cause

a permanent depression in prices. Scholes (1972) however, noted that this would not affect new issues (that is, SEOs) among other things because such issues require the release of a substantial amount of information, in the form of prospectuses etc. *“Market participants will have ample time to assess the planned use of the funds and will reflect the value of this information in the share price prior to the issue. At the time of the issue, firms will be able to sell shares at the new equilibrium price irrespective of whether the price adjusted upward or downward to the value of the information.”* (Scholes, 1972, p184).

Academia however, has produced consistent evidence in favor of the existence of an SEO discount, starting with Smith (1977). Smith found evidence that SEOs were on average priced 0.5 percent below the previous day's closing price. While a statistically significant addition to the total cost of an SEO, the relatively small magnitude of discount implied that the initial interest in his finding was limited. This in turn had the consequence that the first potential explanations to the existence of an SEO discount were produced ‘accidentally’ by other fields of research, such as research on capital structure theory and the more notable IPO underpricing. Recent studies (e.g. Corwin (2003) and Mola and Loughran (2004)) however, have provided evidence that the discount has increased dramatically since Smith (1977), propelling the phenomenon of an SEO discount to the forefront of financial study. However, before venturing into a discussion of theoretical and empirical studies of the SEO discount, it is of interest to briefly dwell upon the decision to issue equity itself. This decision in turn, is intimately linked to the overall considerations of optimal capital structure for a firm – the field of capital structure theory.

This section thus begins with a brief overview of the main developments within the field of capital structure theory. This is interesting, not least since it, as noted was exactly this field that produced one of the first credible explanations to the observed phenomenon of an SEO discount – Myers and Majluf's (1984) influential article on corporate financing and investment decisions under asymmetric information. The following section thus attempts to give a brief and non-exhaustive overview of the advancement in capital structure theory within financial economics since its inception with the well known 1958 article by Modigliani and Miller.

6.2 Capital structure theory – a brief overview

6.2.1 Modigliani and Miller

Modigliani and Miller (1958) established a theory demonstrating that when taxes and the costs of financial distress are not considered, the capital structure of a firm has no impact on its value.

Modigliani and Miller (1958) “...proved that the choice between debt and equity financing has no material effects on the value of the firm or on the cost or availability of capital” (Myers, 2001, p31). Although this construct is far removed from reality, it has provided a strong foundation as the basis for almost all capital structure research over the last fifty years. Modigliani and Miller (1963) later added the effect of the interest shield from corporate taxes into their model. In that article they showed that the net present value of the tax shield has, at least in theory, quite a large effect on the value of a specific firm. The theoretical result of incorporating taxes in the Modigliani and Miller framework is that the optimal capital structure for a firm would see them entirely financed by debt.

6.2.2 The Static Trade Off Theory of Capital Structure

The static trade off theory of capital structure eliminates several of the basic theoretical assumptions in the Modigliani-Miller propositions. “*The trade off theory says that firms seek debt levels that balance the tax advantages of additional debt against the costs of possible financial distress*” (Myers, 2001, p81). Central to the theory is the role played by the potential costs of financial distress, which introduces the concept that the debt a company takes on its balance sheet also demands a risk premium. This risk premium reflects the probability weighted amount an investor must expect to lose in the event of the firm failing. In conjunction with the previously mentioned tax shield this theory ultimately yields a static point where the capital structure is at a theoretical cost optimum. At this point, the marginal advantage of obtaining one additional unit of debt is exactly offset by the marginal effect of the potential costs of financial distress. However, while the static trade off theory is theoretically attractive, it has frequently been found to be insufficient when explaining the debt levels actually observed in firms (Myers, 2001). One response to this apparent weakness of the static trade off theory is the pecking order theory of capital structure.

6.2.3 The Pecking Order Theory

The pecking order theory, unlike the static trade off theory, embraces the fact that firms do not operate in a static environment and hence that firms need some cash on hand enabling them to respond swiftly to changes and rapidly pursue new investment opportunities. Myers and Majluf (1984) argue that financing decisions in companies are not made based on a target debt ratio, but are the result of information asymmetries between managers and investors (Myers and Majluf 1984, p188).

According to Myers and Majluf (1984), the basic concept of the pecking order theory is that management will favor internally generated funds over external capital when needing finance for a new investment. *“The pecking order theory says that the firm will borrow, rather than issuing equity, when internal cash flow is not sufficient to fund capital expenditures. Thus the amount of debt will reflect the firm’s cumulative need for external funds”* (Myers 2001, p31). Following on from this, the capital structure of a firm cannot be explained by a convergence towards an optimal debt ratio like the static trade-off theory predicts. Rather, it will be the outcome of managers choosing from a pecking order of financing opportunities when funding investments. This pecking order predicts that managers will:

1. Use internally generated cash
2. Issue debt
3. Issue hybrid securities
4. Issue equity

6.3 Theoretical foundation of the SEO discount

The theoretical foundation of the existence of a pecking order is essentially the notion that firms cannot issue equity at efficient prices – that is that firms when issuing equity are forced to do so at a discount. In demonstrating this, Myers and Majuf (1984) assumed capital markets to be perfect, except for the belief that only management knows the true value of their firm in its current form and of its investment opportunities. Myers and Majluf (1984) proceed by assuming that the company in question does not hold sufficient cash reserves to take on the current investment. The company is therefore faced with the choice between issuing debt, issuing equity or even foregoing the investment.

Had capital markets been perfectly efficient, the decision of how to raise the capital would have been insignificant, since the cost of raising capital, be it in the form of debt or in the form of equity, would be zero: *“In an efficient capital market, securities can always be sold at a fair price; the net present value of selling securities is always zero, because the cash raised exactly balances the present value of the liability created.”* (Myers and Majluf, 1984, p187). This however, is clearly not observed in the real world, where companies issuing equity are faced with a number of direct as well as indirect costs. The existence of certain indirect costs in connection with an issuance of equity makes the choice between debt and equity nontrivial to Myers and Majluf (1984). The assumption of markets exhibiting only semi-strong-form efficiency implies that firms issuing equity will face the problem of adverse selection.

The problem of adverse selection emerges as the market realizes that managers of the firm are more knowledgeable about the ‘true’ value of the firm and its opportunities than the general market. This in turn implies that “...investors, aware of their relative ignorance, will reason that a decision not to issue shares signals ‘good news’. The news conveyed by an issue is bad or at least less good” (Myers and Majluf, 1984, p188). According to Myers and Majluf (1984), this affects the price that investors are willing to pay for the new shares, thus forcing the issuing firm to price the shares below the current market value, giving rise to the observed SEO discount.

It should be noted that in the original pecking order theory, as proposed by Myers and Majluf (1984), a stock issuance would be seen to be an unattractive financing option, regardless of whether the company is over or undervalued, and as a consequence of this, the pecking order theory predicts that managers would only issue new shares as a last resort i.e. when the firm is in some form of financial distress. This particular prediction is inconsistent with most empirical findings. Indeed Dittmar and Thakor (2007) notice that equity is typically not issued by firms in financial distress. On the contrary, they note that “...firms issue equity when their stock prices are high” (Dittmar and Thakor, 2007, p1). They explain this observation with the idea that the security issuance decision depends on how it will affect the firm’s investment choice and in turn, how this choice will affect the post-investment stock price of the firm. Their model predicts that equity will be issued primarily when agreement between investors and managers on the value of an investment opportunity is high. This, according to Dittmar and Thakor (2007) occurs when the stock prices are high. Regardless, the adverse selection framework of Myers and Majluf (1984) brought about a potential explanation to the SEO discount as initially observed by Smith (1977).

An alternative explanation to why markets may require that equity issuances are priced at a discount to ‘real’ value is given by Rock (1986) who studies the discount associated with initial public offerings. The notion of an IPO discount originates in an analysis by Ibbotson (1975) who found that IPOs were underpriced by an average of 11.4 percent. An underpricing which he found disappeared within weeks of the initial offering. This apparently inexplicable excess return subsequent to the initial floatation, Ibbotson (1975) ultimately termed a ‘mystery’.

Rock (1986) takes his departure from the framework of Grossman (1976) that demonstrated that if one group of investors poses superior information about the ‘real’ value of an asset, the information can be inferred by anyone from the equilibrium price. This notion essentially gives rise to the previously stated paradox that: “If anyone can infer private information from the equilibrium price, no one pays to collect information. Yet if no one collects information, the price

reveals none, and an incentive emerges to acquire it.” (Rock, 1986, p187). Rock (1986) proposes an alternative approach, stating that if the price of an asset, which is widely observable, does not correspond to a unique level of demand, which cannot be observed, the main channel through which inside information is communicated to the market ceases to function. As long as this is the case, an informed investor can profit from her superior information by bidding for ‘mispriced’ securities, thereby being compensated for her costly gathering of information about the ‘real’ value of the asset.

Rock (1986) goes on presenting a model, essentially an auction theoretical framework, with two classes of investors – informed and uninformed. The informed investors have superior knowledge of the true value of the firm and its prospects. Surprisingly perhaps, the issuer itself and the investment bank are counted among the uninformed. Rock argues that while the firm and its issuer do know a considerable amount about the firm, they essentially give up this informational advantage as they reveal their proprietary knowledge to the market upon issuance.

They do so directly, through the disclosure of material information about plans as well as current activities when issuing a prospectus, and indirectly through how ‘aggressively’ the issuance is priced relative to other ‘comparable’ offerings. The latter Rock (1986) argues, happens automatically, as the investment bank implicitly, by means of their reputation, certifies that the price of the issuance reflects the prospects of the firm in question. Further Rock (1986) notes that “*...even though the firm and its agent know more than any single individual in the market, they know less than all the individuals in the market combined.*” (Rock, 1986, p190). The ‘real’ value of the issuance is assumed to fluctuate randomly, so that some offers are actually underpriced, and thus attractive, while some are in fact overpriced and hence not attractive for investors. With these assumptions established the model is comparatively straight forward. Informed investors will only subscribe to the undervalued and attractive issuances, thus on average ‘crowding out’ the uninformed investors from these offers. The uninformed investors will thus invest in an unproportionately large fraction of the ‘bad’ issuances, creating essentially a winners curse problem.

Assuming that the informed investors do not possess enough wealth to subscribe to the entire issue, the firm ‘needs’ the participation of the uninformed investors in addition to the informed. The uninformed investors (however ignorant) realize their comparative disadvantage. In order to attract sufficient capital, the firm thus needs to deliberately underprice all issuances, ensuring that uninformed investors do not shun the offering altogether (Rock, 1986). While as noted, Rock

(1986) studies IPOs, Loderer et al. (1991a) confirm that this insight can indeed be meaningfully transferred to the case of SEOs, stating that: *“The same situation arises when firms issue additional common or new classes of preferred stock. Underpricing could be necessary to entice uninformed investors to subscribe to the new issues”* (Loderer et al., 1991a, p37).

While as noted most of the potential explanations for the existence of an SEO discount initially arose from other fields of study, Parsons and Raviv (1985) constitute a notable exception, as they attempt specifically to account for the SEO discount. Like Rock (1986), Parsons and Raviv assume the existence of two distinct types of investors. But while in Rock (1986) the investors possess varying degrees of information, Parsons and Raviv (1985) assume two groups of investors with different reservation prices – a high valuation group and a low valuation ditto. Further, they view the issuance and pricing decision much as a two stage game, where dynamics in both the pre-issuance market as well as the subsequent, post-issuance market influences the pricing. The firm faces a population of investors who are asymmetrically informed. Each investor knows only his own valuation and not that of any other investor. Neither the firm nor its investment banker has knowledge of the valuation of any of the investors.

The issuer sets the initial price such that he expects to attract investors with a high valuation of the firm’s new project. This price must be sufficiently low in order to encourage the high valuation investors to invest at this initial price instead of ‘waiting’ and buying at a subsequently lowered price. Realizing that they will be successful in purchasing at a lower price only in the event that the issue is undersubscribed at the initial price, the underwriter can ‘threaten’ to charge an initial price which extracts some of the surplus from these high valuation investors. However, as a consequence of asymmetric information he cannot set this price at a level where he extracts the entire surplus. Parsons and Raviv note that: *“Therefore, since in the market for old securities taking place before the new issue arrives investors can purchase a share with certainty, the competitive price will be driven to a level higher than the initial offering price. This explains why, in empirical studies, it is observed that the initial offering price is below the market price prevailing prior to arrival of the new issue”* (Parsons and Raviv, 1985, p379).

Apart from their varying explanations to why an SEO discount may rationally be observed, these three studies (Myers and Majluf (1984), Parsons and Raviv (1985), and Rock (1986)) have in common, a comparatively theoretical approach. Altinkiliç and Hansen (2003) summarize the progress in the field since its inception, concluding quite despondently that *“Explanations for discounting of seasoned equity offers remain limited and untested”* (Altinkilic and Hansen, 2003,

p286). The comparative absence of thorough and empirically tested explanations as of this time may in part have been explained by the relatively limited magnitude of SEO discount that was initially observed.

6.4 Empirical findings of the SEO discount

In his study, as noted, Smith (1977) discovered a statistically significant, but rather slender average offering price discount of 0.54 percent for the 328 offerings in the period of 1971-1975. The findings of the relatively few subsequent studies were similar in magnitude. Altinkiliç and Hansen (2003) elegantly summarized the concurrent empirical discoveries of the field in a table, finding that SEO discounts reported in previous studies averaged just 0.71 percent. The highest reported average SEO discount of any study during that period was that of Loderer et al. (1991a) who studied 680 Nasdaq and 926 NYSE/Amex offers by industrial and utility firms during the period of 1980 through 1984. They found the average Nasdaq SEO to be offered at a discount of 1.64 percent. At the same time however, they found little evidence of a consistent SEO discount in NYSE/Amex offerings. This lead them to speculate that the finding of a significant discount in the case of Nasdaq offerings was a creature of the market microstructure of that particular exchange rather than a general phenomenon nested in the realm of financial economics.

In contrast, Altinkiliç and Hansen (2003), studying a sample of 1,703 SEOs on NYSE/Amex and Nasdaq in the period from 1990 through 1997 found an average discount of 2.47 percent. Simultaneously, but utilizing a larger sample, Corwin (2003) found that seasoned equity offerings in the USA were underpriced by an average of 2.2 percent during the 1980s and 1990s, with the discount increasing substantially over time. According to Corwin “*SEO underpricing averaged 1.15 percent for offers from 1980 to 1989, increased to 2.92 percent for offers from 1990 to 1998, and reached as high as 3.72 percent in 1996*” (Corwin, 2003, p2249). Corwin notes that this is equivalent to almost two million dollars of lost proceeds for the average seasoned equity offer in 1998, which in turn accounts for almost 22 percent of total direct and indirect issue costs. In a similar study of 4,814 seasoned equity offerings in the USA during 1986 to 1999, Mola and Loughran (2004) found an average discount of 3 percent. While Corwin (2003) reports the average discount in different sub-periods, Mola and Loughran (2004) also disaggregate the observed discount on several other parameters.

Mola and Loughran (2004) define average ‘money left on the table’ as “*...the dollar discount multiplied by the number of shares in the offering...*” (Mola and Loughran, 2004, p4). They discovered a significant difference between offerings underwritten by an investment bank with a

top-tier analyst team and offerings underwritten by investment banks *without* a top-tier analyst team. Noticeably, Mola and Loughran (2004) found that: *“In 1999, the average amount of money left on the table by underwriters with a top-tier analyst group is \$8.9 million, compared to \$3.8 million by the other bankers”* (Mola and Loughran, 2004, p4).

Mola and Loughran (2004) further identified an apparent positive relation between the ratio of the size of the offering to the market value of the company and the observed discount. They found the average discount between 1996 and 1999 to be as high as 4.5 percent for companies issuing a high ratio of new equity to company market value, where ‘high’ was defined as being equal to or greater than the mean value of the distribution, which in their sample was 0.2. That is, firms issuing equity worth more than 20 percent of their outstanding equity.

Mola and Loughran (2004) put forth four different testable hypotheses relating to these observed indirect costs, subsequently testing them in their sample.

Firstly, Mola and Loughran (2004) hypothesised that the increasing discount may be due to a changing composition of the issuers, and also note that a greater uncertainty surrounding an offering should lead to a higher expected discount. They demonstrated that while the sample used by Smith (1977) consisted solely of equities listed on the NYSE and the Amex, issuers listed on NASDAQ represented an increasing amount of the market for seasoned offerings, and that NASDAQ offerings indeed exhibit a higher average discount. This finding is corroborated by the research of Altinkiliç and Hansen (2003), who determine the average SEO discount for NYSE/Amex issuances to be 1.47 percent while that of Nasdaq was found to be more than twice that, at 3.01 percent.

Another proxy for uncertainty which Mola and Loughran (2004) test is the aforementioned relative size of the offer to the total market value of the firm, which they again demonstrated had increased over the years. Mola and Loughran (2004) concluded that the changing issuer composition may indeed explain part of the observed increase in the offering discount. However, the changing issuer composition alone was not seen to be a fully explanatory factor as the study revealed an observed tendency of increasing discounts across all groups.

