Explaining the On-The-Run Effect: Implications for Financial Reporting

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ABSTRACT OF THE DISSERTATION

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This dissertation proposes and tests a model for liquidity in the corporate bond market. It uses the second law of thermodynamics, to explain liquidity. In the academic literature from the physical sciences, it has been said that the principle of entropy gives rise to the regularities found in nature (Swenson 2000) [60]. The on-the-run phenomenon is regularly found in the bond markets. The on-the-run phenomenon is the yield difference observed when a new bond issue comes to market from the same issuer and gets a better price (lower yield given equivalent duration) from the market than the older issue. This is an apparent conflict with the no-arbitrage condition that two securities having the same risk and maturity must have the same price. This dissertation shows that this theoretical rule is, indeed, not violated. The yield differential is the illiquidity cost of the older issue that has increased as a result of progressing through stages which typically occur in an entropy process. This dissertation finds that a model employing an entropy measure largely explains the on-the-run phenomenon, by accounting for over two-thirds of the liquidity differential for on-the-run corporate bonds. Further, bond liquidity captured as entropy exhibits an equivalent explanatory impact on yield to maturity as credit risk. The study continues with a proposal to improve financial reporting by

requiring firms to include aggregate entropy measures, by asset class, for all holdings of marketable securities, securities available-for-sale, and securities held-to-maturity, as a means of making financial reporting more relevant and informative. High entropy portfolios show superior performance in financial crisis periods, but will underperform low entropy portfolios in normal times.

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Chapter 1 Introduction

Prior to 2003, the US corporate bond market was an opaque over-the-counter market in that trading price and volumes were not readily available. Therefore, important information about this market could only be estimated based on reports from individual dealers, which were not necessarily representative of the market as a whole. This made academic research very challenging at best. In Houweling, Mentink, and Vorst (2005) [33], the authors noted, "Empirical papers that examined liquidity in bond or equity markets used both *direct* measures (based on transaction data) and *indirect* measures (based on bond characteristics and/or end-of-day prices). For corporate bonds, where most transactions occur in the over-the-counter market, these *direct* measures are often not reliable and difficult to obtain."

Since that time, the Financial Industry Regulatory Agency (FINRA) through an effort known as the Trade Reporting and Compliance Engine (TRACE) has made detailed transaction data available on prices, volumes, and other market variables for secondary bond sales. This offers a rare opportunity to study an over-the-counter market via a level of transparency not available before or in any other over-the-counter market. TRACE was launched on July 1, 2002 and implemented in three phases over roughly the next three years.

This study seeks to use this relatively new data to investigate the use of a proposed entropy-based model of liquidity. Heretofore there has been no formula for bond liquidity. I endeavor to distill liquidity down to a single descriptive quantity, i.e. make liquidity observable and reportable. This creates an index measure that can be used to compare liquidity differences between fixed-income securities, individually and over time. As part of a response to the challenge set forth in Spiegel (2008) [59] for "an overarching set of principles that supplied predictions at least roughly consistent with the market data", it also has properties that explain the on-the-run phenomena and that can be useful in the balance sheet valuation of marketable fixed-income debt.

The dictionary defines liquidity as:

> 1. The degree to which an asset or security can be bought or sold in the market without affecting the asset's price. Liquidity is characterized by a high level of trading activity. Assets that can be easily bought or sold are known as liquid assets.
> 2. The ability to convert an asset to cash quickly. Also known as "marketability".

In a liquid market, the items can be bought or sold quickly without affecting price. In their textbook, **The Econometrics of Financial Markets**, Campbell, Lo, and MacKinlay (1997) [10] refer to liquidity as "Ability to buy or sell significant quantities of a security quickly, anonymously, and with minimal or no price impact." They say further that it is the most important attribute for an asset.

As this is the generally understood and widely accepted understanding of liquidity, I would like to proffer the idea that it may no longer be necessary to use distant proxies for liquidity, such as bid-asked spread, price dispersion, and others. It is now possible to see the price and volume for every trade in a particular bond issue. I would like to suggest that, on average, it is most efficient for the market to trade corporate bonds in the largest lot size that gets the lowest unit trading cost. For example, bonds that trade regularly in lot sizes of $1 million or more, do so because these big pieces can move without incurring high trading costs. Conversely, bonds that do not trade in big pieces have that characteristic because they cannot trade at that size without incurring high trading costs. Therefore, in this study, I consider a bond to be liquid to the extent that it trades in lot sizes of $1 million or more. At a minimum, this demonstrates the market's ability to accommodate order flows for the issue. The supposition here is that liquid bonds have ordered flow or very simply that a corporate bond issue cannot be illiquid with substantial order flow and conversely, a corporate bond issue cannot be liquid without substantial order flow. Support for this point of view can be found in the study by Banerjee and Graveline (2013) [8] state that liquid issues get an increase in order flow from short sellers because, "short-sellers are required to deliver the specific security that they initially borrowed and sold short. As such, they naturally prefer to use liquid securities that can be bought back easily." Therein, this preference for liquid securities from short-sellers functions to identify those securities that are liquid by their increased trading activity.

The first objective here is to explain the "on-the-run" situation with bond liquidity.

A study done by Pasquariello and Vega (2009) [49] states that, " the on-the-run phenomenon refers to the stylized fact that, in fixed income markets, securities with nearly identical cash flows trade at different yields and with different liquidity," For example, "…the most recently issued (i.e., on-the-run, new, or benchmark) government bonds of a certain maturity are generally more expensive and liquid than previously issued (i.e., off-the-run or old) bonds maturing on similar dates." This is contrary to the principle that two debt securities having the same risk and the same maturity must have the same price.

Iceberg Analogy

In this dissertation liquidity is modeled in accordance with the second law of thermodynamics, entropy. When conceptualizing liquidity as entropy, or rather stages of entropy, it becomes clear why the on the run phenomenon exists.

Consider an iceberg breaking away from a glacier. The iceberg begins to float away. Although the water in which it floats is cold, it is still warmer than the iceberg. Immediately after the break, the iceberg had a certain mass and weight. But, after floating for only moments in the water as a separate piece, it became infinitesimally and irreversibly smaller than it was the moment it broke away. The entropy process had begun. That small yet irreversible reduction in the mass of the iceberg is like the small and normally irreversible reduction in liquidity of a new issue only moments after being free to trade in the secondary market.

The idea of using entropy is not new in business research. The Herfindahl-Hirschman Index used to measure industry concentration and corporate diversification is an adaptation of the entropy formula used in the physical sciences. Having tested both I find that the unmodified entropy formula taken directly from applications in physics has the advantage over the Herfindahl-Hirschman Index in modeling liquidity.

When considering that liquidity is priced (see Chen, Lesmond, and Wei 2007) [12], an entropy-based model of liquidity lends an explanation to the on-the-run phenomenon. Referring back to my iceberg analogy, consider that another iceberg of the exact same mass and weight breaks off of the glacier into the same-temperature water. The only difference being that the second iceberg breaks off and begins the float away at some period of time after the first. The first iceberg to float away began the entropy process earlier; therefore, it is at a different stage of entropy than the second iceberg. Likewise, the bond issue to be released into the secondary market first will be at a different stage of entropy than the second; it will be less liquid and that will show up in the price. Please note that I also find that the liquidity / entropy is not linear, therefore adjusting the initial size of the second iceberg will not have it match the state of entropy of the first.

Chapter 2 Implications for Financial Accounting Relevance

These results have important implications for the debate on the optimal accounting system. According to Sapra 2008[54], “accounting is relevant only because we live in an *imperfect* world where transaction prices may not correspond to the hypothetical market prices that would prevail in frictionless competitive markets.” Therefore, the consequences of these imperfections are essential to the debate about mark-to-market, mark-to-model and historical cost accounting. Fair value accounting is a way to measure assets and liabilities that appear on a company's balance sheet.