Secondly, Mola and Loughran (2004) hypothesised that the increasing discount may be ascribed to investors short-selling the stock in *“...a manipulative way to affect the offer price of new shares”* (Mola and Loughran, 2004, p9). Thus under the assumption that investment banks use the prior closing price as a reference in setting the offer price, such a manipulative pressure could

force the firm to offer its shares at a high discount in order simply to ‘market’ the new shares. However, they did not find support for this hypothesis.

Corwin (2003) looks further into this issue, testing the effects of the adoption of rule 10b-21 by the Securities and Exchange committee (SEC)¹², prohibiting investors to cover a short position with stock purchased in a new offering, provided that the short was established between the filing date and the distribution date. While originally intended at solving the aforementioned problem of manipulative price pressures, scholars have argued that *“restrictions on short sales may have the unintended effect of restricting informational short sales, thereby reducing the informativeness of prices and increasing required underpricing”* (Corwin, 2003, p2256). Corwin however finds only weak evidence that the increase in offer price discount during the 1990’s is explained by the adoption of SEC-rule 10b-21.

Mola and Loughran (2004) further hypothesize that increased investment banking power may explain their observations. They analyzed the trends in seasoned equity offering pricing patterns and compared them with those found in initial public offerings. In this comparison, they found an increasing tendency for investment bankers to round down the offering price to the nearest whole integer in both cases. The frequency of integer pricing was found to increase from 29 percent of all cases in the period 1986 to 1989, to 44 percent of all cases during 1996 to 1999.

The tendency to price down to the nearest whole integer would in itself explain approximately 1.5 percent of the discount in e.g. the case of a firm with a closing share price of USD 50.75, subsequently offering new shares at USD 50.00. This discovery of an increasing tendency to set offer prices at a lower whole integer is corroborated by Corwin, who further makes the interesting observation that: *“This practice is reflected in larger underpricing for low priced stocks...”* (Corwin, 2003, p2250). Mola and Loughran (2004) summarize that: *“The offer price setting practice that investment bankers follow increasingly leaves more money on the table.”* (Mola and Loughran, 2004, p13). They explain this tendency with managers of issuing firms *“...focusing on selecting an underwriter who will aggressively talk up their stock... Although more money is being left on the table in the seasoned offerings than in the past, firms are accepting the increased discount due to their belief that by having an influential analyst transmit positive reports, their stock will see elevated valuation levels”* (Mola and Loughran, 2004, p22). This in turn explains the counter intuitive observation mentioned previously of investment banks with top-tier analyst teams being associated with significantly more money left on the table.

¹² SEC-rule 10b-21 was adopted on August 25th, 1988

This view is supported by Cliff and Denis (2004) who study the significance of post issuance analyst coverage in IPOs, citing evidence that research coverage has come to play a central role in the security issuance process in recent years. They argue that if companies value research coverage, one should expect them to be willing to allocate resources to acquire this coverage. It is, they note however unclear how the payment for such service is made in the case of IPOs, which leads them to empirically examining their hypothesis that issuing firms pay for analyst coverage via the underpricing of the offering. This insight is strongly supported by Mola et al. (2010) who in the working paper, “Is there life after loss of analyst coverage, conclude that analyst coverage does indeed create a significant value for firms. And that loss of analyst coverage seems to have stark consequences for firms, both in terms of stock performance as well as in terms of ‘risk’ of delisting.

The final hypothesis of Mola and Loughran (2004) can be called the ‘leaving a good taste’ hypothesis, that is: *“Issuers are willing to leave some money on the table for investors at earlier offerings because firms want to come back later for additional funding”* (Mola and Loughran, 2004, p9). This hypothesis rests on the assumption that without investors remembering that they got a good deal at an earlier stage, firms will need to put in a greater effort at marketing the seasoned equity offering, which is then evident in a higher discount. In testing this hypothesis, Mola and Loughran (2004) looked into the average seasoned equity offering discount by dividing the period of study into sub periods and controlling for the extent to which the firm issued equity in the prior year. They noted that: *“In the later two subperiods, firms issuing equity within one year of a prior offering report significantly lower average SEO discounts than firms with no recent offerings”* (Mola and Loughran, 2004, p10).

They found the average indirect cost of the discount during 1996 to 1999 of firms with no prior year offerings to be 3.9 percent compared to an average discount of 2.2 percent for firms with a recent history of issuing seasoned equity. This led them to the conclusion that investors indeed seem to require a smaller discount for issuances undertaken by firms with a history of issuing. However, Mola and Loughran (2004) also noted that this conclusion contained the potential bias that frequency of issuance is likely to be correlated with firm size. This in turn is likely to affect the offering price discount as developed in hypothesis one, which concludes that the discount is positively related to the perceived uncertainty of the offering. That is, the offerings by larger firms are likely to be perceived as less uncertain than those of smaller firms – an insight that closely resembles that of Altinkiliç and Hansen (2000).

This issue may however be somewhat countered by the finding of Corwin (2003) that the offering price discount is positively related to offering size. Corwin (2003) hypothesised that the observed offering price discount may in fact be a result of either a permanent or temporary price pressure. Corwin explains that “...one could view a seasoned offer as a permanent shift in the supply of existing shares. If the aggregate demand curve for the firm’s shares is downward sloping, this increase in supply will result in a permanent decrease in the stock price” (Corwin, 2003, p2254).

Alternatively, Corwin (2003) suggested one could view the seasoned equity offering as a temporary liquidity shock that the market must absorb. This may imply that “...a discounted offer price may be necessary to compensate investors for absorbing the additional shares” (Corwin, 2003, p2254). This would further suggest that the market would return to its normal pre-issuance level, leaving investors with a positive return. In summary, Corwin (2003) expected larger stock issues to be comparatively more underpriced than smaller stock issues and that this effect would be most pronounced for securities with a relatively inelastic demand. Corwin (2003) found it strongly supported that the indirect cost of the seasoned equity offering discount does indeed reflect a temporary price pressure.

6.5 A relation between the SEO discount and market liquidity

The notion of stock prices exhibiting a finite level of elasticity is intimately linked to the concept of asset illiquidity. Elasticity of stock prices was extensively researched by Loderer et al. (1991b). They confirmed this insight, noting that the demand for individual financial assets may have finite price elasticity for a variety of reasons, one of which is that: “Investors may value liquidity, that is, the ability to trade cheaply and with little delay in reaction to new information”. (Loderer et al., 1991b, p623). They continue, pointing out that: “Assuming finite price elasticities, less liquid securities should be characterized by larger relative bid-ask spreads.” (Loderer et al., 1991b, p639).

That liquidity is a crucial component of stock price elasticity is further supported by Gao and Ritter (2010) who include two different measures of liquidity in their estimate of price elasticity for a given asset. Hypothesizing that illiquidity may play a role in the SEO discount is not quite a new phenomenon. Eckbo et al. (2007) cite Amihud and Mendelson (1988) in arguing that managers seeking to maximize current stockholder wealth should take market liquidity into account when making corporate financing decisions. This view is shared by Altinkiliç and Hansen (2003) who state that: “...as the offering becomes more difficult to place, higher discounting is

needed to attract capital suppliers and compensate them for bearing the burden of more illiquidity of longer term investing.” (Altinkilic and Hansen, 2003, p286).

Ellul and Pagano (2006) develop a model where the IPO underpricing is demonstrated to be positively related to after market liquidity. Their model is fundamentally based on the model of Rock (1986), presented above. Ellul and Pagano (2006) assume the existence of two types of private information: a signal that becomes public as soon as shares start trading after the IPO and some residual private information that is disclosed at some later date. While the first creates the standard adverse selection problem in the primary market, the second yields an adverse selection problem in the secondary market and will be reflected in the subsequent bid-ask spread of the asset in question. Ellul and Pagano (2006) point out that: *“IPO underpricing will impound also the costs caused by the latter to the extent that some investors expect to liquidate their shares in the aftermarket.”* (Ellul and Pagano, 2006, p382). The impact of aftermarket illiquidity on IPO underpricing is thus expected to be larger in markets where such ‘flippers’ are abundant. Ellul and Pagano (2006) test for the presence of such liquidity effects on IPO underpricing, studying a sample of 382 IPOs on the London Stock Exchange from June 1998 through December 2000. Controlling for the variables suggested by other theories of IPOs, they find that IPO underpricing is higher for shares featuring lower expected liquidity and higher liquidity risk, thus confirming their hypotheses. While illiquidity in the particular specification of their model results from asymmetric information, they note that the model is quite robust as: *“...its results would be qualitatively unchanged if the bid-ask spread resulted from the inventory holding costs or order processing costs of dealers, rather than information asymmetries”* (Ellul and Pagano, 2006, p387). They conclude that their results highlight an important and neglected link between market microstructure and corporate finance, namely that secondary market liquidity affects the cost of equity capital for companies that choose to go public.

It would seem reasonable to expect that this insight could be transferred from studies of IPOs to those dealing with seasoned offerings, as has been demonstrated possible with several other findings in those fields, not least as Loderer et al. (1991a) persuasively argue that it is essentially the same factors that drive IPO underpricing and SEO discount. One should thus rationally expect to find the SEO discount positively related to measures of secondary market liquidity. A recent study provides support in favor of this view. Asem et al. (2009) study the role of liquidity and investor sentiment in price discounts on 2,406 SEOs on the Australian over the period from 2002 through 2008.

Asem et al. (2009) set out arguing that a key implication of Amihud and Mendelson (1986) is: *“that SEO price discount should be larger for firms with illiquid stocks since it is more costly and harder to subsequently sell these stocks than liquid stocks”* (Asem et al., 2009, p3). Further they point out that a separate strand of research suggests that asset prices are influenced by certain behavioral biases such as ‘investor sentiment’, and that it has been demonstrated that the SEO discount is lower during periods of strong investor sentiment. In spite of this apparently clear connection they note, it is surprising that these effects have not been studied, and they thus set out investigating to what extent a decline in investor sentiment has a more pronounced effect on the SEO discount for illiquid assets as compared to assets with a greater level of liquidity. Intuitively, they note: *“This is important because, as investor sentiment wanes, investors might become increasingly sensitive and unwilling to bear the costs of holding illiquid assets which, in turn, would affect stocks with different liquidity profiles differently. As such, one would expect that a decline in investor sentiment will increase the SEO price discount of firms with illiquid stocks more than those with liquid stocks”* (Asem et al., 2009, p4). Asem et al. (2009) find strong evidence in favor of all three hypothesis; the SEO discount was on average greater for firms with a lower level of liquidity, greater during periods of declining investor sentiment, and finally that there seems to be an important interactive effect between the two, implying that liquidity seems to matter more in periods of waning investor sentiment.

A quite different approach to gauging the effect of illiquidity on SEOs is adopted in a recent working paper by Stulz et al. (2012) with the first draft released in April this year. Stulz et al. (2012) investigate the impact of market liquidity on the relative frequency of equity offerings (initial as well as seasoned). They too work under the assumption that: *“...equity issuance is more costly for existing shareholders when a firm’s stock is less liquid.”* (Stulz et al., 2012, p2), and find it strongly supported that frequency of equity issuance is inversely related to market liquidity.

Stulz et al. (2012) create a sample consisting of 68,806 equity issuances from 36 different countries across the globe from 1995 to 2008, obtaining for each market the quarterly number of equity issuances and scaling them with the total number of firms listed in that market. They then proceed estimating the change in liquidity employing the Amihud (2002) measure of illiquidity in conjunction with a rather complex model, additionally controlling for a wide variety of confounding effects, among these investor sentiment. The subsequent analysis reveals that equity issuances are not affected symmetrically by liquidity shocks, as they; *“...find that negative shocks have a much stronger effect and that there is little evidence that positive shocks have an effect at all.”* (Stulz et al., 2012, p6).

Overall, Stulz et al. (2012) conclude that equity issuances across the world are strongly related to equity market liquidity, and the authors interpret their findings to be: “...*supportive of the view that in imperfectly liquid markets, the demand for shares is downward-sloping and that corporations take into account the slope of the demand curve for shares in their financing decision.*” (Stulz et al., 2012, p25). They note that while their study has encompassed a focus on market-level liquidity and its overall impact on equity issuances, further research should examine to what extent illiquidity as measured at the firm level affects financing policies too.

That is essentially what this thesis aims to do. This thesis complements the study by Stulz et al. (2012) in two significant ways. Firstly, while Stulz et al. (2012) as noted focused on market wide liquidity, this present study will employ illiquidity on the firm level in its analysis. This is interesting not least because the level of liquidity varies substantially between the individual assets of a market, which in turn likely has the implication that a shift in market wide liquidity affects the individual firms in a different and possibly nonlinear way. Firms with very liquid shares may thus be less affected than firms with comparatively illiquid shares. Furthermore, in a pragmatic sense, firm level illiquidity is what owners and managers of a company can possibly address and improve.

Secondly, while Stulz et al. (2012) are analyzing relative frequency of issuance as a function of shifts in illiquidity, this paper attempts to gauge the effects of secondary market liquidity on the actual costs of issuing equity. That is, while Stulz et al. (2012) analyze how liquidity affects the overall decision of whether or not to issue equity, this paper analyzes how illiquidity affects the combined cost of issuance for those that in fact decide to issue equity. While one might argue that the study by Stulz et al. (2012) contains important additional information from those that decided not to issue equity, the approach of this paper contributes with interesting insights about the actual variance in the costs facing those that did.

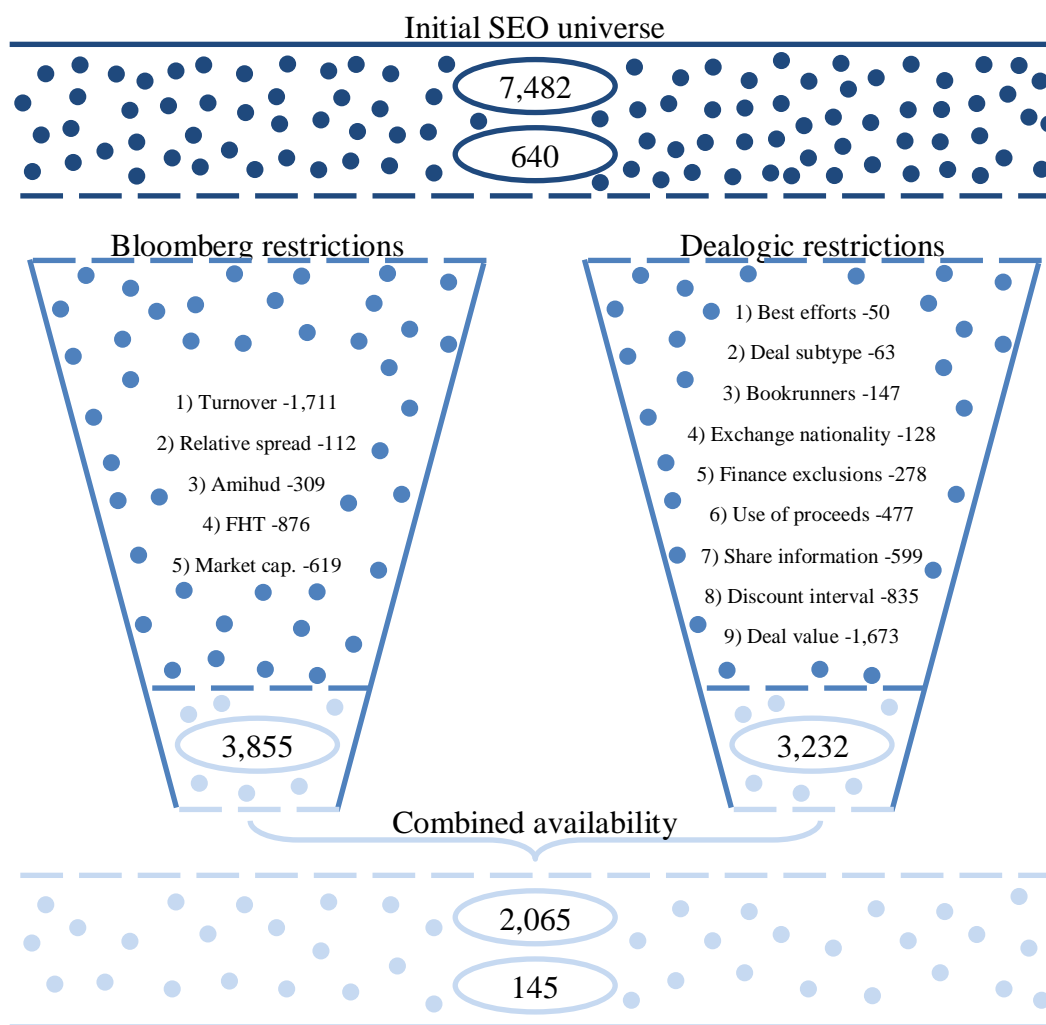
Before attempting to quantify the proposed relation between liquidity and direct and indirect costs, the paper will proceed with an introduction of the dataset employed in this thesis.

7 Data

Data for this study is obtained from the data providers Dealogic and Bloomberg, where the Dealogic Equity Capital Markets (ECM) Analytics Database is used to identify the SEOs and their characteristics; Bloomberg is used to obtain the necessary supporting financial information

for each observation. The Equity Capital Markets (ECM) module in Dealogic returns an initial universe of 7,482 SEO's analyzing the period from January 1, 2000 to December 31, 2011 in Europe, of the gross universe, 640 observations hold information about the gross fee. The figure below illustrates the subsequent screening process which returns the final sample.

Figure 6



Combining the above restrictions of data availability from Bloomberg as well as Dealogic returns a sample of 2,065 SEOs, and of these, 145 have information on gross fee. This implies that the 'two' datasets have been reduced by 72 percent (dataset without fee) and 77 percent (dataset with fee) respectively from the initial universe.

7.1.1.1 Bloomberg

The combined effect of including the measures 1) turnover, 2) relative spread, 3) Amihud, 4) FHT and 5) market cap causes a reduction in available observations of 48 percent. In section 3.4 the

method used for calculating turnover, relative spread, Amihud and FHT is explained. Market cap¹³ is calculated as a daily average over the last 12 months before the SEO. Further it's required that there are at least 200 observations over a year, hereby making room for differences in trading days across exchanges.

7.1.1.2 Dealogic

Dealogic is a platform, widely used by investment banks and other industry professionals, to obtain information about historic transactions in the mergers and acquisitions market as well as in the equity capital markets. Thomson Financial Securities Data Company's (SDC) new issues database is another much cited provider of ECM data, however Gao and Ritter (2010) find that Dealogic's classification of offer methods are substantially more accurate than those reported by Thomson (Gao and Ritter, 2010, p37). As shown in the figure above, nine different restrictions are imposed, each requiring one or more specific matters to be fulfilled. The following paragraphs explain what these restrictions cover and how they reduce the initial dataset by 57 percent.

1) *Best efforts*: the observations are restricted not to be best effort deals, implying that the deals have to be underwritten. This restriction is made to ensure that the investment bank in question in fact carries some level of financial risk when underwriting the SEO. This restriction reduces the number of included observations by 50.

2) *Deal subtype*: the deal subtype is required to be categorized as a follow-on. This insures that the offering contains primary shares. That is, that the offering increases the outstanding equity of the firm and not merely a sale of existing shares (a pure secondary offering). It is required that the deal subtype is reported and clearly indicated. The following six categories are included; cash placing, accelerated bookbuild, guaranteed preferential allocation, fully marketed, bought deal or a combination of a cash placing and a guaranteed preferential allocation. The latter is treated as a cash placing in the multivariate regressions, as the issuance method guaranteed preferential allocation does not hold any information about the risk incurred by the underwriter, see section 4.3. This restriction reduces the number of included observations by 63.

3) *Bookrunners*: the restriction requires there to be at least one bookrunner, this information is used to estimate the lead manager reputation, based on the market share of the investment bank(s) involved in the particular SEO. The market share is calculated on a yearly basis by measuring the relative market share based on deal value. If an investment bank has a

¹³ Market capitalization is calculated using the functions EQY_SH_OUT and PX_LAST in Bloomberg

market share of a least 3 percent in a particular year it's considered a leading investment bank. This distinction is made along the same rationale as proposed by Butler et al. (2005), namely that market share is a proxy for reputation, and that "*Investment banks with better reputation may work harder during the SEO to ensure that the issue is successful*" (Butler et al., 2005, p335). This hypothesized relation between reputation and workload implies that Butler et al. (2005), suggest a positive relation between underwriter reputation and the gross fee. It should be noted that the 3 percent market share threshold is somewhat arbitrary, and one might argue it is set rather low. However, on the other hand it does have to cover all players on the European market, containing a multitude of small local players. If there are multiple bookrunners on the same offering, the investment bank with the highest market share is used to indicate the reputation. This restriction reduces the number of included observation by 147.

4) *Exchange nationality*: it is required that the company is listed on a European exchange, meaning that European companies only listed outside Europe are excluded from the analysis. This leaves the following issuer nationalities in the dataset; Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Faroe Islands, Finland, France, Georgia, Germany, Gibraltar, Greece, Guernsey, Hungary, Ireland, Isle of Man, Italy, Jersey, Kazakhstan, Kyrgyzstan, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Russian Federation, Slovak Republic, Spain, Sweden, Switzerland, Turkey, Ukraine and United Kingdom. This restriction reduces the number of included observations by 128.

5) *Finance exclusions*: the company is not allowed to be a financial institution, which is a criterion following the methodology used by Butler et al. (2005) and several other papers. The reasoning is that the fee incurred by financial institutions is not comparable to that of non-financial institutions since financial institutions can underwrite themselves. The exclusions cover the specific industries: 'Finance-Commercial & Savings Banks', 'Finance-Investment Banks', 'Finance-Provincial Banks', 'Finance-Savings & Loan'. These specific industry classifications are made by Dealogic based on a specific industry code of the firm's business. This restriction reduces the number of included observations by 278.

6) *Use of proceeds*: it is required that the purpose of the issuance is stated, i.e. whether the SEO is made for financing an acquisition, or is for specific project financing, general corporate purposes etc. However, often multiple purposes are stated which makes the interpretation of this information harder. This restriction reduces the number of included observations by 477.

7) *Share information*: General share information is required to be reported, covering information about shares offered, and number of shares outstanding pre and post deal. This restriction is seen as an indicator that the quality of the observation is acceptable. A filing of an SEO with no such information on the number of shares, we fear could reflect general uncertainty about the information on the issuance. This restriction reduces the number of included observations by 599.

8) *Discount interval*: in addition to the offer price, the closing price one day and one week before the offering is required to be known, for calculating the SEO discount for the two intervals. Furthermore the one-day-SEO discount is required to be in an interval of ranging from a 60 percent discount to a 20 percent premium for. This entails the inclusion of certain issuances priced not at a discount but at a premium to the previous day's closing price. This practice is in line with most previous research (Corwin (2003), Mola and Loughran (2004) etc.), but while there is an abundance of papers including these 'premium' issuances, explanations to this phenomenon are scarce. The only creditable explanation we have been able to uncover is that of Chan and Chan (2011) who state that; *"While new shares in seasoned equity offering are commonly issued at a discount, they are sometimes priced at a premium if the SEO conveys positive signal about the firm value. ... if the SEO is to raise capital to finance investment projects, it can signal a higher firm value valuation than the prevailing market price"* (Chan and Chan, 2011, p11). As with the market share threshold for calculation of the bookrunner reputation, the SEO discount interval is also somewhat arbitrary; the interval is set to reflect a reasonable range of outcomes, based on the speculation that offerings priced outside this range could be considered outliers, initial research indicated that the results were robust to inclusion of a broader scope of offering discounts/premiums. This restriction reduces the number of included observation by 835.

9) *Deal value*: Finally it is required that the deal value is clearly stated and that the offering is greater than EUR 5m. The reason for applying a lower boundary to the deal value is that very small issues, is that the market for such small issues can be viewed as fundamentally different. This is among other things based on conversations with industry professionals who speak of a 'reservation price' when engaging in deals. The market for smaller deals is thus argued to be fundamentally different in nature. While Butler et al. (2005) apply a lower boundary of USD 20m, we argue that the general smaller European equity markets justify a somewhat lower bound. This restriction reduces the number of included observations by 1,673.

Having thus presented the restrictions that form the data for the empirical analysis of this thesis, the following section will present summary statistics of the data and discuss variations between the small and large dataset, i.e. between the dataset with and without information on gross fees.

7.2 Summary statistics of small dataset

Table 6 reports summary statistics for the 145 observations, in addition to the SEO discount, holding information about the gross fee. Looking at the four descriptive parameters, offering size, relative offer size, market cap and return volatility, it becomes clear that the observation are skewed to the right (mean is higher than the median). This right skewness is also apparent for the four liquidity measures, turnover, relative spread, amihud and FHT, however the nature of the liquidity index returns a distribution that is more symmetric around the mean. Turning to the direct and indirect cost it is evident that the standard deviation is much higher for the SEO discount than for the gross fee (9.39 versus 1.17 percent). Note that market cap., return volatility, turnover, relative spread, amihud and FHT are calculated as an average of daily observations over the 12 months preceding the offering, in appendix 1 the summary statistics are compared to averages calculated using 3 and 6 months of data respectively.

Table 6

Summary statistics - small dataset					
<i>Sample description</i>	Mean	Std. Dev.	25th %	Median	75th %
Offering size (EURm)	450	1,350	36	91	298
Relative offer size (%)	21.7	16.2	9.2	17.8	27.5
Market cap. (EURm)	5,720	20,039	154	457	1,555
Return volatility (%)	3.30	1.86	2.02	2.73	4.24
<i>Liquidity measures</i>					
Turnover (EURm)	22.04	67.58	0.30	1.40	6.92
Relative spread (%)	2.08	2.61	0.48	0.98	2.71
Amihud ¹	3	25	0.0013	0.0124	0.1546
FHT	1.25	1.67	0.17	0.47	1.64
Liquidity index	0.50	0.26	0.26	0.51	0.73
<i>Direct and indirect cost</i>					
Gross fee (%)	2.61	1.17	1.60	2.60	3.50
SEO discount (%)	5.55	9.39	8.59	3.85	0.34
Note 1: Amihud measures are reported in per million turnover traded					

Table 7 shows that the number of SEOs fluctuates over the 12 year period with a standard deviation of 7.3. Moreover the table reveals variations in the SEO discount and the gross fee over the sample period, with a standard deviation across the years of 2.40 for the SEO discount and 0.31 for the gross fee, the pattern showed in table 6 is confirmed.

Table 7

Summary statistics - small dataset			
<i>Years</i>	<i># obs.</i>	<i>Avg. SEO discount (%)</i>	<i>Avg. Gross fee (%)</i>
2000	12	8.19	2.57
2001	14	1.97	2.22
2002	7	2.42	2.60
2003	11	7.58	2.73
2004	17	4.96	2.69
2005	7	3.63	3.49
2006	13	4.19	2.75
2007	16	4.51	2.38
2008	7	4.57	2.89
2009	32	9.12	2.56
2010	4	1.46	2.45
2011	5	2.57	2.42
<i>Summary</i>			
Total	145	5.55	2.61

7.2.1.1 Correlation matrix of liquidity measures

The correlation matrix below shows how the four included liquidity measures correlate when analyzing the small dataset. Comparable correlations are made using daily observations over 3 and 6 months, and can be found in appendix 2. However, they are consistent with the results reported below. In addition to the four liquidity measures, market cap is added to the matrix, as it's often used as proxy for liquidity. Along with the four liquidity measures, market cap. shows high correlation across all measures. The analysis is carried out, first by ranking each observation within each group of measures, second by calculating the correlation between the five different groups of measures.

Table 8

Correlation matrix - small dataset (12 months)					
<i>Liquidity measures</i>	1	2	3	4	5
1) Turnover	-				
2) Relative spread	.8309	-			
3) Amihud	.7961	.7672	-		
4) FHT	.8076	.8639	.6651	-	
<i>Other</i>					
5) Market cap.	.8565	.7761	.6085	.7774	-

7.3 Summary statistics of large dataset

The table below shows summary statistics for the 2,065 observations holding information about the SEO discount, note that the 145 observations from the small dataset are all included in this sample. The four descriptive parameters, offering size, relative offer size, market cap and return volatility, are still skewed to the right, as was observed in the small dataset. The four liquidity measures; turnover, relative spread, amihud and FHT have right skewness too. Comparing the indirect cost between the small and large dataset it is visible that the average SEO discount and the standard deviation is smaller for the large dataset. As for the small dataset, the figures market cap., return volatility, turnover, relative spread, amihud and FHT are calculated as an average of daily observations over the 12 months preceding the offering; comparable figures calculated using 3 and 6 months of data can be found in appendix 3.

Table 9

Summary statistics - large dataset					
<i>Sample description</i>	Mean	Std. Dev.	25th %	Median	75th %
Offering size (EURm)	171	503	17	46	123
Relative offer size (%)	15.8	14.3	6.0	10.4	21.8
Market cap. (EURm)	3,125	11,854	88	344	1,413
Return volatility (%)	3.00	1.61	1.86	2.55	3.70
<i>Liquidity measures</i>					
Turnover (EURm)	13.54	44.52	0.22	1.01	5.88
Relative spread (%)	2.35	2.97	0.47	1.17	3.08
Amihud ¹	140	6,194	0.0020	0.0184	0.2177
FHT	1.36	1.89	0.16	0.53	1.81
Liquidity index	0.50	0.26	0.27	0.49	0.73
<i>Direct and indirect cost</i>					
Gross fee (%)	n.a.	n.a.	n.a.	n.a.	n.a.
SEO discount (%)	4.75	8.07	7.33	2.78	0.19

Note 1: Amihud measures are reported in per million turnover traded

Table 10 below shows clear variations in the number of SEOs over the 12 year period with a standard deviation of 92.3. It is observed that the years 2000, 2001 and 2002 contain substantially fewer observations compared to the other years of the sample. While this could be an issue with the particular database, it may also simply reflect that these years saw few issuances. The variation in the SEO discount is smaller than the one reported for the small dataset (standard deviation of 1.31 versus 2.40).

Table 10

Summary statistics - large dataset		
<i>Years</i>	<i># obs.</i>	<i>Avg. SEO discount (%)</i>
2000	29	6.14
2001	57	3.22
2002	73	3.40
2003	105	5.50
2004	137	3.89
2005	227	4.58
2006	237	3.73
2007	328	4.26
2008	138	4.15
2009	275	7.92
2010	269	5.06
2011	190	3.47
<i>Summary</i>		
Total	2,065	4.75

7.3.1.1 Correlation matrix of liquidity measures

Following the analysis on the small dataset, the table below shows the correlation between the four liquidity measures and market cap. It appears that the correlations are generally unchanged across the four liquidity measures and higher when looking at market cap. Comparable correlations are made using daily observations over 3 and 6 months, and can be found in appendix 4. However, they are consistent with the results reported below.

Table 11

Correlation matrix - large dataset (12 months)					
<i>Liquidity measures</i>	1	2	3	4	5
1) Turnover	-				
2) Relative spread	.8385	-			
3) Amihud	.7975	.6976	-		
4) FHT	.7657	.8641	.6072	-	
<i>Other</i>					
5) Market cap.	.8915	.8431	.6608	.8033	-

7.4 Comparison of small and large dataset

Having presented the general characteristics for the small and large dataset, table 12 below reports the relative ratio between the reported figures across the two samples. It gives an overview of how

the two dataset vary across the different characteristics. The issuances in the small dataset are generally made by larger companies, who issue more capital in absolute and relative terms. Further, the return volatility is higher in the smaller sample. And finally it can be noted from the four liquidity measures that it is evident that the small dataset consists of companies that are in general more liquid.

Table 12

Summary statistics - small and large dataset					
<i>Sample description</i>	Ratio between small and large dataset				
	Mean	Std. Dev.	25th %	Median	75th %
Offering size (EURm)	2.62x	2.68x	2.19x	2.00x	2.42x
Relative offer size (%)	1.37x	1.13x	1.54x	1.72x	1.26x
Market cap. (EURm)	1.83x	1.69x	1.75x	1.33x	1.10x
Return volatility (%)	1.10x	1.15x	1.09x	1.07x	1.15x
<i>Liquidity measures</i>					
Turnover (EURm)	1.63x	1.52x	1.39x	1.38x	1.18x
Relative spread (%)	0.89x	0.88x	1.02x	0.84x	0.88x
Amihud1	0.02x	0.00x	0.66x	0.68x	0.71x
FHT	0.92x	0.88x	1.06x	0.88x	0.91x
Liquidity index	1.01x	1.01x	0.95x	1.05x	1.00x
<i>Direct and indirect cost</i>					
Gross fee (%)	n.m.	n.m.	n.m.	n.m.	n.m.
SEO discount (%)	1.17x	1.16x	1.17x	1.38x	1.73x

Having presented the data and the process that produced it the paper proceeds with a brief discussion of the econometric methodology that will be applied in the subsequent empirical analysis.

7.5 Econometric methodology

The empirical analysis in the following sections utilize two fundamentally different econometric approaches in analyzing the direct, indirect and total costs associated with an SEO - a univariate and a multivariate methodology.

The univariate approach creates equal sized portfolios according to one variable, subsequently splitting this in tertiles according to the liquidity index. The differences from highest to lowest liquidity tertile is tested using Wilcoxon's Rank Sum Test (also commonly referred to as the Mann-Withney U Test), the nonparametric counterpart to the Student's t-test. Applying the Rank

Sum Test is in line with both Butler et al. (2005), Corwin (2003) and several other similar studies. A nonparametric test is in some cases preferred as it could be described as: “...a statistical procedure that has certain desirable properties that hold under relatively mild assumptions regarding the underlying populations from which the data are obtained” (Hollander and Wolfe, 1999, p1).

Nonparametric tests may in certain cases have several advantages over the parametric alternatives in that they do away with the normality assumption underlying most parametric tests, are often quite intuitive, and are comparatively robust to outliers etc. The Wilcoxon Rank Sum Test ranks the observations across two groups according to value, and then subsequently sums the ranks. Under the H_0 hypothesis that the means of the two groups do not differ significantly, the summed rank of the two groups would be similar. If however the two sums differ substantially it implies that one group generally obtains say a higher rank than the other enabling one to reject the H_0 hypothesis, confirming that the means of the two groups are statistically significant.