There is great concern from banks and insurance companies about having to mark asset values to market prices in times of financial crisis. For this reason, fair value accounting, as specified by US GAAP (FAS 157) and IFRS (IAS 39) is not fair value accounting in its pure form. Significant adjustments can be made, to observed transaction prices, at the discretion of the reporting entity under certain circumstances. Huizinga 2009 finds “that banks, and especially distressed banks, use discretion in the classification of (debt) securities so as to inflate the book value of these securities. Our results provide several pieces of compelling evidence that banks' balance sheets offer a distorted view of the financial health of the banks, especially for banks with large exposures... and suggest that recent changes that relax fair value accounting may further distort this picture.” [35]

FAS 157 defines fair value as ‘‘the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date.” When quoted prices in active markets for identical assets or liabilities are available, they have to be used as the measurement for fair value (Level 1 inputs). If not, Level 2 or Level 3 inputs should be used. Level 2 applies to cases for which there are observable inputs, which includes quoted prices for similar assets or liabilities in active markets, quoted prices from identical or similar assets in inactive markets, and other relevant market data. Level 3 inputs are unobservable inputs (e.g., model assumptions). They should be used to derive a fair value if observable inputs are not available, which is commonly referred to as a mark-to-model approach (Adapted from Yong 2008 and Huizinga 2009) [66, 35].

FAS 157 also stipulates that quoted prices in active markets must be used as fair value when available. However, it does not go on to quantify or define an active market. It further requires that, in the absence of such prices, an entity should use valuation techniques and all relevant market information that is available so that valuation techniques maximize the use of observable inputs.

The entropy measure is derived from available inputs. TRACE data are all that is required. There is no management judgment or discretion involved. The value of the entropy measure is very informative to users of financial accounting information as it relays in a single quantity the liquidity available to a security. In the same way that income is related to cash flow, corporate bond valuation is related to entropy. In the first case, income is the estimate where cash flow is the fact; verily, in the second case, corporate bond valuation is the estimate where entropy is the fact. Users of accounting information are able to regard cash flow as either a source of support for reported net income or a source of skepticism for reported net income. Similarly, high entropy may lend support (i.e., believability) to a corporate bond's value, or skepticism.

To understand my conclusion that the entropy measure is an excellent estimator for liquidity, let me referred to Pearl 2000 [50] for an appreciation of what a (mathematical) model is and how it relates to reality.

These concepts are not complex. The definition of a model has two important, characterizing, features:

1. A model matches the reality that it describes in some important ways.
2. A model is simpler than that reality.

Pearl (2000, p. 202) [50] defined a *model* as "an idealized representation of reality that highlights some aspects and ignores others." A *mathematical* model is one that captures these two features within one or more mathematical equations. Luce (1995) [44] suggested that "mathematics becomes relevant to science whenever we uncover structure in what we are studying." There is an important tension embedded within this definition. As the model matches reality better, it necessarily becomes less simple. Or, as it becomes simpler, it necessarily loses some of its match to reality.

The next logical step would be to posit a more complex model that has a closer match to reality and to statistically evaluate whether the increased complexity is worth the loss of simplicity. I contend that the simplicity and formidable information value of having this single value for liquidity makes it a necessity for responsible financial reporting.

Chapter 3 Motivations

Quantifying Liquidity

To my knowledge, heretofore, liquidity has not been distilled down to a single value. This dissertation proposes to do so. The entropy measure that I put forth allows for comparison of liquidity *within* asset classes (e.g. corporate bonds) and hopefully, with further development, *across* asset classes, as well.

The model for the entropy measure allows for definition of “normal” or expected liquidity, therefore investigations of what causes “abnormal” or unexpected behaviors in liquidity become possible. Various firm-specific effects like the quality of accounting information, levels of corporate governance, debt covenants, earnings surprises, etc. can be tested for their impacts on liquidity. Also, macroeconomic variables such as inflation, GDP growth and Federal Funds rates can be tested for their ability to forecast aggregate liquidity, and vice versa.

This model can be useful in portfolio hedging strategies. In a market model with continuous paths, the price process behaves locally like a Brownian motion and the probability that the security moves by a large amount over a short period of time is very small. Amin (1993) [6] held that, “Such behavior generally leads to a complete market… in such a market every terminal payoff can be exactly replicated (therefore) options are redundant assets (and) would not be necessary.” (Cont and Tankov 2009) [17] Further, a fundamental point the application of Constant Proportion Portfolio Insurance (CPPI) is “one of liquidity of the underlying: many CPPI strategies are written on bonds which may be thinly traded, leading to jumps in the market price due to liquidity effects." Modeling liquidity accurately would be of critical importance to such strategies.

In real markets, the presence of jumps in observed prices make perfect hedging impossible. When available, options enable the market participants to hedge risks that cannot be hedged by using only the underlying securities. Portfolio managers could employ an insurance strategy that consists of holding a proportion x_t of the risky asset in the portfolio, where x_t is given by

$$x_t = m\frac{V_t - F_t}{V_t} \tag{1}$$

where V_t is the portfolio value, F_t is the 'floor', i.e., the 'insured' lower bound on the portfolio value, and m is a constant multiplier. When the portfolio value approaches the lower bound, the proportion of risky asset tends to zero. In a continuous-path model with frequent trading, the portfolio will therefore never go below the barrier F_t. Taking a large multiplier, one can then construct a portfolio with a very important upside potential and almost no downside risk. However, this illusion breaks down as soon as one takes into account the jump risk: there is always a non-zero probability that due to a sudden downward jump in the risky asset price, the investor will not have a chance to withdraw before the portfolio value drops below F_t. (Adapted from Cont, Tankov, and Voltchkova 2007) [18]

It is this jump risk that makes a precise liquidity model important. Options for corporate bonds are seldom available so, in order for the above insurance strategy to be effective the manager must account for the liquidity of the different components of the portfolio. Having a numerical value for liquidity that moves along an expected path allows for portfolio adjustments that can, in part, substitute for unavailable options.

The scenario above refers to a "risky" asset which may lead to the presumption that the other asset has no risk. It is not my intention to make a distinction between absolutes, but rather a relative distinction. Corporate bonds are still risky, but they are relatively less so than collateralized mortgage debt, particularly with respect to liquidity risk. At a conference in December 2005, keynote speaker Richard Roll likened liquidity to pornography by citing the Supreme Court saying, "It's hard to define but we know it when we see it. [53]" In the recent Subprime Crisis, we saw that corporate bonds were certainly the more liquid, and least risky of the two. In the case where corporate bonds are the least risky asset, it will be important to monitor composite liquidity as holders may need to raise cash due to impairment of the risky assets. In a study of the sub-prime crisis, Manconi, Massimo and Yasuda (2012) [46] find that institutional investors that granted withdrawal rights to clients (e.g. mutual funds) had a much greater need for liquidity in their corporate bond portfolios, because they were subject to "runs" like banks. The study further showed that another class of institutional investors (e.g., insurance companies and pension funds) – which face longer-term end investors and are equipped with long lock-ups, penalties for early withdrawals, and predictable payout schedules – were under less pressure to sell assets than mutual funds.

Mutual funds were forced to liquidate assets when faced with either current redemption claims or anticipate claims for the foreseeable future. Indeed Manconi et al.

(2012) [46] state that “as the resale value of securitized bonds – mortgage-backed securities (MBS), asset-backed securities (ABS), collateralized debt obligations (CDO), and so forth – plummeted, the whole asset class became ‘toxic’… Mutual funds (were) reluctant to sell the more illiquid, ‘toxic’ assets and book losses at fire sale prices (thereby exacerbating the investor flight), they would instead sell other, more liquid assets, such as corporate bonds.” The theory of this dissertation expects that those mutual funds whose corporate bond holdings had higher average entropy values (and therefore greater liquidity) would have had less value destroyed, in this circumstance. However, that is not explicitly studied in this dissertation.