The multivariate regressions are performed using an ordinary least squares estimator (OLS). The OLS estimator estimates the parameters of the regression function that minimize the sum of squared residuals between the predicted and the observed value. Put differently, in a graphical sense, the OLS estimator minimizes the sum of squared vertical distances between the actual observations and the regression function. The OLS estimation method relies on a number of assumptions, such as linearity in the parameters, explanatory variable being independent of the error term, the error term being normally distributed with zero mean and homoscedastic variance. These will be addressed when relevant under following sections presenting our results.

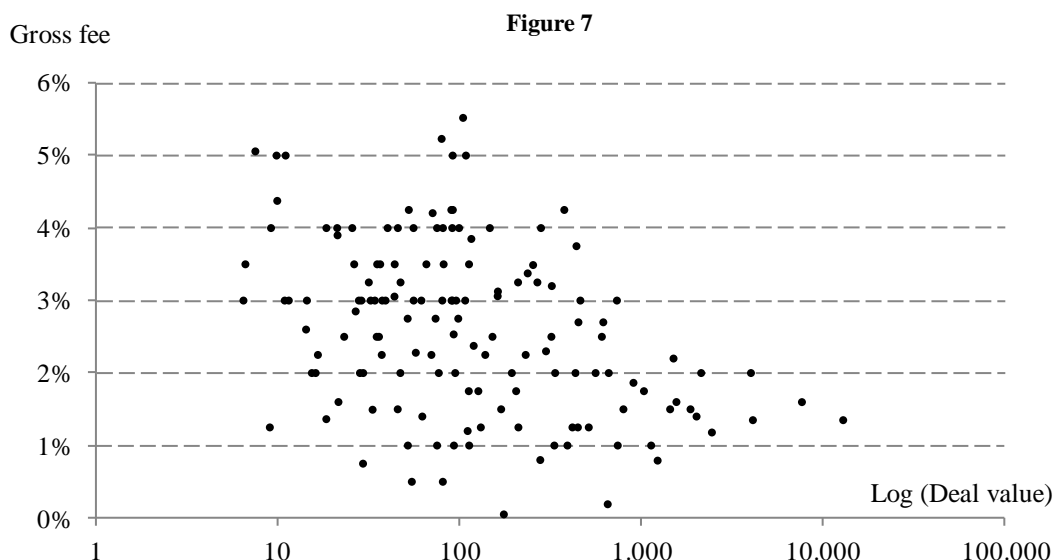
8 Results – direct and indirect cost

The following section presents firstly an analysis of the direct cost associated with the gross fee. This analysis is carried out on the sample consisting of 145 observations. Subsequently the same sample is analyzed with regard to the SEO discount. Finally, a similar analysis is conducted on the larger sample consisting of 2,065 observations.

8.1 Empirical analysis of the Gross fee – small sample

This section analyses the gross fee. As noted, the gross fee is defined as the difference between the price at which the investment bank buys the shares from the issuer, and the price at which the investment bank floats the shares in the market – the offer price.

However, before addressing the topic of secondary market liquidity in relation to the gross fee, it is of interest to examine the composition the sample. Figure 7 presents a scatter plot of the dataset containing information on the gross fee against the principal amount of the offering (Deal value) in million Euros, note that the x-axis is log scaled.



Much in line with Butler et al. (2005) we observe a modest clustering on round percentages. However, the sample contains substantial variance in fees, also conditional on offering size.

8.1.1 Univariate results – Gross fee

The average gross fee across the entire sample is 2.61 percent, which is lower than that found by Butler et al. (2005) (4.80 percent), Gao and Ritter (2010) (4.82 percent), and Bortolotti et al. (2008) (3.46 percent). This difference may be ascribed to the noted selection bias that the observations containing information on gross fee are generally larger in our sample. As stated the average market cap. of our small sample is EUR 5.720m compared to that of Butler et al. (2005) of USD 1.178m.

As the starting point of a thorough analysis of the gross fee and its relation to secondary market liquidity, all of the observations are presented in table 13, divided in tertiles (thirds) by their liquidity index value.

Table 13

Gross fee by Liquidity index					
Obs.	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
All (145)	3.23%	2.74%	1.84%	74.9%	< 0.0001 ***

Table 13 clearly indicates that firms with a higher secondary market liquidity pay lower gross fees on average, which confirms the initial observations of Butler et al. (2005). The least liquid third commands on average 74.9 percent higher fees than their most liquid counterparts, or stated differently, face an increase of 139 basis points. The Wilcoxon Rank Sum test confirms that the difference in average fees between first and third liquidity tertile is indeed statistically significant.

As evident from the discussion in section 5 there are several variables explaining the gross fee. The effect of liquidity as demonstrated in table 13 may thus in part contain several underlying confounding effects. To further shed light on the relation between liquidity and gross fees, tables 14 through 16 present the average gross fees sorted in two dimensions.

Based on the discussion in section 5 of important economies of scale in gross fees, table 14 presents the dataset initially split in to three equal sized portfolios based on the size of the principal amount (deal value). Subsequently the observations of each portfolio are split in tertiles based on their liquidity index value. This yields portfolios of 15 to 17 observations.

Table 14

Gross fee by Deal value-Liquidity index					
Deal value Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Smallest	3.30%	2.85%	2.60%	27.1%	0.0647
2	3.47%	2.86%	2.38%	46.1%	0.0073 **
Largest	2.28%	1.97%	1.67%	36.5%	0.0260 *

It is initially observed that our results are consistent with the hypothesis of economies of scale in the gross fee. The smallest deal value group pays an average gross fee of 2.93 percent while the largest group pays 1.98 percent. This implies that ceteris paribus it seems relatively cheaper to undertake large issuances. Moreover, it is evident that this relation holds true across all liquidity tertiles. However, analyzing the average deal value of the tertiles (EUR 27m, EUR 96m, and EUR

1,235m) reveals a substantial difference in the average deal value of the largest deals as compared to the two other. This may serve to explain why the average fees of the two smaller deal value tertiles act in a comparatively similar fashion, while those of the third deal value tertile are substantially lower.

Regarding the effect of liquidity on gross fees, it is observed that the gross fee-liquidity relationship is consistent across all size tertiles. In the group consisting of the smallest deals, the least liquid issuers pay an average fee of 3.30 percent, while their more liquid counterpart pay only 2.60 percent, a difference of 70 basis points. For the third size tertile, this difference is 61 basis points. This indicates a slightly lower absolute ‘effect’ of liquidity on gross fees for larger deals. However, one could also assess this effect in terms of the percentage change in the fee, as is done in the ‘% Δ ’ column of table 14. This approach is in line with Butler et al. (2005). Consistent with their findings, our results indicate a somewhat larger relative effect of illiquidity on gross fees for larger issues as compared to smaller (36.5 percent vs. 27.1 percent).

The difference in average gross fees of the smallest deal value tertile fails to obtain statistical significance on a reasonable confidence-level. This may in part be due to our comparatively small sample. It may however also reflect the fact that we have adopted a more lax approach to exclusion of observations based on deal value. While Butler et al. (2005) exclude observations with deal values below USD 20m this analysis has included all but observations with deal values below EUR 5m. As noted this has been done in part to reflect the fact that the European stock markets are substantially smaller than the American, and in part to retain a sufficient number of observations.

As previously discussed, the hypothesis of economies of scale in investment banker fees has been criticized by among others Altinkilic and Hansen (2000) noting that the observed effect may in reality be driven by the confounding effect that larger issuances are generally done by larger firms, which are on average of a higher ‘quality’ than smaller firms. Table 15 attempts control for this size-effect by, in a similar fashion to table 14, splitting the dataset in three portfolios based on the relative issue size (‘% Co. sold’).

This analysis furthermore has advantage of being similar to that of Corwin (2003), who notes that the principal amount of the offer as a percentage of the pre-offer market value of equity was a significant determinant of the SEO discount. It is hypothesize that the share of the company that is being offered to the market may well impact the fee that investment bankers would require, as *ceteris paribus* it would be harder to place a larger fraction of a firm.

Table 15

Gross fee by % of Company sold-Liquidity index					
% Co. sold Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Smallest	2.38%	1.91%	1.55%	53.5%	0.0040 ***
2	3.10%	2.79%	2.14%	45.1%	0.0017 ***
Largest	3.52%	3.50%	2.61%	35.0%	0.0076 **

The results of table 15 confirm this hypothesis indicating clearly that the gross fees of the larger offers (measured as a percentage of the pre-offer market value of equity) are consistently larger. The largest ‘% Co. sold’ group pays an average gross fee of 3.21 percent while the smallest ‘% Co. sold’ group pays 1.95 percent. This implies that ceteris paribus it is more expensive for a firm to place a relatively larger offering.

Regarding the observed link between gross fee and liquidity a robust relation remains across all ‘% Co. sold’ tertiles. The relative effect on average gross fees of liquidity however, seems to diminish somewhat as larger fractions of the companies are offered, declining from 53.5 percent in the smallest ‘% Co sold’ tertile to 35 percent in the largest tertile. We propose two explanations to this phenomenon. Firstly, when the issuance increases the outstanding equity substantially, as pre-issuance secondary market liquidity is a poor predictor of the post-issuance liquidity (which we argue may be what investment banks are more concerned with in determining their fees). This in turn entails pre-issuance liquidity being a less efficient predictor of the gross fee in cases where the offering is large in a relative sense. Secondly, looking further into the composition of the sample reveals that the average relative issue size in the large ‘% Co. sold’ tertile is 39.9 percent. Floating such a large amount of shares (relative to 18 and 7.4 percent in the two other tertiles), as compared to the size of the firm, will likely ‘dry out’ all short term liquidity for even the most liquid security. One might thus argue that secondary market liquidity does not ‘matter’ very much in such issuances – the investment bank has to ‘create the demand’ in all cases.

On the other hand, analyzing the absolute difference in fees, rather than relative difference the effect actually increases slightly going from 83 to 91 basis points. This analysis therefore, is highly dependent on how one chooses to interpret changes in fees.

As explained the investment bank carries a risk while holding the new shares of the issuing firm. It is commonly acknowledged that securities with higher volatility require a higher fee. Following

Butler et al. (2005), Eckbo and Masulis (1992) and several others, one should therefore expect that volatility explains part of the variance in the gross fee. Table 16 attempts to control for this effect by, splitting the dataset into three portfolios based on 12 months average return volatility.

Table 16

Gross fee by Volatility-Liquidity index					
Volatility Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Lowest	2.84%	2.21%	1.45%	95.6%	< 0.0001 ***
2	3.16%	2.57%	1.85%	70.8%	0.0018 ***
Highest	3.34%	3.45%	2.59%	29.1%	0.0234 **

Table 16 corroborates this idea, as more volatile firms on average pay larger gross fees across all liquidity tertiles than do their less risky counterparts. The least volatility group commands an average gross fee of 2.18 percent while the group with the highest volatility requires an average gross fee of 3.12 percent.

Regarding liquidity, the gross fee-liquidity relation remains robust across all portfolios on a 1 or 5 percent confidence level. The table further reveals that the relative effect of liquidity on gross fees diminishes as volatility increases. Thus while for the least volatile tertile the least liquid firms pay on average 95.6 percent higher fees than their most liquid counterparts, this difference is a mere 29.1 percent for the most volatile firms. This indicates that liquidity is not as crucial a determinant of gross fees when dealing with very risky companies, which intuitively makes sense as investment banks may charge comparatively higher fees to very volatile issuing firms regardless of their stock liquidity as the issuance would be perceived as ‘risky’ in spite of a high level of liquidity.

In addition to controlling for both absolute and relative deal size as well as volatility other aspects may, as noted, influence the gross fee paid to investment banks when issuing equity. One thing, profoundly affecting the fee, is the choice of floatation method (see e.g. the discussion of Gao and Ritter (2010) in section 5. Table 17 reports the frequency of issuance methods conditional on liquidity tertile.

Table 17

Observed issuance methods across liquidity tertiles			
Issuance method	Least liquid tertile	2	Most liquid tertile
Fully Marketed	7	10	13
Accelerated Bookbuild	3	13	28
Bought Deal	0	1	3
Cash Placing	30	20	3
Guaranteed Preferential Allocation	9	4	1
<i>Total observations</i>	49	48	48

Table 17 reveals substantial differences in the distribution of flotation methods conditional on liquidity. The least liquid firms of our sample seem to prefer cash placings and guaranteed preferential allocations, while accelerated bookbuilds are strongly preferred by the most liquid firms. This effect, as well as the effect of the previously presented variables should be controlled for simultaneously. This requires a fundamental different methodological approach.

8.1.2 Multivariate results – Gross fee

In addition to the one way nonparametric ANOVA approach of tables 14 through 16, one could assess the relation between gross fee and liquidity through an ordinary least square regression (OLS-regression) Table 18 present the output from various models.

Table 18

Regression results for Gross fee									
Variables	Regression number								
	1	2	3	4	5	6	7	8	9
Intercept	0.0369 (0.000)	0.0396 (0.000)	0.0326 (0.000)	0.0374 (0.000)	0.0369 (0.000)	0.0369 (0.000)	0.0394 (0.000)	0.0396 (0.000)	0.0313 (0.000)
Liquidity index	-0.0215 (0.000)	-0.0175 (0.000)	-0.0155 (0.000)	-0.0065 (0.172)	-0.0061 (0.207)	-0.0609 (0.208)	-0.0012 (0.824)	0.0001 (0.982)	-0.0105 (0.017)
Log(Deal value)	-	-0.0023 (0.132)	-0.0023 (0.123)	0.0018 (0.337)	0.0021 (0.272)	0.0020 (0.330)	-0.0004 (0.844)	-0.0002 (0.913)	-0.0042 (0.020)
Return volatility	-	-	0.1790 (0.000)	0.1482 (0.002)	0.1513 (0.002)	0.1513 (0.002)	0.1660 (0.000)	0.2394 (0.000)	0.2686 (0.000)
Log(Size)	-	-	-	-0.0060 (0.002)	-0.0059 (0.002)	-0.0059 (0.003)	-0.0066 (0.001)	-0.0068 (0.001)	
Lead manager reputation	-	-	-	-	-0.0011 (0.594)	-0.0012 (0.603)	-0.0017 (0.422)	-0.0009 (0.683)	-0.0018 (0.403)
Multiple bookrunners	-	-	-	-	-	0.0002 (0.936)	0.0004 (0.842)	0.0005 (0.800)	0.0011 (0.566)
Fully marketed	-	-	-	-	-	-	0.0083 (0.000)	0.0073 (0.002)	0.0072 (0.002)
Years	-	-	-	-	-	-	-	YES	YES
Adj. R ²	0.2298	0.2337	0.3083	0.3431	0.3399	0.3351	0.3974	0.3976	0.3620

Where ‘fully marketed’ is a dummy variable taking the value of 1 if the issuance was conducted as a fully marketed offering, and 0 if otherwise. This is because of the fundamentally difference in the amount work required for investment bank. This is in line with our discussion of issuance methods in section 4.3, as well as the insights from the studies by Gao and Ritter (2010) and Bortolotti et al. (2008). ‘years’ is a vector of dummy variables consisting of the years 2000 through 2010 with 2011 as base year.

As hypothesized, the liquidity index maintains a negative relation to the gross fee across all models except model 8 where it is effectively zero (this is discussed below). From model 1 we get that the liquidity index alone explains roughly 23 percent of the variance in the gross fees of our sample. Further controlling for deal value and return volatility increases the explanatory power of the model to more than 30 percent, with volatility having a large and significant positive relation to gross fees. As hypothesized, firms with more volatile returns pay larger fees. Additionally

controlling for size (average daily market cap in EURm over the last 12 months), lead manager reputation, multiple bookrunners indicator, fully marketed, and years increases the adjusted R^2 to 39.76 percent.

It is notable that few of the parameters are statistically significant. Especially it is somewhat surprising that neither the liquidity index nor deal value have any significant relation to the gross fees. This is in stark contrast to Butler et al. (2005), who found a significant relation between liquidity and gross fee. It is possible that this is due to the high correlation between liquidity and market cap, as evident from data section (section 7), as well as the aforementioned close link between market cap and deal value. If explanatory variables of a multiple regression model are highly correlated with one another it breaches one of the fundamental assumptions of the classical linear regression model – that of no multicollinearity.

While not biasing the parameter estimate, the presence of multicollinearity in a regression model increases the standard errors, thus reducing the significance level (Gujarati, 2003). Problems of multicollinearity, by nature, closely resemble those of working with small samples (micronumerosity), and larger samples typically mitigate the issues of multicollinearity (as long as it not a case of perfect multicollinearity), as larger samples produce more precise estimates. It is therefore entirely possible that Butler et al. (2005) encountered a similar level of multicollinearity, but obtained significance nonetheless as a consequence of their vast sample (nearly 2,400 observations). A commonly applied way of detecting multicollinearity is by calculating the variance inflation factors (VIF) of the variables in the model. These are presented in table 19.

Table 19

Variation inflation factors for Gross fee regressions						
Variables	VIF					
	4	5	6	7	8	9
Intercept						
Liquidity index	2.94	3.01	3.01	3.39	4.30	2.02
Log(Deal value)	3.25	3.41	4.06	4.76	4.96	2.40
Return volatility	1.09	1.11	1.11	1.13	1.79	1.04
Log(Size)	5.30	5.32	5.55	6.79	8.44	-
Lead manager reputation		1.54	1.65	1.79	1.95	1.63
Multiple bookrunners			1.51	1.52	1.63	1.44

As a rule of thumb a VIF in excess of 5 indicates multicollinearity so severe that one should consider excluding the variable from the model. In all models where size is included, it obtains a VIF in excess of 5, reaching as high as 8.44 in model 8. This is clear evidence of severe multicollinearity. Dropping a variable should be done with care, as excluding a variable that really ‘belongs’ in the model can potentially induce an ‘omitted variable bias’ into the parameters of the other variables of the model. We are not gravely concerned about this issue, since we are not interpreting the actual parameter estimate – rather, we are ascertaining that it is significantly below zero. Model 9 of table 18 thus drops the variable ‘size’, which clearly solves the problem of multicollinearity.

Model 9 finds that liquidity is significantly negatively related with the fee, consistent with the hypothesis that firms with higher secondary market liquidity pay lower gross fees when issuing equity. The residuals from the regression (not reported) generally seem well behaved. They are reasonably normally distributed with no substantial skewness and only slight excess kurtosis.

The explanatory power of the model diminishes somewhat, yielding an adjusted R^2 of 36.2 percent. This R^2 , along with that of the other models is lower than those of Butler et al. (2005). This may in part be due to the fact that our sample is composed of equity issuances from various markets. One should expect certain differences to exist in the structure of these markets. Therefore, conducting a similar study on a single market would likely yield a higher explanatory power. However, the finding of a significant relation between liquidity and gross fee across a group of markets, and constrained by relatively few observations is interpreted as substantial evidence that secondary market liquidity is a significant predictor of the gross fee associated with an equity offering, also in a European context.

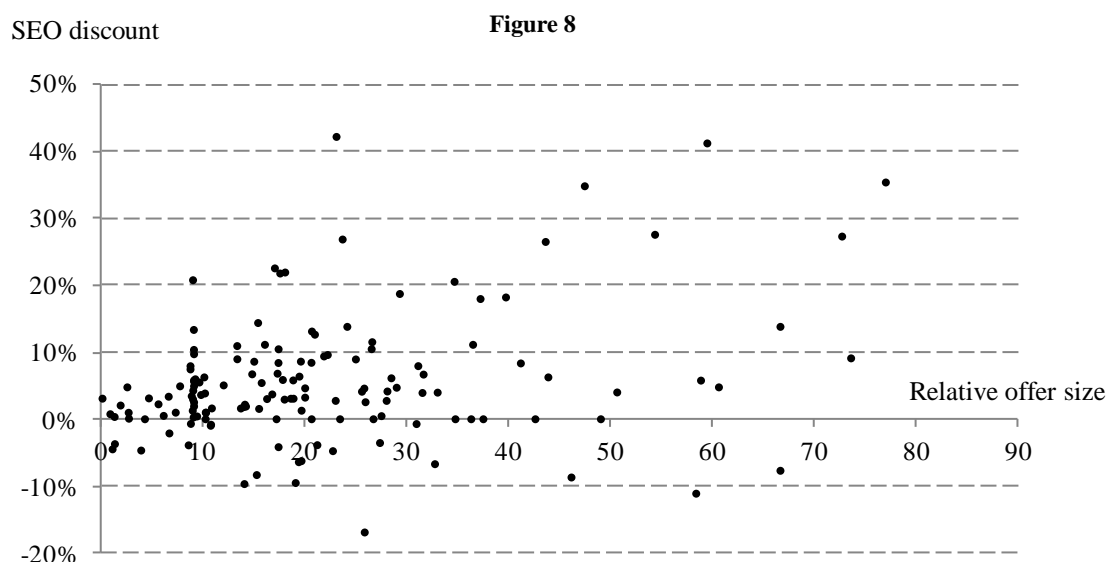
In summary, the multiple regression confirms that larger deals are significantly associated with lower fees. The regression also confirms that volatility has a strong and significant, positive relation to the gross fee and furthermore that issuances conducted as fully marketed offerings have significantly higher average gross fees, when controlling for other factors. The variables lead manager reputation and multiple bookrunners are not significantly different from zero. Finally, and importantly; simultaneously controlling for all these factors, secondary market liquidity retains a statistically significant negative relation to the gross fee.

This thesis has argued that the direct costs alone are not sufficient in explaining the full scale of costs incurred by the owners of an issuing firm. There are, as noted additional important indirect costs stemming from the wealth transfer potentially induced from the well documented SEO

discount. Along this line we have argued that the SEO discount too may be profoundly affected by the secondary market liquidity of the issuing firm. The thesis therefore proceeds by analyzing the SEO discount of our sample, and investigates whether this is significantly related to the liquidity of the issuers.

8.2 Empirical analysis of the SEO discount – small sample

This section analyses the SEO discount, which is defined as the percentage difference between the offering price and the previous day's closing price. In line with the results regarding the direct costs, figure 8 presents a scatter plot of the dataset containing information on the SEO discount against the relative offer size (percent of company sold).



We observe a substantial variance in SEO discount, conditional on relative offer size is observed. A significant clustering around 10 percent issuance size is evident.

8.2.1 Univariate results – SEO discount

The average SEO discount across the small sample is 5.55 percent, which is substantially higher than that found by Corwin (2003) (3.72 percent in 1996) and Altinkiliç and Hansen (2003) (3.01 percent for Nasdaq issues). This could be interpreted as the tendency observed by Corwin (2003) of SEO discounts increasing over time having continued since his analysis ended in 2000. Alternatively it may reflect that the SEO discount is generally higher in Europe than in the US.

As the starting point of a thorough analysis of the SEO discount and its relation to secondary market liquidity, all of the observations are presented in table 20, divided in tertiles by their liquidity index value.

Table 20

SEO discount by Liquidity index					
Obs.	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
All (145)	7.36%	6.59%	2.66%	176.8%	< 0.0001 ***

Table 20 confirms the hypothesized relation between liquidity and SEO discount, as it indicates a statistically significant difference between the average SEO discount of the least and most liquid tertile, with the more liquid SEOs appearing to happen at a substantially lower average discount. SEOs of firms belonging to the most liquid tertile of the sample were on average discounted by 2.66 percent to the previous day's closing price. In comparison, the least liquid tertile saw an average SEO discount of 7.36 percent.

However, as in the case of the gross fee, this effect may in part be a function of other confounding factors. In the same fashion as previously, table 21 thus attempt to control for the size of the issuance, creating equal sized portfolios according to deal value, subsequently spitting in tertiles according to the liquidity index.

Table 21

SEO discount by Deal value-Liquidity index					
Deal value Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Smallest	10.47%	5.15%	2.76%	279.6%	0.0128 **
2	8.02%	9.37%	3.85%	108.4%	0.0960
Largest	3.55%	4.67%	1.10%	223.1%	0.0718

The finding of declining discounts in larger deals might appear somewhat surprising at the first glance. Intuitively, if one believes that SEO discount is related to price pressure, one should expect larger deals to require more discount to be floated. This however is likely due to the same confounding effect driving the results of table 14 that larger SEOs are typically undertaken by larger firms. The liquidity seems to retain a substantial explanatory power over the SEO discount

when controlling for deal value, with the most liquid of the small deal value tertile being discounted by an average of 2.76 percent, compared to 10.47 percent for the least liquid tertile. This corresponds to a substantial increase in indirect costs of 771 basis points.

Attempting to control for the confounding effect of larger deals being done by larger firms, table 22 controls for the deal value (as a percentage of pre-deal market value of outstanding equity). This approach is essentially similar to what Corwin (2003) applied when testing his ‘temporary price pressure’ hypothesis.

Table 22

SEO discount by % of Company sold-Liquidity index					
% Co. sold Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Smallest	4.56%	3.14%	0.92%	393.1%	0.0147 **
2	7.95%	5.56%	2.96%	168.8%	0.0935
Largest	8.81%	6.16%	9.98%	-11.7%	0.3885

In this case it is clearly observed that the SEO-discount increases as larger fractions of the firm are offered for sale. The average SEO discount across all liquidity groups for the smallest ‘% Co. sold’ tertile is 2.91 percent, while that of the largest is 8.31 percent. This confirms Corwin’s (2003) insight, that larger deals, measured as a percentage of the pre deal outstanding equity, indeed require substantially larger discounts.

Liquidity has a substantial and statistically significant relation to the SEO discount in the portfolio consisting of the smallest deals where the SEO discount of the most liquid firms exhibit a negligible discount, while the least liquid tertile have an average SEO discount of 4.56 percent. Liquidity retains a substantial relation in the second ‘% Co. sold’ tertile, however, this relation is not quite statistically significant.

In the portfolio consisting of the largest ‘% Co. sold’ deals, the relationship has in fact inverted and the most liquid are now slightly more discounted than the least liquid. The relation is however in no way significant, and is interpreted as a fundamental lack of relation to liquidity when the deal is very large as compared to the pre deal market value of equity in this small sample. This is somewhat surprising, as one might intuitively expect liquidity to matter more when a larger fraction of the firm is offered. A possible explanation is firstly, that the post SEO liquidity of the firm would likely deviate substantially from that prior to the SEO, making pre-SEO secondary

market liquidity a poor predictor of post-issuance secondary market liquidity. The subscribers to the issuance (in the primary market) will, when reselling their shares at some point in the secondary market, be faced with this potentially very different level of illiquidity.

A third explanation is linked to the choice of methodology applied in this study (and indeed that of Butler et al. (2005) too). By creating equal-sized portfolios one opens a door to a certain selection bias among the portfolios formed. Looking into the distribution of the separate ‘% Co. sold’ tertiles we find a substantial difference in the average liquidity index. Where the largest ‘% Co. sold’ group has an average liquidity index of 0.367 the average for the lowest tertile is 0.674. That is the larger issue (in relative terms) are generally done by quite illiquid firms and vice versa. While there is a substantial difference in the average liquidity between the tertiles, the liquidity values are quite evenly dispersed. The standard deviation of the largest ‘% Co. sold’ is 2.34 percent only marginally smaller than the 2.72 of the smaller ‘% Co. sold’ tertile.

This could be seen as indicating that the importance of liquidity is not linear as changes in liquidity seem to matter less when you are in the realm of illiquidity. A 0.1 change in the liquidity index might thus have a smaller influence on the SEO discount when moving from 0.3 to 0.4 in liquidity index value than when moving from 0.7 to 0.8. This insight is obviously based on the assumption that the liquidity measures underlying the liquidity index are reasonably normally distributed. As evident from section 7 this is not the case in this sample and such an interpretation should be done with extreme care.

A different approach, potentially addressing this issue of selection bias among tertiles could be splitting portfolios not in equal sizes but rather according to certain specified liquidity thresholds. This is quite simply not meaningful, given the small sample in this study. Further, it would undoubtedly create another problem, in testing significance reliably on groups of substantially varying sizes. Finally, as discussed in the above example, one might argue that it is simply the nature of the data.

To investigate this matter further, establishing that liquidity may still to some extent predict SEO discounts even for large offerings, the SEO of the British travel agency Thomas Cook Group in September 2009 offers anecdotal evidence. The gross proceeds from the issuance were EUR 1,031m equivalent to 43.9 percent of the total equity prior to the offering. The company had a liquidity index value of 0.855, placing it among the most liquid observations in the sample. The issuance was offered at a discount of 6.25 percent, and while this figure is larger than the average

SEO discount of the high liquidity small issues (0.92 percent) it is substantially below the average SEO discount of the most liquid large deal tertile (9.98 percent).

In addition to the relative offer size, both Corwin (2003) and Mola and Loughran (2004) demonstrate that the level of risk has a significant relation to the SEO discount. Table 23 therefore controls for the level of risk of the issuing firm, dividing the dataset into three equal sized portfolios according to volatility, measured as 12 month average daily standard deviation of return.

Table 23

SEO discount by Volatility-Liquidity index					
Volatility Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Lowest	6.91%	6.04%	1.81%	282.0%	0.0452 *
2	6.25%	5.34%	1.14%	448.9%	0.0019 ***
Highest	8.39%	8.49%	5.51%	52.1%	0.3885

The data again confirms previous studies finding that less risky firms indeed issue equity at a lower discount than do firms with more volatile returns. The average SEO discount across all liquidity groups for the least volatile tertile is 4.96 percent while that of the most volatile firms is 7.46 percent.

Liquidity seems to have a significant relation to the SEO discount of two least volatile tertiles (albeit only at a 90 percent confidence level in the case of the smallest), while the effect diminishes and the significance altogether vanishes in the portfolio of the most volatile firms.

This indicates that liquidity does have an impact in the case of low-risk stocks but that this effect vanishes as volatility increases, which, as in the case of the analysis of the gross fees, is intuitively sensible as issuances by very risky firms would be perceived as ‘risky’ by the market regardless of the general level of liquidity in the asset in question. The issuance would thus command a relatively large discount regardless of liquidity. Measured in absolute terms, the difference from low to high liquidity for the least volatile group is 511 basis points while that of the most volatile group is only 288 basis points, supporting the above hypothesis.

As noted, the somewhat inconsistent degree of statistical significance might be a creature of large variance in a relatively small sample (145 observations). The following presentation of the multivariate OLS regressions seems to some extent to suffer from this exact problem too.

8.2.2 Multivariate results – SEO discount

Table 24 presents the multivariate analysis of the SEO discount observed in the small sample

Table 24							
Regression results for SEO discount							
Variables	Regression number						
	1	2	3	4	5	6	7
Intercept	0.0998 (0.000)	0.0466 (0.130)	0.0678 (0.081)	0.0675 (0.088)	0.0710 (0.062)	0.0762 (0.095)	0.0542 (0.176)
Liquidity index	-0.0879 (0.003)	-0.0504 (0.154)	-0.0219 (0.642)	-0.0219 (0.637)	-0.0245 (0.604)	-0.0424 (0.463)	-0.0695 (0.082)
% Company Sold	-	0.1585 (0.041)	0.1441 (0.067)	0.1435 (0.071)	0.1397 (0.073)	0.1186 (0.121)	0.1284 (0.096)
Log(Size)	-	-	-0.0118 (0.354)	-0.0118 (0.345)	-0.0135 (0.284)	-0.0127 (0.466)	
Return volatility	-	-	-	0.0133 (0.978)	0.0018 (0.997)	-0.5968 (0.303)	-0.5576 (0.341)
Lead manager reputation	-	-	-	-	0.0065 (0.702)	-0.0007 (0.967)	-0.0049 (0.778)
Years	-	-	-	-	-	YES	YES
Adj. R ²	0.0548	0.1125	0.1100	0.1036	0.0980	0.0815	0.0854

It is noted that the liquidity index is a statistically significant explanatory variable only in model 1. As other variables are introduced, it loses significance. It is however worth noting that the coefficient consistently indicates that a higher level of secondary market liquidity is associated with lower levels of SEO discount. The general weakness of the model is further reflected in the low adjusted R², which peaks in model 2 at 11.25 percent.

In line with the discussion of issues with multicollinearity especially between the firm size and the liquidity index, model 7 drops the size variable. The residuals from this regression (not reported), apart from the relatively severe heteroskedasticity, seem well behaved. They are reasonably normally distributed with no substantial skewness and only slight excess kurtosis. Dropping the

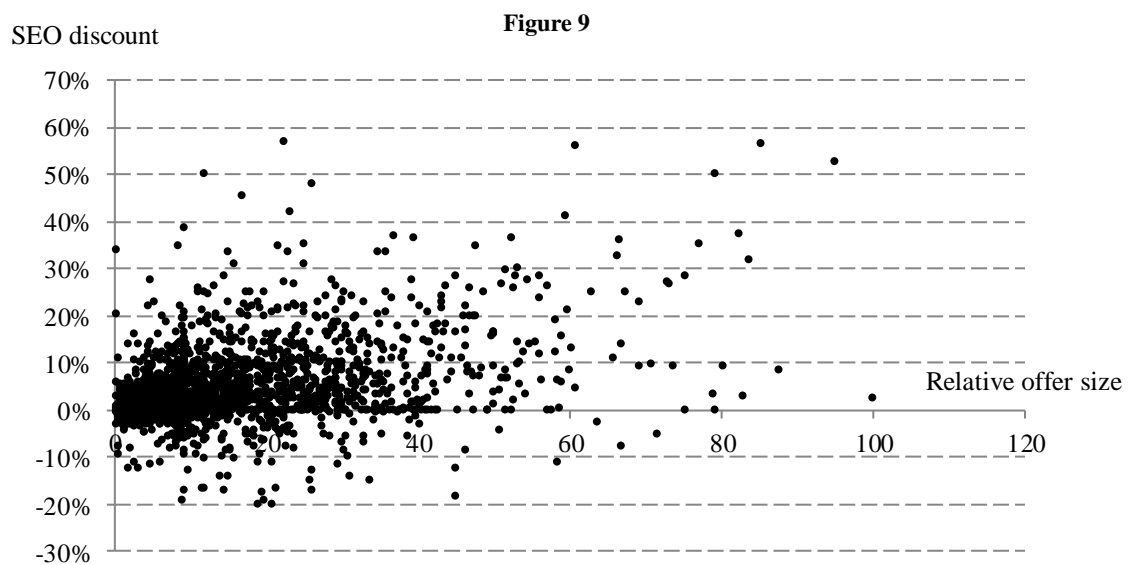
size variable again substantially improves the model, where adjusted R^2 is improved slightly from model 6. While not quite statistically significant, ‘% Co. sold’ is clearly still negatively related to the SEO discount. The liquidity index is now exhibiting signs of significance and the coefficient is negative as hypothesized. In addition to reflecting a relatively small sample, the lack of substantial significance in the regressions on SEO discount may reflect the issues of heteroskedasticity, which are more pronounced in the SEO discount than in the gross fee. Heteroscedasticity occurs when the variance of the errors varies across observations. If the errors are heteroscedastic, the OLS estimator remains unbiased, but becomes inefficient. More importantly, estimates of the standard errors are inconsistent. The White’s heteroskedasticity consistent estimator is robust to these issues, but may be less efficient, especially in smaller samples (Long and Ervin, 1998).