Explaining the On-the-Run Phenomenon

The on-the-run phenomenon is a puzzle, but the mystery is easily solved by allowing for an entropy-based model of liquidity. This is the central point of this part of the dissertation. Toward that end the remainder of the dissertation is organized as follows: Chapter 4 reviews theories and related literature. Section 4 presents the hypotheses. Section 5 explains the composition of the data set. Section 6 introduces the methodology of modeling liquidity in accordance with entropy. Section 7 explains model development. Section 8 shows and discusses empirical results. Section 9 provides additional tests to check robustness of my results to alternative model specifications. The final section concludes the study.

Chapter 4 Theories and Related Literature

The global financial crisis had its origins in the US subprime mortgage market in 2006-2007, but has since spread to virtually every financial market around the world. The most important aspect of this crisis, which sharply distinguishes it from previous crises, is the rapidity and the degree to which both the liquidity and credit quality of several asset classes deteriorated. While clearly both liquidity and credit risk are key determinants of asset prices, Friewald, Jankowitsch, and Subrahmanyam (2012) [27] emphasize that it is important to quantify the relative effects, and particularly how much they changed during the crisis. It is here that this dissertation endeavors to make a contribution by developing an entropy-based measure for liquidity that can be used to detect and measure changes. The changes to which I refer are both changes in value from period to period and changes from what would be the expected value for any period given the specifications of the model.

Friewald et al. (2012) [27] conducted their study of the crisis using several proxies for liquidity, including bond characteristics, trading activity and several alternative liquidity measures proposed in the literature, i.e. the Amihud measure (2002) [4], that proxies for market impact of a return for a given trading volume; the Roll measure (1984) [52], that relies upon efficient markets maintaining that the price of an asset bounces back and forth within the bid-ask band as it is traded therefore the spread can be calculated from the serial covariance of the change in price; the percentage of zero returns which holds that in the presence of transaction costs, investors will trade infrequently (Constantinides 1986) [16], and thus the magnitude of the proportion of zero returns is representative of illiquidity; and price dispersion measures, where one method, employed by Dick-Nielsen et. al (2012) and Feldhutter (2012) , [24] considers how prices spread from trade-to-trade throughout the trading day, while the other method, employed by Jankowitsch et al (2011) [38] considers the spread of trade prices from a benchmark supplied by an outside commercial vendor of bond valuations, the Markit Financial Information Services Company. They find that most of the liquidity proxies exhibit statistically as well as economically significant results; however the trading activity variables are particularly important in explaining the bond yield spread changes.

In a study of the Treasury bond market, Goyenko, Subrahmanyam, and Ukhov (2011) [28] find that “bond returns across maturities could be forecast by ‘off-the-run’ but not ‘on-the-run’ illiquidity. Thus, off-the-run illiquidity, by reflecting macro shocks first, is the primary source of the liquidity premium in the Treasury market.” The entropy measure proposed in this dissertation allows for bond market segmentation according to stages of the entropy process, therefore the designations of “on-the-run” and “off-the-run” need no longer be modeled as dichotomous. The entropy-based liquidity measure is a continuous variable that can be used to verify and predict the path of liquidity.

The attribute of liquidity is also important because it influences expected returns by way of a liquidity premium embedded in bond prices (see e.g. Amihud, Mendelson, and Pedersen, 2005) [65].

The literature on how liquidity affects asset prices is extensive. In recent years, the illiquidity of corporate bonds has been seen as a possible explanation for the “credit spread puzzle,” i.e., the claim that yield spreads on corporate bonds are larger than what can be explained by default risk (see e.g. Huang and Huang, 2003; Elton, Gruber, Agrawal, and Mann, 2001; Collin-Dufresne, Goldstein, and Martin, 2001) [34, 23, 15].

Earlier papers include the paper by Amihud and Mendelson (1986) [5] contend that transaction costs result in liquidity premiums in asset prices in equilibrium, due to different trading horizons of investors. Duffie, Garleanu, and Pederson (2007) [22] further find that transaction costs are driven by search frictions, inventory holding costs, and bargaining power in the OTC market structure. In a more recent paper, Acharya, Amihud, and Bharath (2009) [1] argue that these frictions change over time and are higher in times of financial crises, due to binding capital constraints and increased holding and search costs.

Alquist (2010) [3] finds that “(bond) market liquidity is a priced common risk factor…the price for bearing liquidity risk is economically significant. Overall, this evidence underscores the importance of understanding the effect of market liquidity on bond prices.” This study is similar to the work of many other authors on the topic of credit risk modeling. They repeatedly find that risk-free interest rates, asset value information and credit risk are not the only factors that drive corporate bond prices. (See, e.g. Longstaff, Mithal, and Neis, 2005; Nashikkar, Subrahmanyam, and Mahanti, 2011) [43, 48]. Studies using CDS structural models concur (See, e.g. Chen, Fabozzi, and Sverdlove, 2010) [13].

Further studies showing that liquidity proxies are significant explanatory variables for credit spreads are Houweling, Mentink, and Vorst (2005), de Jong and Driessen (2006), Sarig and Warga (1989), and Covitz and Downing (2007) [33, 20, 55, 19].

Essentially, all these papers find that liquidity is priced in bond yields. They all grew from the work of Lawrence Fisher who, in 1959, solved the mystery of why two fixed-income securities can seem to offer the same risk for the same maturity, and yet have different yields in the market. Fisher explained that “risk premium on a firm's bonds depends first on the risk that the firm will default on its bonds and second on their marketability” (Fisher 1959) [26]. Dividing a bond’s risk into these two components allowed for the explanation. Credit risk and liquidity risk are distinctly different. Liquidity, as modeled in this dissertation, is a property decaying in time passing through successive stages of the entropy process, just like the melting iceberg. Therefore it will be different for each bond issue according to different starting sizes and priorities in time.

Notwithstanding the importance of understanding liquidity dynamics there remain critical gaps in the literature on bond market liquidity. Goyenko (2011) [28] observes that, “these lacunae arise because the bond market is not homogeneous but its constituent securities vary by maturity and seasonedness (i.e., on-the-run status).”

The more well-known competing proxy formulas for liquidity are:

Amihud Measure

This liquidity proxy is a well-known measure originally proposed for the equity market by Amihud (2002) [4], which is conceptually based on Kyle (1985) [42]. It relates the price impact of trades, i.e., the price change measured as a return, to the trade volume measured in US dollars. The Amihud measure at day *t* for a certain bond over a particular time period with N_t observed returns is defined as the average ratio between the absolute value of these returns r_j and its trading volumes v_j, i.e., :

$$\text{Amihud}_t = \frac{1}{N_t} \sum_{j=1}^{N_t} \frac{|r_j|}{v_j} \tag{2}$$

A larger Amihud measure implies that trading a bond causes its price to move more in response to a given volume of trading, in turn, reflecting lower liquidity. (Friewald et al. 2012 cite Amihud 2002) [27]

Roll Measure

This measure developed by Roll (1984) [52] shows that, under certain assumptions, adjacent price movements can be interpreted as a bid–ask bounce which, therefore, allows us to estimate the effective bid–ask spread. This bid-ask bounce results in transitory price movements that are serially negatively correlated and the strength of this covariation is a proxy for the round-trip costs for a particular bond, and the author holds this as a proxy for liquidity. More precisely, the Roll measure is defined as

$$\text{Roll}_t = 2\sqrt{-\text{Cov}\,(\Delta p_t, \Delta p_{t-1}\,)} \qquad (3)$$

where Δp_t is the change in prices from *t-1* to *t*. The authors note that the minus sign "-"in the above equation is meant to set negative covariances to positive values, while positive covariances are set to zero. (Friewald et al. 2012 cite Roll 1984) [27]