In conclusion this inquiry yields consistent but statistically weak evidence of secondary market illiquidity being a relevant predictor of the SEO discount in our small sample.

While with regard to the gross fee, the analysis is bound by this relatively small sample, it is in fact possible to conduct the analysis of the SEO discount on a substantially larger dataset. The following section thus makes use of that.

8.3 Empirical analysis of the SEO discount – large sample

Again a scatter plot in figure 9 of the dataset containing information on the SEO discount against the relative offer size (percent of company sold) is presented.



Substantial variance in SEO discount, conditional on relative offer size is still observed. A certain clustering around an SEO discount of zero percent is evident.

8.3.1 Univariate results – SEO discount

The average SEO discount in the large sample is 4.75 percent. This again is higher than that found in previous empirical studies, which we ascribe to the same reasons as discussed earlier.

In an attempt to address the issues relating to a comparatively small sample size, the larger sample (with information on the SEO discount only) is employed. This sample consists, as noted, of 2,065 observations. Employing a larger sample has several advantages. Firstly it reduces the impact of potential outliers that may induce substantial noise in analyses conducted on smaller samples. Secondly, the aforementioned issues of multicollinearity, are ceteris paribus lessened when a larger sample is employed.

Table 25

SEO discount by Liquidity index					
Obs.	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
All (2,065)	8.11%	4.30%	1.83%	343.2%	< 0.0001 ***

Not surprisingly a substantial difference in average SEO discount is found across the liquidity tertiles.

As before, it is relevant to control for various confounding effects. Table 26 reports the average SEO discount for the portfolios formed by deal value and liquidity tertile. Table 26 strongly indicates that average SEO discount is substantially and significantly lower in the lost liquid tertile than in the least liquid fraction.

Table 26

SEO discount by Deal value-Liquidity index					
Deal value Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Smallest	9.49%	6.96%	4.73%	100.8%	< 0.0001 ***
2	6.91%	4.10%	1.94%	256.1%	< 0.0001 ***
Largest	4.96%	2.37%	1.25%	296.9%	< 0.0001 ***

We observe that the larger sample produces a relation between liquidity and deal value, which is substantial and significant across all tertiles. Table 26 indicates the SEO discount to be most severe in the case of small issuances with low liquidity. It generally finds the largest deal value tertile to be the least underpriced. This is somewhat surprising finding is, as noted a consequence of the tendency toward a positive correlation between firm size and size of principal offering.

Table 27 addresses this, analyzing the effect of illiquidity on the SEO discount, controlling for the relative deal size.

Table 27

SEO discount by % of Company sold-Liquidity index					
% Co. sold Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Smallest	3.91%	1.68%	0.93%	319.7%	< 0.0001 ***
2	5.58%	4.12%	2.61%	113.8%	< 0.0001 ***
Largest	10.60%	7.84%	5.46%	94.2%	< 0.0001 ***

Again, the finding of Corwin (2003) that larger deals (measured as a percentage of outstanding equity) require a larger discount. While the tertile of the smallest deals required an average discount of 2.18 percent across all liquidity groups, the groups of the largest deals were on average discounted by a staggering 7.97 percent. Liquidity retains a substantial effect on SEO discount, with a very high level of statistical significance. The larger dataset reveals that as in table 22 on the small dataset, the effect of illiquidity seems more pronounced in smaller ‘% Co. sold’ tertiles.

This seems to confirm that the importance of liquidity in determining SEO discounts diminishes as deals become larger in a relative sense. While in table 22 the effect vanished altogether on the tertile of the largest deals, in table 27 however, the relation remains statistically significant across all portfolios including the portfolio containing the largest deals.

This could be seen to confirm the hypothesis that the absence of difference in average SEO discount for the largest ‘% Co. sold’ deals of the small sample is caused by a low frequency of larger and liquid firms issuing large proportions of equity. In a sense this thus confirms the anecdotal evidence of the Thomas Cook Group.

While a significant effect of liquidity is retained, the relative effect of illiquidity on the SEO discount in the large ‘% Co. sold’ tertile is still substantially lower when compared to the smallest ‘% Co. sold’ tertile (94.2 vs. 319.7 percent). However, this again is a question of how one chooses to interpret the figures. Expressed in absolute terms, deals in the largest ‘% Co. sold’ tertile has an average difference across the liquidity tertiles of 514 basis points versus 298 basis points for the smaller ‘% Co. sold’ tertile. This, contrarily to the first interpretation, entails a larger ‘real’ effect.

Again, controlling for the effect of risk, table 28 confirms the insights from the analysis of the smaller dataset, while obtaining substantially more consistent levels of statistical significance.

Table 28

SEO discount by Volatility-Liquidity index					
Volatility Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Lowest	4.61%	2.32%	0.92%	404.1%	< 0.0001 ***
2	6.14%	3.85%	1.98%	210.2%	< 0.0001 ***
Highest	10.56%	8.12%	4.25%	148.6%	< 0.0001 ***

Table 28 again confirms the insight of Corwin (2003) and Mola and Loughran (2004) that issuances of more risky firms require larger discounts. While the average SEO discount across all liquidity tertiles of the least risky group is 2.62 percent, that of the most risky group stands at 7.64 percent.

Table 28 further confirms that the effect of illiquidity seems larger in the case of risky firms than in the case of firms with relatively stable returns. While the difference in SEO discount from belonging to the most liquid tertile to the least liquid tertile is staggering 404.1 percent in the least risky group, the ‘impact’ is reduced to 148.6 percent in the most risky group. The absolute difference is 631 versus 369 basis points when looking across the liquidity tertiles for the highest and lowest volatility tertiles respectively.

The larger sample size enables one to further scrutinize the significance of these relations, as it is possible to split the dataset in both dimensions in quintiles rather than tertiles. The results of this analysis are available in appendix 5. Generally they confirm the insights from the analysis based on tertiles. All results are still significant at a 1 percent confidence level.

In summary, the larger sample generally corroborates the insights from the analysis of the SEO discount on the small sample, finding secondary market liquidity a statistically significant predictor of the SEO discount.

As previously noted, the above discussed effects may interact in a variety of ways. To reliably establish that there is indeed a relation between secondary market liquidity and SEO discount, one must again control for the relevant variables simultaneously utilizing a multiple regression framework. As before this analysis is done via an OLS regression.

8.3.2 *Multivariate results – SEO discount*

Table 29 presents the results of the OLS regressions on various models on the dataset containing 2,065 SEOs.

Table 29							
Regression results for SEO discount							
Variables	Regression number						
	1	2	3	4	5	6	7
Intercept	0.0992 (0.000)	0.0511 (0.000)	0.0636 (0.000)	0.0310 (0.004)	0.0274 (0.012)	0.0173 (0.183)	0.0133 (0.188)
Liquidity index	-0.1034 (0.000)	-0.0581 (0.000)	-0.0347 (0.006)	-0.0382 (0.002)	-0.0362 (0.004)	-0.0325 (0.013)	-0.0383 (0.000)
% Company Sold	-	0.1610 (0.000)	0.1540 (0.000)	0.1372 (0.000)	0.1403 (0.000)	0.1404 (0.000)	0.1422 (0.000)
Log(Size)	-	-	-0.0089 (0.022)	-0.0039 (0.320)	-0.0020 (0.622)	-0.0026 (0.568)	
Return volatility	-	-	-	0.7988 (0.000)	0.7937 (0.000)	0.6921 (0.000)	0.7065 (0.000)
Lead manager reputation	-	-	-	-	-0.0064 (0.054)	-0.0091 (0.007)	-0.0098 (0.003)
Fully Marketed	-	-	-	-	-	0.0097 (0.328)	0.0093 (0.350)
Years	-	-	-	-	-	YES	YES
Adj. R ²	0.1118	0.1714	0.1731	0.1940	0.1946	0.2007	0.2010

The issue, noted in section 8.2, of heteroskedasticity persists in the large sample. These regressions too are therefore performed with White's heteroskedasticity consistent standard errors.

While it was noted that this estimator has been suggested to be somewhat inefficient in smaller samples, it should perform efficiently in this large sample (Long and Ervin, 1998).

It is initially observed that the liquidity index remains a statistically significant explanatory variable across all models. Further, in line with the hypothesis all models consistently show that a higher level of secondary market liquidity is associated with lower a SEO discount.

Again, the variable 'size' is dropped in model 7 due to multicollinearity especially between the firm size and the liquidity index. The residuals from this regression (not reported), apart from the relatively severe heteroskedasticity, seem well behaved. They are reasonably normally distributed with no substantial skewness and only slight excess kurtosis. Dropping the size variable in model 7 increases the adjusted R^2 marginally to 20.1 percent. It is notable that excluding 'size' from the regression changes the parameter estimate of the liquidity index only slightly, giving some comfort to the fear of omitted variable bias that we raised in the multivariate analysis of the small dataset. The parameter estimate of liquidity index in model 7 is interpreted as indicating that an incremental increase in the liquidity index of one decile is associated with, on average, 0.38 percentage point lower SEO discount. Such an interpretation should be applied with extreme care. For one, the liquidity measures underlying the liquidity index are not normally distributed, as evident from section 7. Secondly, such a relation is hardly linear across the entire range of SEO discounts in this sample.

The variable '% Co. sold' is as predicted significantly positively related to the SEO discount, and we observe that the parameter estimate consistently is similar to that found in the regressions on the small sample. This suggests that an incremental increase in the relative offer size of 10 percentage points on average is associated with an approximately 1.4 percentage point larger SEO discount.

The return volatility too retains its significant explanatory power when controlling for all relevant variables simultaneously. Model 7 produces a parameter estimate of 0.7 implying that a one percent increase in average daily volatility is on average associated with a 0.7 percentage point increase in the SEO discount. It is thus fair to say that volatility seems to have a weak influence on the SEO discount as compared to '% Co. sold'.

Lead manager reputation is significantly negative relation to the SEO discount. With a parameter estimate of -0.0098, investment bank with a good reputation lowers the SEO discount by 0.98

percentage points. This is in line with the finding by Mola and Loughran (2004) who note a significant negative relation between underwriter reputation and SEO discount.

When compared to Corwin (2003) the adjusted R^2 remains relatively low, as he manages to explain as much as 37 percent of the variance in the SEO discount with his model. This difference in explanatory power may in part be attributed to the fact that Corwin (2003) conducts his analysis on a single market (the US) whereas the present analysis spans the entire Europe. The more focused sample of Corwin (2003) enables him to control for various factors that are impossible in this present dataset.

Finally it should be noted that the key interest in the present study is to investigate the existence of a relation between liquidity and cost of issuing equity, rather than attempting to explain the variance in the direct or indirect cost to the greatest extent possible.

The level of significance and consistency in this analysis on the large sample as compared to that of the OLS regression on SEO discount in the smaller dataset finally indicates that the previously discussed issues of lacking significance in the OLS regression on gross fee as well as the mixed results of the univariate analysis, may very well similarly be attributed to a lack of data, rather than to an actual lack of significance.

In summary the empirical analysis of the SEO discount on the large sample of this study, speaks of a significant and reliable relation between secondary market liquidity and SEO discount, both in a univariate framework as well as when controlling for relevant variable simultaneously in a multivariate model.

In line with previous arguments we believe that neither direct nor indirect costs should be viewed in isolation when analyzing the costs faced by owners of a firm embarking on issuing seasoned equity. The subsequent section briefly discusses to what extent direct and indirect costs may interact in one way or another, before arriving at a short explanation of how we estimate the total costs of an SEO.

9 Total cost

9.1 Theory of the Total cost of an SEO

As argued, a firm contemplating issuing seasoned equity should be concerned neither solely with the direct cost associated with the gross fee it must pay the investment bank for the transaction,

nor exclusively the indirect costs its owners may incur as a consequence of an offering discount. Rather it is the total associated with the issuance that should be of interest, as this is what essentially affects its cost of capital.

Having discussed and analyzed the determinants of both gross fees as well as SEO discounts, separately, this raises the question of how the gross fee and the SEO discount may possibly interact in a given offering. This is not immediately obvious, and Kim et al. (2005) argue that the two may be related in one of three ways. They may be unrelated to each other, they may be negatively related, or they may be positively related. On the one hand, one could argue that the two should be expected to be negatively correlated with each other, which entails one essentially acting as a substitute for the other. This rests on two primary arguments.

Firstly, as noted the SEO discount can also be viewed as an indirect form of compensation to the investment bank. Being able to sell ‘cheap’ shares to the clients of the bank is beneficial to the bank itself, and further, an SEO discount may be viewed as a way for the issuer of purchasing subsequent analyst coverage. Secondly the two could be argued to interact in a more direct fashion. In this line of thought the bank could ‘settle’ for a lower gross fee if they are subsequently ‘allowed’ to discount the offering relatively more. Financially this would make sense, as both the effort and the risk associated with floating the offering would *ceteris paribus* be smaller if the offering is priced at a larger discount. Both the effort in marketing the issuance and the risk of ending with a net position in the share would be expected to diminish in the SEO discount.

This hypothesis is supported by Yeoman (2001) who develops a variety of models of the joint decision of underwriting spread and offering price. Yeoman (2001) argues that the issuer fundamentally seeks to maximize its value by maximizing the net proceeds from the offering. While Yeoman (2001) initially explains a model where the fee and the offering price are determined simultaneously, he subsequently develops a model allowing for sequential determination of fee and offering price respectively, noting that: *“The issuer and the managing investment bank agree to the spread early in the process before the underwriting syndicate is formed, while the offering price is determined at the time of the offering.”* (Yeoman, 2001, p183). In this sequential framework, selecting an optimal fee and offering price combination is challenging, since several variables determining the optimal strategy at the time of the offering, such as the market value of the share, the number of shares to be issued etc. are unknown at the time of agreeing on a gross fee.

In consequence, Yeoman (2001) notes, when the offering price is set after the gross fee has been determined, the gross fee becomes a parameter rather than a variable, and the investment bank must simply determine an offer price that satisfies the competitive equilibrium that Yeoman (2001) derives. This function predicts that the optimal offering price is a decreasing function of price uncertainty, which is consistent with previously discussed theories, and is an increasing function of the underwriting fee. That is, a higher fee is *ceteris paribus* consistent with a higher offering price and consequently a lower SEO discount. It should however be noted that while this finding is statistically significant for IPOs, Yeoman fails to obtain significance in the case of SEOs.

On the other hand one might argue that the previous expositions of the determinants of both gross fees as well as SEO discounts revealed that they, to a significant extent, seem to be driven by some of the same fundamental factors, such as risk and secondary market illiquidity. One could therefore alternatively hypothesize that the gross fee and the SEO discount should be expected to be positively correlated with one another, and as such act as complements.

Kim et al. (2005) note that: *“Under the complementarity hypothesis, low-quality issuers would be charged an even higher underwriting spread than what they were actually charged if the underwriter had not received indirect compensation from underpricing. Underwriters and issuers may prefer this two-dimensional pricing system in order to reduce transparency rather than to directly charge low-quality issuers an obviously higher underwriting spread that may have negative informational consequences for the firm.”* (Kim et al., 2005, p1404). This prediction is consistent with Mola and Loughran (2004) who included the gross fee as an explanatory variable in their attempt to explain the SEO discount. Mola and Loughran (2004) found that higher gross fees were statistically significantly associated with a higher SEO discount.

Kim et al. (2005) proceed with an elaborate analysis of the potential relation between underwriter spreads and SEO underpricing, employing a 3SLS model including a number of instrument variables that affect the SEO underpricing and not the gross fee and vice versa. This methodology is robust to the joint endogeneity in the two variables and produces strong evidence in favour of a positive relation. It should be noted that, unlike our empirical study, Kim et al. (2005) study the SEO underpricing rather than the SEO discount. This allows for a direct comparison with the case of IPOs. Kim et al. (2005) however explicitly conclude that: *“...this positive correlation is robust to using the offer price discount as our measure of indirect costs for SEOs.”* (Kim et al., 2005, p1405).