Price Dispersion Measure

A new liquidity proxy recently introduced for the OTC market is the price dispersion measure of Jankowitsch, Nashikkar, and Subrahmanyam (2011) [38]. This measure is based on the dispersion of traded prices around the market-wide consensus valuation. A low dispersion around the valuation indicates that the bond can be bought close to its fair value and, therefore, represents low trading costs and high liquidity, whereas high dispersion implies high transaction costs, and hence, low liquidity. This measure is derived from a market microstructure model and shows that price dispersion is the result of market frictions such as inventory risk for dealers and search costs for investors. It presents a direct estimate of trading costs based on transaction data. In Jankowitsch et al. (2011), the traded prices are obtained from TRACE and the market valuations from Markit[1]. The price dispersion measure is defined as the root mean squared difference between the traded prices and the respective market-wide valuation weighted by volume, i.e., for each day t and a particular bond, it is given by

[1] Markit was founded in 2001 by Lance Uggla and a group of executives working in credit trading at TD Securities. The London-based company is a financial information services company providing independent data, valuations, trade processing, and loan portfolio management. The Markit Group Limited has over 2,800 employees worldwide. The New York offices are located at 620 8th Ave # 35, New York, NY 10018.

$$\text{Price dispersion}_{\,t} = \sqrt{\frac{1}{\sum_{k=1}^{K_t} v_k} \sum_{k=1}^{K_t} (p_k - m_t)^2 \; v_k} \qquad (4)$$

where p_k and v_k represent the K_t observed traded prices and their trade volumes on date t and m_t is the market- wide valuation for that day. Hence, the price dispersion is designed to approximate the potential transaction cost for a trade. (Friewald et al. 2012 cite Jankowitsch et al. 2011) [27]

External Liquidity

Chen, Liao and Tsai (2011) [14] offer a succinct description of "external liquidity" (which is the type to which this dissertation refers) as the ability that a security can be quickly traded in large quantities at a low cost and without significantly moving the price. This dissertation holds that the extent to which such large trades routinely occur in a security is the extent to which that security is liquid, therefore the initial dependent variable used to test the entropy measure is the volume of trading occurring in large lot sizes.

Chapter 5 Hypotheses

This chapter provides an overview of the research questions and hypotheses tested. The approach is to develop a precise model that can be used to examine the impact of various economic events, accounting information, bond features, and risk characteristics on expected liquidity.

$H1_0$: The Entropy Measurement Index does not add statistically significant incremental information to the estimate of corporate bond liquidity.

$H1_A$: The Entropy Measurement Index adds statistically significant model precision in estimate corporate bond liquidity.

Duffie et.al. (2007) [22] and Jankowitsch et al. (2011) [38] argue that in OTC markets the liquidity premium is driven by transaction costs due to search frictions, inventory holding costs, and bargaining power. “Liquidity differences across individual bonds seem to be rather pronounced: very few bonds are traded frequently, while most other bonds are hardly ever traded at all (see Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik 2008) [45] for details of a cross-sectional comparison for the US corporate bond market). Moreover, trading in the US corporate bond market involves much higher transaction costs compared to related markets such as the stock market. Thus, we would expect a significant liquidity premium, as argued in Amihud and Mendelson (1986) [5].” This dissertation expects that the progression through the various stages of entropy have a priority in time over escalating transaction costs. This is to posit that it is the natural increase in transaction concentration that provokes the increase in transaction costs. The entropy index measure is a trading diversity index;

therefore a higher entropy index value indicates more diverse trading activity (higher liquidity) and, a lower entropy index value indicates more concentrated trading (lower liquidity).

In keeping with the iceberg analogy, the initial size and time in the water for the iceberg equates to initial size and time trading in the secondary market for the new bond issue, thus this dissertation expects that these bond characteristics will impact liquidity to a large extent. However, to show that liquidity follows the path of entropy in the physical sciences, the entropy index measure should add significantly to the precision of the mathematical model.

$H2_0$: Bond issue size is unrelated to liquidity.

$H2_A$: Bond issue size, in parallel with the properties of entropy, is at significant determinant of liquidity.

The study of entropy specifically regards the science dealing with heat and changes to chemical and physical processes. This dissertation investigates the proposition that a bond's liquidity dissipates much in accordance with the way that thermal energy flows spontaneously from regions of higher temperature to regions of lower temperature. The ability to trade the bond issue in large institutional lot sizes is a diminishing function in time, just as the energy distribution of energy states follows a predictable and foreseeable reduction.

One of the most important predictors and determinants of entropy is molar mass. Entropy increases with molar mass. The more molecules we have means more probability of arrangement and as molar mass is related to molecules quantity, then entropy will increase with the increase of the molar mass. Thus, it is expected that higher liquidity coincides with large issues sizes. Indeed, the iceberg would take longer to dissolve into water, in accordance with how large it is when it breaks away from the glacier.

Considering that issue size, as a proxy for the size of the iceberg, is such a large and important component, overall market factors and firm specific factors are expected to have comparably little effect on liquidity.

$H3_0$: Other bond characteristics (e.g. age, coupon and original maturity) are unrelated to liquidity.

$H3_A$: Other bond characteristics, beyond issue size, are significant determinants and predictors of liquidity.

The other bond characteristics considered as liquidity proxies herein are *coupon*, *rating*, *maturity*, and *age*. In general, prior literature expects that bonds with the larger coupons to be less liquid. Bonds with long maturities are considered to be less liquid, because of the buy-and-hold nature of those investors who buy these securities, according to Friewald (2012) [27]. These measures are tested for their contribution to creating a precise model for predicting liquidity.

H4$_0$: Entropy is unrelated to the "on-the-run" effect.

H4$_A$: The decline in entropy over time is manifest by the "on-the-run" effect.

In nature the effects of entropy begin immediately. Each new stage of the entropy process has the property of being more stable than the previous stage. The rate of change can be influenced (hastened or slowed) by exogenous or environmental factors, but is virtually never reversed.[2] **.**The on-the-run phenomenon is reflective of the immediacy of the entropy process. Bonds becoming less liquid as they age can be seen as going from less stable, high activity states to more stable, low activity states. And, bonds do not re-aggregate into large blocks for institutional trading purposes once broken down into smaller retail-size pieces. This is consistent with the property that entropy does not reverse. Thus, the entropy measure is expected to demonstrate that corporate bond liquidity behaves like entropy, showing an immediate and persistent difference in bond issues coming to market at different times.

H5$_0$: The amount of trading volume occurring in small transactions is unrelated to liquidity.

[2] It should be noted here that this dissertation does not expect that this model will hold for equities and corporate bonds that are in or near default. Merton (1974) held that every corporate bond had an equity component in that each combined a pure debt instrument with a short position in a put option on the issuer's equity. For investment-grade bonds, the put option is out-of-the-money and generally has a negligible effect on the bond. However, for the bond that poses substantial default risk, the put is at least near-the-money and has a significant influence on the bonds trading characteristics, especially the price. This dissertation reasons that such differences would also extend to liquidity characteristics.[47]

$H5_A$: Increasing trading volume occurring in small transactions is consistent with an increase in liquidity.

If it were possible to measure the amount of water that came from the melting iceberg as an amount distinguishable from the seawater in which it floats then that amount of water would be indicative of the stage of entropy for the iceberg, when controlling for the initial size of the iceberg and the amount of time in the water. With corporate bonds, the amount of volume taking place in small trades is analogous to how much the iceberg has melted, of course, controlling for initial size and time in the secondary market. Therefore, this dissertation expects that the volume of small trade activity will add precision in adjusting the entropy measure to the correct stage.

Chapter 6 Data

Data Source Description

According to the TRACE Fact Book, 2010, Financial Industry Regulatory Authority, Inc. ("FINRA") launched TRACE on July 1, 2002 [25]. TRACE rules required virtually all transaction information in TRACE-eligible securities to be reported to FINRA. The public dissemination of transaction information was implemented in three phases. The time in which a trade had to be reported was also gradually reduced.

At the TRACE launch on July 1, 2002, that time was 75 minutes. This time frame was reduced in stages to 45 minutes on October 1, 2003, 30 minutes on October 1, 2004 and 15 minutes on July 1, 2005, to allow for increasingly timely data to the public with minimal impact to the reporting firms.

During Phase I, effective on July 1, 2002, the public transaction information was disseminated immediately upon receipt for the larger and generally higher credit quality issues: (1) Investment grade debt securities having an initial issue of $1 billion or greater; and (2) 50 non-investment grade (high yield) securities disseminated under the Fixed Income Pricing System (FIPS) that were transferred to TRACE. Under these criteria, NASD disseminated information on approximately 520 securities by the end of 2002.

Phase II, fully effective on April 14, 2003, expanded public dissemination to include the transactions in the smaller investment grade issues: (1) all investment grade TRACE-eligible securities of at least $100 million face value or greater and rated A3/A- or higher; and (2) a group of 120 investment grade TRACE-eligible securities rated Baa/BBB and 50 non-investment grade bonds. As Phase II was implemented, the number of disseminated bonds increased to approximately 4,650 bonds.

In Phase III, fully effective on February 7, 2005, approximately 99% of all public transactions and 95% of par value in the TRACE-eligible securities market were disseminated immediately upon receipt. Most transactions were disseminated immediately upon their receipt by the TRACE System, although the transactions over $1 million in certain infrequently traded non-investment grade securities were subject to dissemination delays, as were certain transactions immediately following the offering of TRACE-eligible securities rated BBB or below. Since January 9, 2006, all of the transactions in public TRACE-eligible securities have been disseminated immediately upon receipt. (Adapted from Trace Fact Book, 2010)[25]

Data Sample Selection

I began the sample selecting corporate bonds that had been issued between January 2002 and January 2011as reported in the Thomson Reuters SDC Platinum database. I then included all other bond issues from the issuers of the bonds in the initial sample set. The addition corporate bonds came from a search of matching issuer CUSIP numbers (CUSIP stands for Committee on Uniform Securities Identification Procedures, and is a unique alphanumeric code that identifies companies with 6 characters and securities with a 3 character extension for a total of 9 characters for each security) in the Wharton Research Data Services ("WRDS") Merging FISD dataset. For this conglomeration of corporate bond issues there were over 8.5 million TRACE transaction records during the time period of this study, January 2003 through March 2011. I removed all transaction records for those corporate issues:

- that were convertible
- that had floating interest rates
- that had initial maturities shorter than five years
- that were finance companies, insurance companies, or any type of bank or thrift
- that did not have TRACE identifiers, and
- that did not have at least 90% of the original issue amount still outstanding. (This was necessary because I cannot tell when the reductions happened so my variable for amount outstanding would have been been severely overstated in some months.)

This left a sample of 2,306 corporate bond issues from 625 issuers. At the beginning of the 99-month study time period there were 546 corporate bond issues in the study. New issues raised this number to 2,306 by the end of the study period.

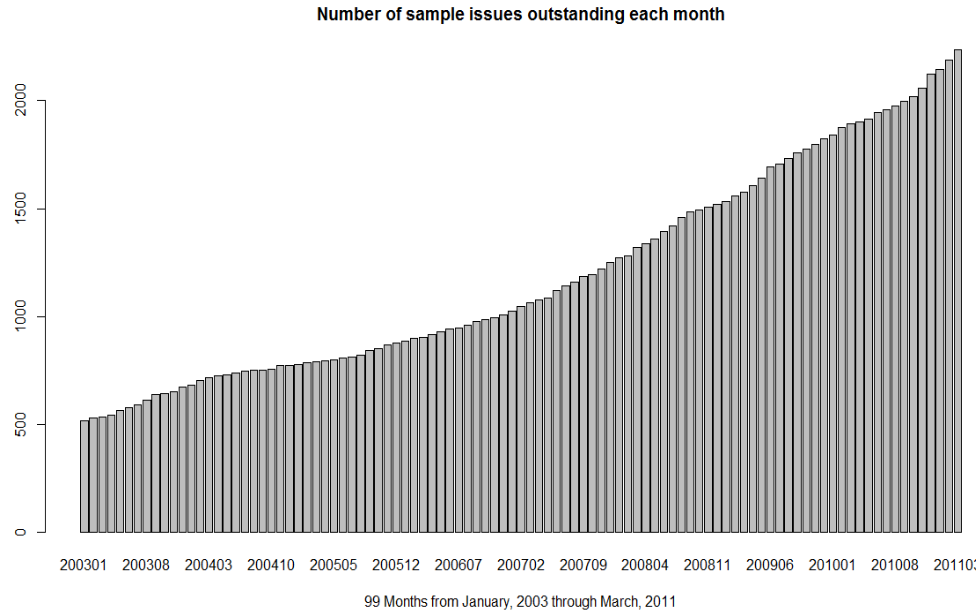

Figure 1 Sample issues count over the study period

This figure shows this study spans 99 months between January 2003 through March 2011; beginning with 625 corporate bond issues in the study sample in the 1st month growing, as shown here, to 2,306 by the 99th month.

I compiled the data monthly to create the variables for use in regression modeling. For each month in the study that a bond issue is outstanding a set of variables is calculated for that bond in that month. There are 123,017of these “bond-months” in the study, after removing 69 bond-months determined to be outliers. The outliers were identified using Studentized residual, Hat-Value, and Cook’s Distance examinations.[3] The outlier examinations were performed with respect to the five continuous variables

[3] A **studentized residual** is the quotient resulting from the division of a residual by an estimate of its standard deviation. The most common measure of outlier leverage is the **hat-value** measure, which maps the vector of observed values to the vector of fitted values, then measures the leverage of each case: an indication of location in joint distribution of the explanatory variables. **Cook's Distance** measures relative change in the coefficients as each case is deleted. Bond-months with large values for any of these three are outliers.

used in the base regression model of this study, which will be described in the Model Development Section.

Data Variable Description

This section describes the variables created for each bond-month that will be used in the models for this dissertation. Hence, each variable captures some parameter of a specific bond in a specific month.

Liquidity

The dependent variable used in the model to represent liquidity is *vol.trd.ge1m*. This is the volume, per bond (for bond *i*), per month (in month *j*), of those trades that are greater than or equal to $1 million. In other words, the amount represented in this variable is in total dollars of the face amounts summed, for all trades that were equal to or greater than $1 million, during the month. The summary statistics for this variable in the sample are:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.000e+00	0.000e+00	0.000e+00	2.537e+07	2.096e+07	1.215e+09

Of the 123,017 records (bond-months) in this study, 61,801 (50.2%) have zero trades of $1million or above, and hence a zero value for this variable.

The distribution of trade volumes, over all bond-months in the study, occurring in trades of greater than or equal to $1million appears below.