The divergence of the conclusions from the empirical studies by Yeoman (2001) and Kim et al. (2005) may in part be explained by the fact that the analysis by Yeoman (2001) makes use of a simpler methodology, relying on a simple OLS regression in evaluating the relation. Another explanation to the results of Yeoman (2001) may be found in his comparatively simple perception of the SEO discount, which he speculates predominantly stems from manipulative trading in the market prior to the issuance. This potential explanation was, as noted earlier, explored in detail by Corwin (2003) who concluded that this explanation had a very limited power.

However, Yeoman (2001) needs not be completely wrong, as the two hypotheses do not exclude one another per se. One might argue that the substitution effect and the complementarity effect may be at play at the same time. However the empirical observations of Mola and Loughran (2004) as well as the investigation of Kim et al. (2005) indicate strong evidence that the complementarity effect is ‘stronger’ in practice, leading it to dominate the substitution effect, if indeed such one exists. In conclusion it seems reasonable to expect to find a positive relation between the direct and the indirect costs of an SEO.

Before analyzing the total cost of the SEOs in our sample empirically, the total cost is defined in the following section.

9.2 Measuring Total cost

When assessing the combined cost of issuing equity one has to consider specifically how to combine the direct cost and the indirect cost. That is how should one define the total cost? This problem arises from the nature of how the gross fee and the SEO discount are calculated respectively. As noted in section 4 the gross fee is calculated as a percentage of the gross proceeds, while the SEO discount is defined as the percentage difference between the closing price one day prior the issuance and the offer price. For the unfamiliar reader, the example below in table 30 illustrates the problem of simply adding the two different costs.

Table 30

Example of how to calculate the total cost	
Input	EUR ¹
Closing price, -1D	100.00
Offer price	95.00
SEO discount	5.00%
Indirect cost	5.00
Gross fee	2.00%
Direct cost	1.90
Total cost	6.90
Relative cost	6.90%
Note 1: except SEO discount, gross fee and total relative cost	

The intuition from the above example is that, for every 100 EUR the company wants to raise, its non-subscribing shareholders incur a “cost” of 6.9 EUR. Or said differently, the non-subscribing shareholders lose 6.9 percent of the proceeds than the firm would be able to raise, if there was no direct and indirect cost. From this example it is evident that simply adding the two percentages would overestimate the total cost by 0.1 percent (7.0 vs. 6.9 percent). When combining these two costs into one, the ‘weight’ of the gross fee in the combined cost will be lowered – under the assumption that there is a SEO discount and not a SEO premium. In the abovementioned example the indirect and direct costs accounts for approximately 72.5 and 22.5 percent of total cost respectively. Clearly, this implies that the overstatement of the total cost would be more severe in cases with a deeper SEO discount and/or higher gross fee. Formally stated, this definition of total cost can be summarized in the following expression:

$$Total\ cost = SEO\ discount + Gross\ fee \cdot (1 - SEO\ discount)$$

With the appropriate method of estimating the total cost associated with an SEO thus established, we shall now turn to the final empirical analysis, attempting to explain total cost.

9.3 Empirical analysis of the Total cost results – small sample

This thesis has extensively argued that it is the combination of the direct and indirect cost that are of interest when companies decide to fund themselves through issuance of new equity. As previously explained the total cost reflects the cost of the issuance incurred by non-subscribing shareholders.

Having established that liquidity seems to play an important role in the analysis of direct as well as indirect cost separately, we now seek to ascertain that this relation holds true when analyzing the total cost. Moreover discussing this nature and characteristics of this relation, we seek to answer how liquidity may predict the total cost. The analysis proceeds in a similar fashion to the previous two sections, beginning with a univariate analysis of the total cost.

9.3.1 Univariate results – Total cost

Table 31 presents the average total costs for each of the three liquidity tertiles. The average total cost across all tertiles is 8.01 percent.

Table 31

Total Cost by % of Company sold-Liquidity index					
Obs.	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
All (145)	10.45%	9.25%	4.33%	141.3%	< 0.0001 ***

Consistent with the hypothesis we observe that the total costs decline in secondary market liquidity, with the least liquid third on average incurring total costs of 10.45 percent. This is 612 basis points higher than the average total cost incurred by the most liquid tertile, which has average total costs 4.33 percent. The total costs of the sample seem skewed, as the observations in liquidity tertile 2 has total costs much closer to those of the least liquid third.

As was the case with the direct and indirect costs separately, several confounding effects may underlie this trend. Table 32 controls for deal value.

Table 32

Total Cost by Deal value-Liquidity index					
Deal value Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Smallest	13.49%	7.88%	5.28%	155.5%	0.0021 ***
2	11.21%	11.97%	6.15%	82.4%	0.0640
Largest	5.75%	6.50%	2.75%	109.2%	0.0360 *

For the two largest deal value tertiles, this skewness is still observed. Indeed in both cases the average total cost of liquidity tertile two exceeds that of the least liquid tertile. This reflects the

pattern observed in table 21. However, looking at the effect across the least to the most liquid tertile there is statistically significance in both the smallest and largest deal value tertile. The conventional wisdom of economies of scale in cost of an SEO is confirmed in the case of total cost, as the smallest deal value tertile incurred an average total cost of 9.03 percent in contrast to 5.08 percent for the largest deals. However, as discussed this economies of scale effect in reality may reflect that in fact that large offerings tend to be issued by comparatively larger companies.

Table 33 controls for the relative deal size.

Table 33

Total Cost by % of Company sold-Liquidity index					
% Co. sold Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Smallest	6.85%	4.97%	2.46%	178.5%	0.0026 ***
2	10.84%	8.21%	5.03%	115.5%	0.0338 *
Largest	12.08%	9.41%	12.31%	-1.8%	0.4925

Total costs clearly increase as deals become progressively larger as measured relative to the pre-deal equity value. While the average total cost across all liquidity groups for the smallest ‘% Co. sold’ tertile is 4.80 percent, the largest deals incurred total costs of an average of 11.27 percent. As was the case with both the direct and the indirect costs separately, liquidity has a stronger relation to total costs for the smallest deals, with the relation altogether vanishing for the largest tertile. For tertile consisting of small issuances the most liquid firms incur a total cost of only 2.46 percent when issuing seasoned equity. This compares to 6.85 percent for their least liquid counterparts. This difference is highly statistically significant. In a practical sense these differences in total cost deriving from different levels of secondary market liquidity are economically important. For a company issuing a relatively small amount of equity, moving from the second liquidity tertile to the most liquid tertile will on average lower their total cost by 251 basis points. Applying this difference on the average deal size (EUR 433.8m) of the liquidity tertile 2 of the smallest ‘% Co. sold’ deals implies that the shareholders would save roughly EUR 11m. For the second size tertile, the most liquid companies faced total costs of 5.03 percent compared to 10.84 percent for the least liquid group.

The vanishing effect of liquidity in the largest ‘% Co. sold’ tertile still persist when looking at total cost. This phenomenon was extensively discussed in the sections 5.1 and 6.4 and was largely

attributed to a comparative absence of high liquidity firms in the large ‘% Co. sold’ tertile. However, if one turns to the gross fee analysis on the small dataset there is a statistically significant difference between the least and most liquid tertile with the least liquid tertile having on average 91 basis points higher fees than the illiquid counterparts. The direct cost component of the total cost exhibit a declining tendency in the liquidity. Recall that looking at the large sample analysis of the SEO discount we found a similar declining trend of the indirect cost of 514 basis points. We interpret this as evidence that total cost for large ‘% Co. sold’ deals would indeed be found to be negatively related to secondary market liquidity, albeit to a lesser extent than smaller deals, if the total cost analysis could be conducted on a larger sample.

In addition to the relative deal size, both direct and indirect costs were previously found to be substantially related to the risk of the issuing firm, as measured by the average daily return volatility. Table 34 controls for this effect.

Table 34

Total Cost by Volatility-Liquidity index					
Volatility Tertile	Liquidity Tertile			% Δ	P-value
	Least liquid	2	Most liquid		
Smallest	9.56%	8.12%	3.23%	196.5%	0.0055 **
2	9.22%	7.79%	2.97%	210.8%	0.0007 ***
Largest	11.53%	11.62%	7.95%	45.0%	0.2428

Total costs vary strongly with liquidity in the two least volatile tertiles of the sample. Thus for both volatility tertiles, the total costs for the most liquid firms are around 3 percent while those of the least liquid firms are over 9 percent. Again the relation seems to fade somewhat away for the issuances of the most risky firms, as is can be observed in figure 10. These vary between 11.53 percent and 7.95 percent for the least and most liquid tertiles respectively. This difference is statistically insignificant.

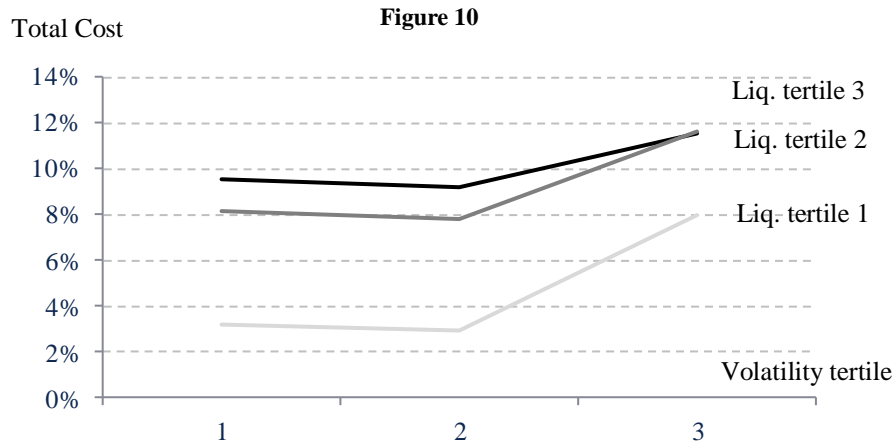


Figure 10 clearly illustrates the diminishing effect of liquidity on total cost as volatility increases. However, there is still a substantial economic difference across liquidity tertiles. For a low volatility company, moving from the second liquidity tertile to the most liquid tertile will on average lower their total cost by 489 basis points. Applying this difference on the average deal size (EUR 258.1m) of the liquidity tertile 2 of the least volatile tertile deals implies that the shareholders would save roughly EUR 13m.

While these analysis clearly indicate that secondary market liquidity does play a role in predicting the total costs that a firm will encounter when issuing new equity, there could again be several other confounding effects acting simultaneously. To control for this, in a similar fashion to the previous empirical studies of this paper, a multiple regression framework is utilized employing OLS estimators.

9.3.2 *Multivariate results – Total cost*

In the following analysis the approaches and insights from the two previous empirical studies are merged. Noting that problems with multicollinearity persist, size is not included as an explanatory variable. Deal value is also excluded, due to its strong correlation with ‘% Co. sold’. Further, as the total cost is a combination of direct and indirect costs, we expect to encounter heteroskedastic error variances, similar to that observed in the analysis of the SEO discount, again. The estimates are thus again produced using White’s heteroskedasticity consistent standard errors.

Table 35

Regression results for Total cost							
Variables	Regression number						
	1	2	3	4	5	6	7
Intercept	0.1337 (0.000)	0.0765 (0.010)	0.0728 (0.026)	0.0728 (0.026)	0.0725 (0.025)	0.0716 (0.028)	0.0776 (0.052)
Liquidity index	-0.1066 (0.000)	-0.0662 (0.051)	-0.0663 (0.053)	-0.0655 (0.071)	-0.0640 (0.071)	-0.0636 (0.074)	-0.0776 (0.046)
% company sold		0.1705 (0.024)	0.1621 (0.032)	0.1623 (0.030)	0.1651 (0.028)	0.1661 (0.026)	0.1411 (0.065)
Return volatility			0.1678 (0.717)	0.1690 (0.716)	0.1637 (0.724)	0.1723 (0.709)	-0.3250 (0.558)
Lead manager reputation				0.0008 (0.959)	0.0009 (0.957)	0.0003 (0.988)	-0.0046 (0.808)
Multiple bookrunners					-0.0048 (0.745)	-0.0052 (0.722)	-0.0092 (0.508)
Fully marketed						0.0043 (0.699)	0.0064 (0.650)
Years							YES
Adj. R ²	0.0866	0.1568	0.1518	0.1457	0.1401	0.1342	0.1138

Liquidity retains a clear negative relation to total cost across all models, although not all models produce high statistical significance. In model 7 the residuals (not reported) seem well behaved, though relatively severe heteroskedasticity is still evident. They are reasonably normally distributed with no substantial skewness and only slight excess kurtosis. Controlling for the variables that we argue are key in explaining total cost of an SEO in model 7, the liquidity index obtains a parameter estimate of -0.0776, which is significant at the 10 percent confidence level. This is interpreted as indicating that an incremental increase in the liquidity index of one decile is associated with, on average, 0.776 percentage point lower total cost. For the mean sized issuance (EUR 450m) such a liquidity improvement would be associated with a reduction in total cost of EUR 3.5m. As the average total cost of our sample is 8.01 percent corresponding to EUR 36m for the average sized issuance, such a liquidity improvement would in this interpretation yield an approximate 10 percent reduction in total cost faced by the non-subscribing issuer. This would indicate that there are strong incentives for firms to undertake liquidity enhancing steps. The concluding discussion briefly touches upon this topic, though an analysis of this interesting subject is left for further research. Again such an interpretation should be applied with extreme

care. For one, the liquidity measures underlying the liquidity index are not normally distributed, as evident from section 7. Secondly, such a relation is hardly linear across the entire range of total cost observations in this sample.

The regressions find that ‘% company sold’ is consistently associated with higher total cost. The parameter estimate exhibits reasonable levels of significance. This finding is in line with the findings of the univariate analysis, and implies that total cost associated with issuing equity increases dramatically as firms embark on larger offerings. This suggests that an increase in the relative offer size of 10 percentage points on average is associated with an approximately 1.4 percentage point larger total cost, which is in line with the finding under the analysis SEO discount.

Somewhat surprisingly volatility is not found to be significantly associated with the total cost. This is contrary to the finding of the analysis of the gross fee. The lack of significance thus stems from the indirect cost component of the total cost. However, the analysis in section 8.3.2 of the SEO discount on the large sample revealed a strong and significant positive relation between SEO discount and volatility. Again this is taken to suggest that performing the total cost analysis on a larger sample would likely find volatility to be a significant explanatory variable.

The variables ‘lead manager reputation’, ‘multiple bookrunners’, and ‘fully marketed’ are not found to be significantly and reliably related to the total cost. The analysis of the SEO discount conducted on the large sample found significant negative relation between lead manager reputation and the indirect cost. One might therefore again hypothesize that a larger sample would produce a significant relation between lead manager reputation and total cost.

Overall the explanatory power across all models is relatively low, accounting for only 10 to 15 percent of the variance in total cost, with model 7 explains a mere 11.38 percent. These figures however are reported as adjusted R^2 . Measured in unadjusted R^2 , model 7 is found to explain 21.84 percent of the variance in total cost.

Notwithstanding, the OLS regressions, in congruence with the univariate analyses, produce what we interpret as reliable and substantial evidence of secondary market liquidity being an important predictor of the total costs associated with carrying out an SEO. Moreover these findings were argued to be economically meaningful suggesting that a 10 percent improvement in the liquidity index on average may be associated with a 10 percent reduction in total cost in our sample.

Before concluding, the subsequent section will provide a brief discussion of the perspectives of these findings along with the other main insights from this thesis.

10 Discussion

Arriving at the insight that secondary market liquidity seems to play an important role in the total costs facing a firm issuing seasoned equity has taken us far afield. The area of research, concerned with security issuance is vast in scale as well as in scope. Indeed Eckbo et al. (2007) commence their major work on this topic with a strong testimony to the complexity of the task lying ahead, noting that; “*The decision to issue securities draws on all of the core areas in financial economics: asset pricing theory, capital structure theory, managerial investment incentives, financial institutions, contracting, and corporate governance*” (Eckbo et al., 2007, p1). Adding to that the highly intricate and multifaceted subject of market illiquidity and one can hardly but have left a question or two unanswered. The accomplishment of this paper, if such one can be said to have been achieved, is therefore more than anything the conjugation of the rich arguments and insights from these widely different fields into a coherent conclusion. Notwithstanding, the authors believe that this juxtaposition of individual fields of thought enlightens existing academic research in several ways.

Firstly, the paper has argued that direct or indirect costs of an SEO should rarely be viewed in isolation. While it may be of interest, for various purposes to study the direct or indirect costs separately, it is ultimately the combined costs incurred by the existing owners of the firm that are decisive with regards to the issuance of new seasoned equity. Further, the empirical study performed in this paper could be seen as an ‘out of sample’ test of the recent insights of Butler et al. (2005) in a European setting. While Butler et al. (2005) firmly conclude that liquidity is an important determinant of the fee paid to the underwriters of an equity issuance in the US, this paper has fortified this conclusion by demonstrating that these insights hold true on a pan-European dataset as well.