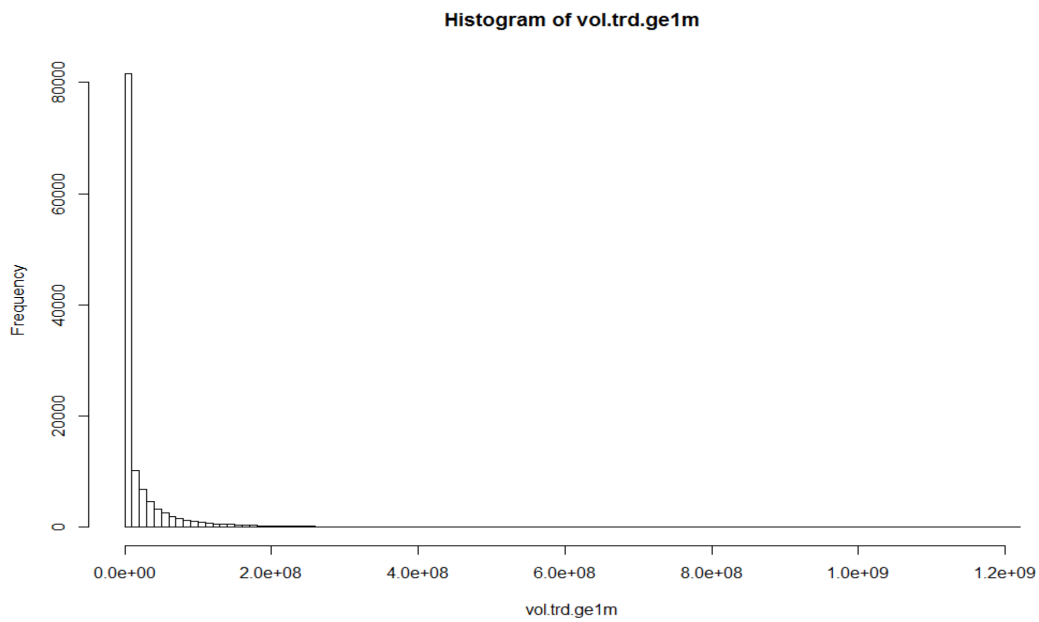

Figure 2 Histogram of volume variable

This figure shows the histogram of the *vol.trd.ge1m* variable used in this dissertation to represent liquidity.

The plot above, Figure 2, shows the distribution for the variable for liquidity, *vol.trd.ge1m*, as a histogram. For corporate bonds, half the bond-months show no liquidity at all. This high frequency of zeros leads to the distribution that is very positively skewed. Logarithms spread out small values and compress the large ones, often producing a more symmetric distribution. In the side-by-side plot below, Figure 3, plot (a) is a re-creation of the plot above in which the frequency bars have been replaced by a density curve; plot (b) is similarly a density curve, however, there has been a log-transformation of the variable. The log-transformed variable reveals that liquidity has more than one mode, a property of the data that is disguised by the skew in the untransformed distribution. At a minimum, this suggests the need for a nonlinear transformation in modeling as well as the need for adaptability in the model to accommodate the large amounts of illiquidity that create the mode at zero.

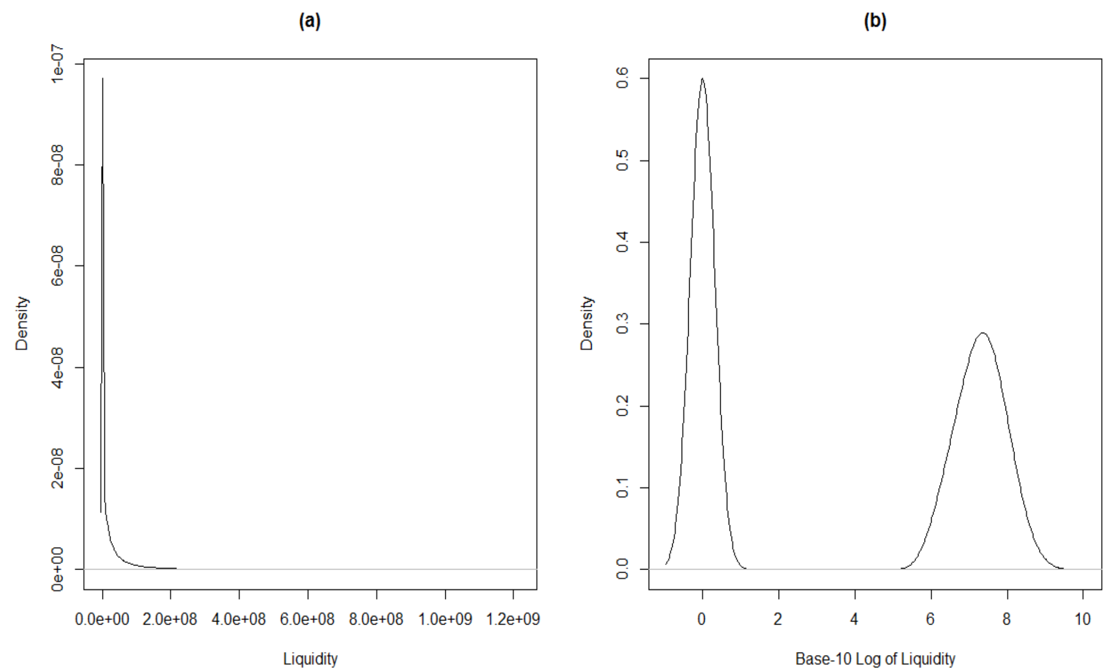

Figure 3 Logarithm transformation

These plotted curves show the distribution of the variable representing liquidity, *vol.trd.ge1m*, in the sample data set (a) before and (b) after log transformation.

Amount Outstanding

The first independent variable used in the model is *amt.out.m*, which stands for "amount outstanding (in millions)". This is the face amount of the issue that is outstanding at the end of the study. This is a single value for each bond issue and, as such, does not vary from month-to-month. Because I did not have data describing the month-to-month tally of the current outstanding amounts, I removed all issues for which the amount outstanding was less than 90% of the original issue amount. The summary statistics for this variable are not calculated over the bond-months in the sample, but rather it is calculated over the bond issues in the sample. This is more meaningful because the value varies from issue-to-issue, not month-to-month for any given bond. The summary statistics are:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.2	150.0	260.0	389.7	500.0	3750.0

There are 2,306 bond issues in the study.

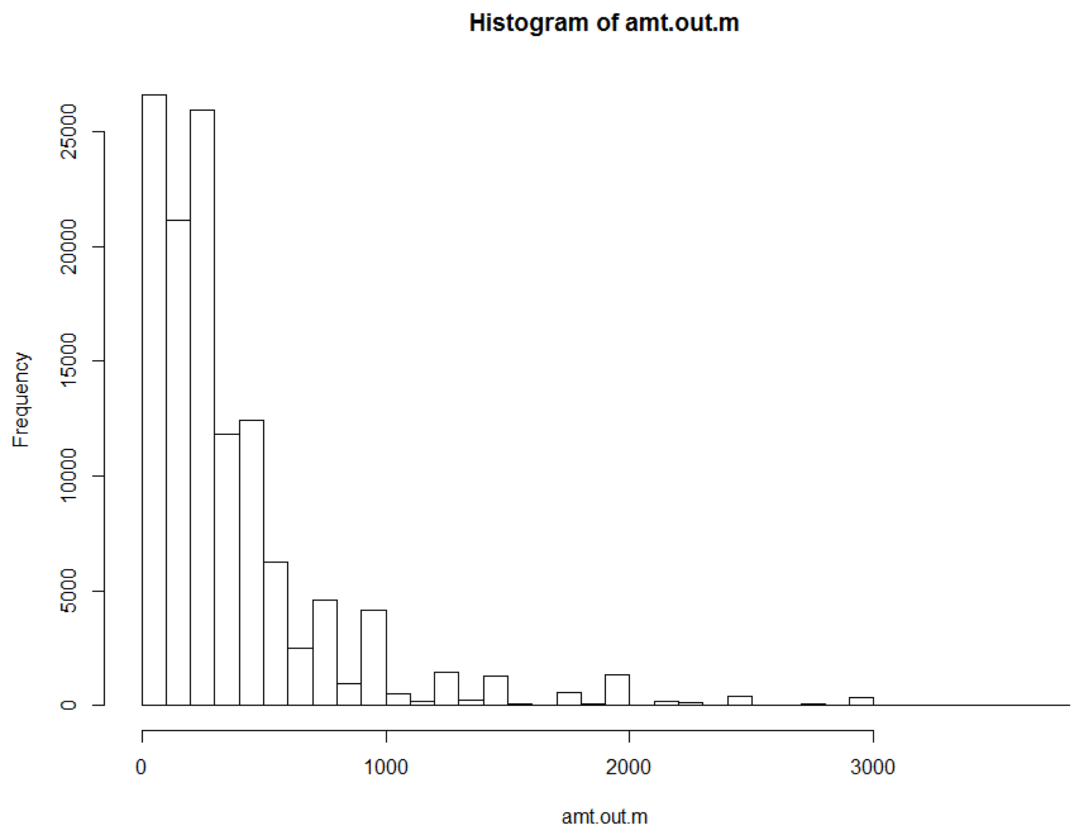

Figure 4 Histogram of amounts outstanding

This figure shows the histogram of the *amt.out* variable, which is the face amount, in dollars, of the issue outstanding in the secondary market.

Age

The variable *age* is the number of months that bond *i* has been trading in the secondary market by month *j* in the study. In other words, *age* is the age, in months, of a given bond in a given month. The summary statistics are:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.00	20.00	49.00	64.89	97.00	675.00

The bar plot of age below reflects that the method in which the sample data were assembled allows new issues into the sample while no issues are retired.

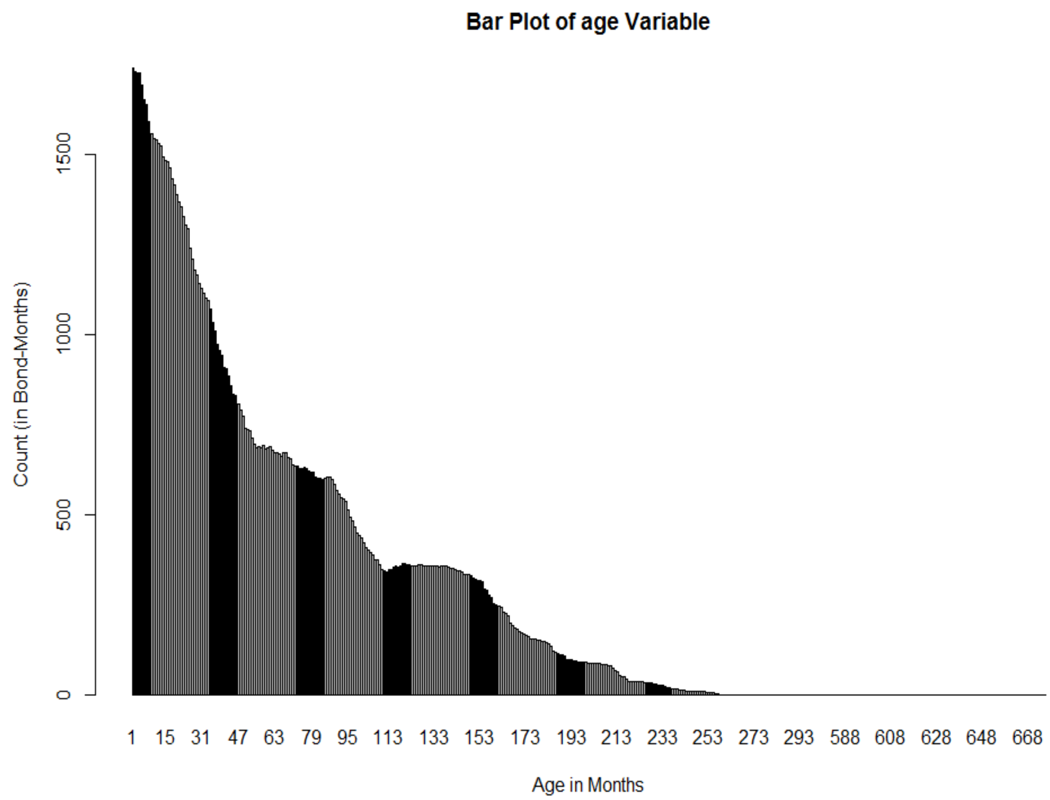

Figure 5 Bar plot of bond issue age

This figure shows the bar plot of the *age* variable with each bar showing the number of bond-month observations having that age, in months, since issue date i.e. the number of months that the issue has been trading in the secondary market.

The scatter plot of the *age* variable versus the liquidity variable, Figure 6, displays a very definite curvilinear relationship between the two. Because the scatter plot below contains roughly123,000 data points, the data points were faded to show the dashed regression line and the smooth line fitted to the data. The smooth line is accompanied by a band illustrating the standard error, which is very narrow until the far right side of the graph. The non-linear transformations used to account for this curvilinear relationship and to develop the model will be discussed in the Model Section.

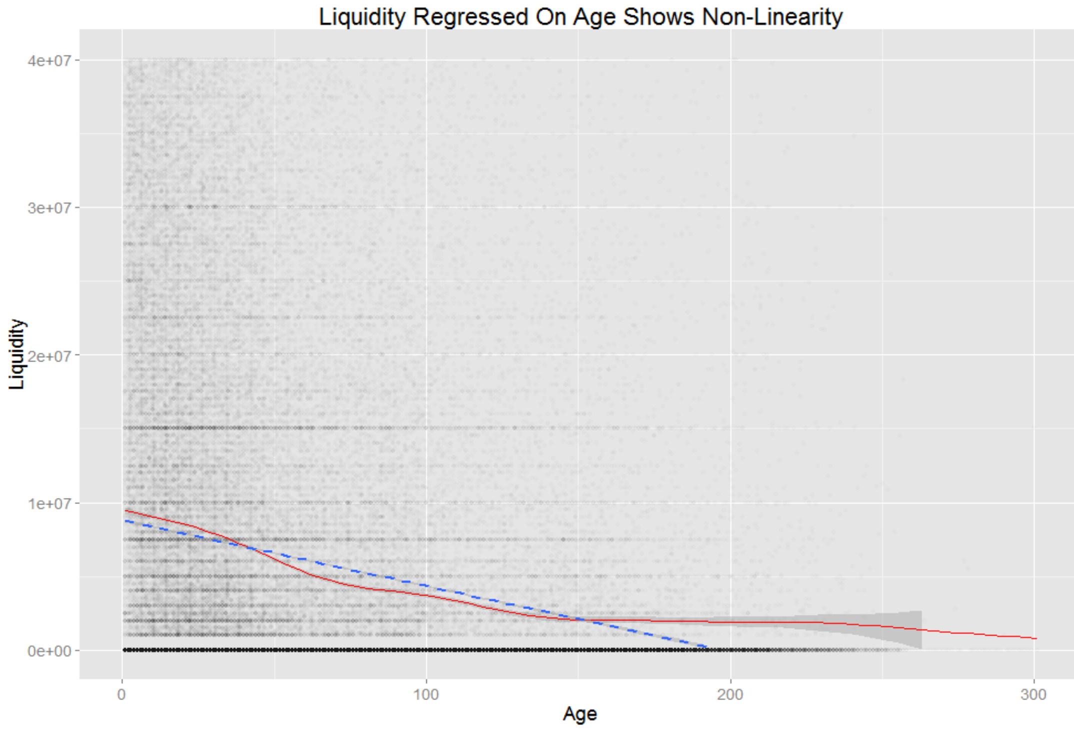

Figure 6 Non-linearity of age variable

This figure shows the scatterplot of Age (in months) vs Liquidity (modeled as volume of trading in lot sizes of $1million and over). The scatterplot's points have been faded to show more clearly the ols regression line (dashed blue line) and the non-parametric line fitted to the data (solid red line). This graph demonstrates that Age's relationship to Liquidity is not linear. Therefore, a non-linear transformation is in order for the variable age.

Bond Characteristics

The variables that capture the bond characteristics are *coupon*, and *init.mat*. The variable *coupon* is simply the face coupon rate of the issue. And, the *init.mat*, which stands for initial maturity at issuance, is anticipated life of the bond from issue date to maturity date in days. The possibility of a clientele effect on corporate bond liquidity is examined by the inclusion of these variables. It may be a case that current income buyers may prefer larger coupons or buy-and-hold buyers prefer maturity ranges. This dissertation makes no claims about how bond characteristics might affect liquidity; the goal at this point is to test regressors and develop a useful model.