The study can furthermore be said to shed an important light on the field concerned with the SEO discount, by demonstrating separately that liquidity is a significant parameter in explaining the discount at which new equity is issued. In that sense, it has formalized the analysis by Corwin (2003) of the potential for certain simple measures of liquidity to explain the SEO discount, highlighting the importance of adopting a holistic view on liquidity.

Regarding the particular field concerned with market liquidity itself, the paper firstly provides a thorough exposition and discussion of various dimensions of liquidity as well as of the multitude of liquidity measures in existence. The insights from this section could potentially be useful in future studies such as those linking liquidity with asset pricing. In relation to the field of liquidity in asset pricing, the paper can be said to add perspective to this vast and complex field through confirming the importance of illiquidity as a key explanatory variable to asset prices in a different context. As noted, these studies can be said to ‘suffer’ from a common challenge in that any test of liquidity as a significant explanatory variable to expected returns, jointly tests that the expected return is in fact priced in accordance with the asset pricing model employed. This issue is to some extent circumvented in the event study approach taken by this paper – one could naturally argue that this approach too, jointly tests the model used to explain the total cost. However, the finding of liquidity as a significant parameter through these independent approaches certainly reinforces this insight even further.

Finally the results of this paper corroborate the findings of the current working paper by Stulz et al. (2012) which attempts to gauge the importance of shifts in market wide liquidity in explaining the observed frequency of equity issuances. As noted the findings of this paper complement their study in that, while Stulz et al. (2012) assesses the overall decision of whether or not to issue equity, this paper investigates the potential relation to the total costs of those that did.

In a broader sense, this paper can be viewed as a contribution to the debate on whether a company should have any interest in the secondary market liquidity of its shares, and thus further, whether society should have any interest in the liquidity of its financial markets. For the individual firm this, as noted, implies that improvements in liquidity have a discernible negative relation to the total costs incurred. Firms should therefore have a strong incentive to engage in liquidity enhancing activities. Such activities could involve investments in communication with the market to improve awareness and understanding of the firm. Improved communication, in this respect, could furthermore serve to mitigate information asymmetries which in turn *ceteris paribus* would reduce bid-ask spreads. Further studies could contribute in this regard by thoroughly analyzing the potential for improving the secondary market liquidity either on the firm level or on a macro level. On a macro level, studies could assess potential improvements to the market micro structure in general. A very relevant topic in this regard could be the recent French law imposing a Tobin tax on financial transactions. Such studies would naturally have to put more emphasis on the particular environment through a greater focus on the specific market under scrutiny.

This paper has employed measures of the secondary market liquidity, as observed prior to the issuance, in attempting to predict the total costs. It has, however, been noted that it is essentially the post-issuance secondary market liquidity that investors likely care about. And while pre-issuance liquidity is probably a good indicator of post-issuance liquidity, it is almost certain that the issuance will affect the secondary market liquidity in some way. Further studies could target this particular question by analyzing the ‘impact’ of an SEO on secondary market liquidity. If certain characteristics of equity issuances are associated with a substantial and positive impact on secondary market liquidity, they should be expected to face lower costs.

While this paper has demonstrated that liquidity is related to the indirect cost stemming from a wealth transfer from old to new shareholders when the issuance is priced at a discount, it has also been noted that this is only the case to the extent that existing shareholders do not subscribe to the offering on a pro-rata basis. While the two extremes (no existing shareholder take-up and complete pro-rata take up) are both unlikely, further studies could shed light on the actual wealth effect that the SEO discount has on existing shareholders. This would involve obtaining data on insider take-up from the issuances, which may be hard to come by. An interesting question could be whether larger SEO discounts are associated with greater insider take-up. If so, it should have an offsetting effect on the effective wealth transfer incurred for the average investor.

On a similar note, further research could also address the topic of illiquidity in relation to rights offers, which are, after all, the more common mode of equity issuance in Europe. As has been argued, analyzing the effective wealth transfer in relation to rights offers would entail acquiring high-frequency data on the secondary market trading in the ‘right’, so as to gauge at what price it actually trades and thus what ‘real discount’ existing shareholders, not subscribing to the issuance in fact incur when selling their right.

Finally, it deserves to be mentioned that further studies could certainly improve the research design of this very paper. This could happen either through obtaining a larger sample, yielding more accurate estimates and/or employing more sophisticated methodological techniques in uncovering the precise nature of the relation between secondary market liquidity and the direct and indirect costs associated with an SEO.

11 Conclusion

The empirical analysis conducted in this paper confirms the hypothesis that secondary market liquidity is a significant and important predictor of the combined cost of issuing equity, finding a reliable and statistically significant negative relation between liquidity and total costs. This analysis was carried out as a two pronged study, looking at both a large sample (holding information SEO discount) and a smaller sub-sample (holding additional information on the gross fee).

We find that liquidity is a highly intricate and multifaceted concept that consists of several dimensions. These dimensions include time related aspects of liquidity, focusing on how swiftly one can convert an asset into cash, as well as issues of transaction costs, captured in various measures concerned with some form of the bid-ask spread. Another dimension is that concerned with volume related aspects of market liquidity. The wide variety of liquidity measures in existence can be meaningfully grouped along several different lines, such as ex-ante and ex-post measures: the prior assess the potential for a trade to occur, and the latter capture trades that in fact happened. Also measures can be either one-dimensional, or can capture more dimensions of liquidity at once. Finally, we argue along the lines of Butler et al. (2005) that it may be meaningful to combine selected liquidity measures into a single index of secondary market liquidity.

Regarding the direct costs associated with an SEO, we find that they consist of a variety of fees paid to various agents providing services in the process of an SEO. A majority of the direct cost consists of the gross fee, which is paid to the investment bank for the service of floating the shares in the market. This process involves the investment bank taking the new shares on its balance sheet, exposing the bank to a certain risk. The gross fee has therefore been found to be positively related to measures of how risky the issuing firm is, which is confirmed in empirical study of our small sample. Our empirical analysis further confirmed the conventional wisdom of economies of scale in the underwriting fee, finding that larger deals paid relatively lower fees. Looking at relative issuance size, the opposite relation was found with issuances offering a proportionally larger amount of equity paying substantially higher fees. The risk that investment banks carry is further, in line with Butler et al. (2005), argued to be related to the market liquidity of the issuing firm. Our empirical analysis confirms this insight, finding that more liquid issuers paid consistently and significantly lower fees than their less liquid counterparts when controlling for risk, as well as the size of the offering in a univariate framework. The effect of illiquidity is found

to be diminishing in volatility as well as in relative offer size. Controlling for several variables simultaneously, the multivariate analysis confirmed this insight that a significant negative relation between secondary market liquidity and gross fees exists.

Historically, the SEO discount has been explained by adverse selection, price pressure and a variety of other factors. Empirically, the SEO discount has been found to be positively related to volatility as well as relative offer size, which is corroborated by our analysis. Further, our empirical study provides evidence that secondary market liquidity is significantly associated with the SEO discount, finding that less liquid issuers are faced with a higher discount. While statistical significance in the univariate analysis on the small sample is somewhat vague, the large sample produced strong evidence of a reliable relation. Our analysis found that the relation between liquidity and SEO discount is less pronounced for more volatile issuers as well as for offerings that are large as compared to the size of the firm. The multivariate analysis on the small dataset confirms this relationship indicating a consistent albeit statistically vague relation. Employing the larger sample again produces strong and significant evidence that illiquidity is associated with higher SEO discounts.

Having argued that it is the combination of the direct and indirect cost that are of interest when companies decide to fund themselves through issuance of new equity, the total costs are analyzed. This analysis establishes a substantial and significant negative relation between secondary market liquidity and the combined costs of issuing equity. Moreover, the relation is interpreted as economically meaningful and important.

When analyzing our multivariate regression, the coefficient of the liquidity index suggests that a 10 percent increase in the liquidity index is approximately associated with an average 10 percent decline in total costs, equal to a saving of EUR 3.5m for the average issuance of our sample. This interpretation should, as stated, be done with extreme care. But in conjunction with the other findings of this thesis, it strongly suggests that secondary market liquidity is a significant and important predictor of the combined cost of issuing seasoned equity. This emphasizes that firms should have a great interest in the market liquidity of their shares, as this may substantially affect the costs at which they can obtain additional equity.

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Appendix

Appendix 1 – Summary statistics with comparable measures calculated using 3 and 6 month data (small dataset)

Summary statistics - small dataset					
<i>Sample description</i>	Mean	Std. Dev.	25th %	Median	75th %
Market cap 3m (EURm)	5,567	21,697	147	433	1,918
Market cap 6m (EURm)	5,576	21,069	150	426	1,798
Market cap 12m (EURm)	5,720	20,039	154	457	1,555
Return volatility 3m (%)	3.17	2.02	1.68	2.56	4.05
Return volatility 6m (%)	3.23	1.99	1.80	2.55	4.16
Return volatility 12m (%)	3.30	1.86	2.02	2.73	4.24
<i>Liquidity measures</i>					
Turnover 3m (EURm)	23.44	77.30	0.25	1.38	5.96
Turnover 6m (EURm)	22.56	73.43	0.31	1.37	6.13
Turnover 12m (EURm)	22.04	67.58	0.30	1.40	6.92
Relative spread 3m (%)	1.86	2.14	0.44	1.01	2.57
Relative spread 6m (%)	1.92	2.25	0.46	1.02	2.58
Relative spread 12m (%)	2.08	2.61	0.48	0.98	2.71
Amihud 3m ¹	2	14	0.0020	0.0169	0.1068
Amihud 6m ¹	1	9	0.0015	0.0113	0.1567
Amihud 12m ¹	3	25	0.0013	0.0124	0.1546
FHT 3m	1.11	1.53	0.12	0.39	1.47
FHT 6m	1.14	1.50	0.15	0.44	1.73
FHT 12m	1.25	1.67	0.17	0.47	1.64
Liquidity index 3m	0.50	0.26	0.27	0.53	0.72
Liquidity index 6m	0.50	0.26	0.27	0.50	0.70
Liquidity index 12m	0.50	0.26	0.26	0.51	0.73
<i>Direct and indirect cost</i>					
Gross fee (%)	0.03	0.01	0.02	0.03	0.04
SEO discount 1d (%)	5.55	9.39	8.59	3.85	0.34
SEO discount 1w (%)	5.89	10.58	-	4.76	10.17
Note 1: Amihud measures are reported in per million turnover traded					

Appendix 2 – Correlation matrix of liquidity measures calculated using 3 and 6 month data (small dataset)

Correlation matrix - small dataset (6 months)					
<i>Liquidity measures</i>	1	2	3	4	5
1) Turnover	-				
2) Relative spread	.8050	-			
3) Amihud	.7696	.6798	-		
4) FHT	.7837	.8376	.6036	-	
<i>Other</i>					
5) Market cap.	.8465	.7689	.5608	.7738	-

Correlation matrix - small dataset (3 months)					
<i>Liquidity measures</i>	1	2	3	4	5
1) Turnover	-				
2) Relative spread	.7808	-			
3) Amihud	.7715	.6572	-		
4) FHT	.7858	.8181	.5522	-	
<i>Other</i>					
5) Market cap.	.8394	.7536	.5577	.7908	-

Appendix 3 – Summary statistics with comparable measures calculated using 3 and 6 month data (large dataset)

Summary statistics - large dataset					
<i>Sample description</i>	Mean	Std. Dev.	25th %	Median	75th %
Market cap 3m (EURm)	3,232	12,295	97	399	1,610
Market cap 6m (EURm)	3,194	12,225	92	371	1,539
Market cap 12m (EURm)	3,125	11,854	88	344	1,413
Return volatility 3m (%)	2.78	1.68	1.65	2.29	3.43
Return volatility 6m (%)	2.86	1.60	1.76	2.41	3.50
Return volatility 12m (%)	3.00	1.61	1.86	2.55	3.70
<i>Liquidity measures</i>					
Turnover 3m (EURm)	14.42	47.43	0.21	1.13	6.41
Turnover 6m (EURm)	14.08	46.27	0.22	1.06	6.23
Turnover 12m (EURm)	13.54	44.52	0.22	1.01	5.88
Relative spread 3m (%)	2.02	2.58	0.41	0.98	2.66
Relative spread 6m (%)	2.14	2.74	0.43	1.04	2.80
Relative spread 12m (%)	2.35	2.97	0.47	1.17	3.08
Amihud 3m ¹	508	22,917	0.0020	0.0150	0.1519
Amihud 6m ¹	258	11,555	0.0017	0.0143	0.1587
Amihud 12m ¹	140	6,194	0.0020	0.0184	0.2177
FHT 3m	1.11	1.71	0.12	0.39	1.38
FHT 6m	1.22	1.80	0.14	0.46	1.50
FHT 12m	1.36	1.89	0.16	0.53	1.81
Liquidity index 3m	0.50	0.25	0.28	0.51	0.72
Liquidity index 6m	0.50	0.26	0.27	0.50	0.72
Liquidity index 12m	0.50	0.26	0.27	0.49	0.73
<i>Direct and indirect cost</i>					
Gross fee (%)	n.a.	n.a.	n.a.	n.a.	n.a.
SEO discount 1d (%)	4.75	8.07	7.33	2.78	0.19
SEO discount 1w (%)	4.47	12.34	-0.05	3.17	8.33
Note 1: Amihud measures are reported in per million turnover traded					

Appendix 4 – Correlation matrix of liquidity measures calculated using 3 and 6 month data (large dataset)

Correlation matrix - large dataset (6 months)					
<i>Liquidity measures</i>	1	2	3	4	5
1) Turnover	-				
2) Relative spread	.8329	-			
3) Amihud	.7842	.6729	-		
4) FHT	.7460	.8399	.5605	-	
<i>Other</i>					
5) Market cap.	.8852	.8376	.6378	.7834	-

Correlation matrix - large dataset (3 months)					
<i>Liquidity measures</i>	1	2	3	4	5
1) Turnover	-				
2) Relative spread	.8272	-			
3) Amihud	.7819	.6599	-		
4) FHT	.7194	.8061	.5213	-	
<i>Other</i>					
5) Market cap.	.8806	.8354	.6252	.7545	-

Appendix 5 – Empirical analysis of the SEO discount (large sample)

Quintile based analysis

The tables below presents results of the analysis of the SEO discount on the large sample based on quintiles. Generally it presents a picture similar to that of the tertile-based analysis. The average SEO discount of the most liquid quintile is still statistically significantly lower than the least liquid quintile across all portfolios on a 1 percent significance level.

SEO discount by Deal value-Liquidity index							
Deal value Quintile	Liquidity Quintile					% Δ	P-value
	Least liquid	2	3	4	Most liquid		
Smallest	12.09%	8.19%	6.43%	6.86%	6.48%	86.6%	< 0.0001 ***
2	9.16%	8.06%	4.14%	4.04%	2.39%	283.8%	< 0.0001 ***
3	6.02%	5.83%	3.25%	2.33%	0.81%	644.5%	< 0.0001 ***
4	7.32%	6.51%	3.74%	2.40%	1.22%	498.3%	< 0.0001 ***
Largest	3.70%	3.51%	2.01%	1.18%	1.07%	245.6%	< 0.0001 ***

The analysis controlling for absolute deal size still contains the same internal issue as discussed above, but is presented for comparison purposes

Controlling for ‘percent company sold’ yields essentially the same results.

SEO discount by % of Company sold-Liquidity index							
% Co. sold Quintile	Liquidity Quintile					% Δ	P-value
	Least liquid	2	3	4	Most liquid		
Smallest	3.80%	1.94%	1.44%	1.01%	0.59%	544.4%	< 0.0001 ***
2	4.95%	4.15%	3.36%	2.44%	1.48%	235.0%	< 0.0001 ***
3	5.32%	4.01%	3.87%	3.31%	1.67%	219.3%	0.0002 ***
4	7.46%	7.84%	6.04%	5.10%	2.98%	150.1%	< 0.0001 ***
Largest	11.92%	12.05%	7.10%	7.83%	7.22%	65.2%	0.0001 ***

It is interesting to observe that this approach reveals that the firms in the most liquid quintile are able to issue small amounts (in a relative sense) of equity at almost no discount. The upper right corner of the table containing the smallest groups of deals from the most liquid quintile of firms reveals an average SEO discount of just 0.59 percent.

The table below presents the analysis when controlling for the level of risk as measured by the average daily standard deviation of stock returns over the 12 months prior to the issuance.

SEO discount by Volatility-Liquidity index							
Volatility Quintile	Liquidity Quintile					% Δ	P-value
	Least liquid	2	3	4	Most liquid		
Smallest	5.53%	3.79%	2.11%	1.07%	0.74%	649.6%	< 0.0001 ***
2	5.64%	2.90%	2.59%	2.01%	1.25%	349.7%	< 0.0001 ***
3	6.78%	4.09%	4.12%	2.93%	1.62%	319.6%	< 0.0001 ***
4	10.54%	8.04%	3.56%	2.98%	1.62%	551.4%	< 0.0001 ***
Largest	11.39%	8.44%	11.85%	8.07%	5.07%	124.4%	0.0024 ***

This ‘closer look’ reveals that liquidity seems to retain its ‘impact’ on SEO discounts up until the quintile consisting of the most volatile stocks, where the effect is reduced to a 124.4 percent difference from the most to the least liquid quintile.