Entropy

The variable *E* is the Entropy Measure. This measure increases with liquidity, i.e. the higher the value of E, the greater the liquidity of the asset.

The entire next section is devoted to explaining how this measure was developed and how it is calculated. It is the contention of this dissertation that *E* models liquidity, follows an expected path, is easy to calculate given pre-existing reporting requirements, and provides important information on asset risk in a single value.

The summary statistics for the entropy measure, *E*, are:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.0000	0.0000	0.6931	1.3010	2.4780	6.5890

Of the 123,017 records (bond-months) in this study, 57,271 (46.6%) have *E* values equal to zero.

The plot below demonstrates the expected path of liquidity as it shows the average entropy value for first twenty-four months (after issuance) of bonds in the sample data. A smooth curve and its standard error have been fitted to the data using the loess algorithm[4]. I propose that this typifies behavior of liquidity in the corporate bond market at level of the individual bond issues.

[4] Also known as LOWESS for (Locally Weighted Scatterplot Smoothing) is a locally weighted polynomial regression. At each point in the data set a low-degree polynomial is fitted to a subset of the data, with explanatory variable values near the point whose response is being estimated. The polynomial is fitted using weighted least squares, giving more weight to points near the point whose response is being estimated and less weight to points further away.(Weisberg2010)[64]

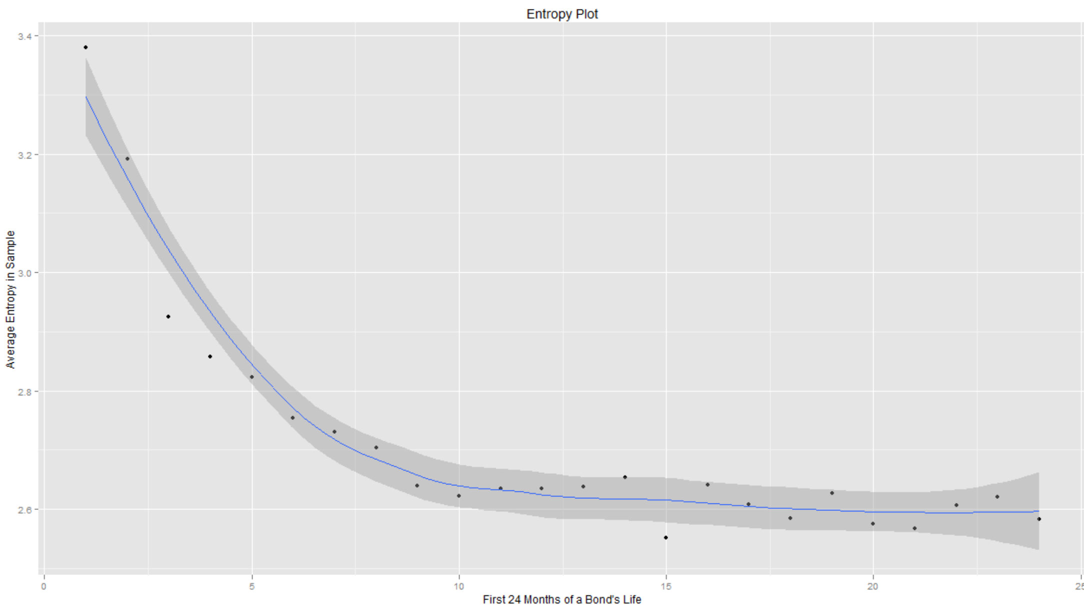

Figure 7 Entropy graph

This figure is a graph that shows the average entropy index measure, *E*, for the first twenty-four months in the secondary market for the sample of corporate bonds in this study. The study is done over ninety-nine months that include the Ford/GM and Subprime crises. A smooth curve is fitted to the above data points using the lowness algorithm along with a standard error band.

The plot shown above displays a curve fitted to the average entropy index measures for the first 24 months that the corporate bonds sampled for this dissertation traded in the secondary market. To test the robustness of the shape of the curve, I divided the data into subsets representing normal periods and two crisis periods (the GM/ Ford crisis - March 2005 to January 2006 and the Subprime crisis - July 2007 to January 2009) in order to examine the fitted curve for the different economic cycles. The shape of the curve was substantially unchanged. Indeed, the initial stages of entropy would seem to be very robust and consistent over different economic environments. This observation is consistent with the Alquist (2010) [3] finding that "illiquid bonds (have) greater sensitivity of the returns to fluctuations in market liquidity."

Retail/Small Trade Activity

Retail/Small trade activity is modeled using two variables; the two variables are *num.trd.le100k* and *vol.trd.le100k*.[5] The variable *num.trd.le100k.m* is the number of trades for a given bond, in a given month, that are less than or equal to $100,000 in face amount. The summary statistics are:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.00	0.00	5.00	42.73	29.00	3403.00

The variable *vol.trd.le100k.m* is the sum of the volume of trades for a given bond, in a given month, that occurred in trades of less than or equal to $100,000 in face amount (in millions). The summary statistics are:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	0	119000	1013000	747000	75890000

Of the 123,017 records (bond-months) in this study, 44,139 (35.9%) have *num.trd.le100k* and *vol.trd.le100k.m* values equal to zero, i.e. no trades in face amounts less than or equal to $100,000.

[5] With respect to those trades that are below $1 million in face value and above $100,000 in face value, there is no variable included in this dissertation designating trades of this size because these intermediate size trades were not found to add predictive value to the model, nor is it consistent with the theory of this dissertation that they should.

The simple correlation between these two variables is 0.96. They obviously show the same effect on liquidity. Therefore, I will use the volume variables as the large trades are represented by volume.

Credit Rating

The variable *rating* is a numerical representation of the Moody's rating for the bond placed in the order where higher numbers equate to higher ratings; the range is from lowest (Ca set to 1) to highest (Aaa set to 20)[6]. Table 1 below is a mapping of the Moody's ratings, column 1- Moody's, to the numbers that I have assigned to them for analysis, column 3 - Numeric. The middle column, column 2 - Count, is the number of corporate bond issues in the sample set with that rating.

[6] Moody's appends numerical modifiers 1, 2, and 3 to each generic rating classification from Aa through Caa. The modifier 1 indicates that the obligation ranks in the higher end of its generic rating category; the modifier 2 indicates a midrange ranking; and the modifier 3 indicates a ranking at the lower in of that generic rating category.

Table 1 Index to numeric Moody's ratings

This Table has the first column showing the Moody's rating. The second column is the number of issues in the sample that have that Moody's rating. The third column is number assigned to that rating in the dataset.

Moody's	Count	Numeric
Aaa	20	20
Aa1	2	19
Aa2	30	18
Aa3	109	17
A1	137	16
A2	428	15
A3	329	14
Baa1	284	13
Baa2	440	12
Baa3	310	11
Ba1	91	10
Ba2	33	9
Ba3	9	8
B1	26	7
B2	29	6
B3	28	5
Caa1	9	4
Caa2	4	3
Caa3	4	2
Ca	2	1

Seasonality

The variable *dum.dec* is a dichotomous (dummy) variable that takes the value of one, "1", for those bond-months that are in the month of December, and the value of zero, "0" for all other months. This variable was created because preliminary tests for seasonality showed that December months was the least liquid month consistently.

On-The-Run Issues

The variable *dum.onrun* is a dichotomous (dummy) variable that takes the value of one, "1", for all issues that are the most recent for an issuer, provided that said issuer has more than one issue in the market/sample during that calendar month. Otherwise, the value for this variable is zero, "0".

Issues from Single-Issue Issuers

The variable *dum.sngl* is a dichotomous (dummy) variable that takes the value of one, "1", for all issues that are from issuers that have no other corporate bond issues outstanding in the market/sample at that time. Otherwise, the value for this variable is zero, "0".

Chapter 7 Entropy Measures

A modified version of the entropy measure adapted from the physical sciences has been in use in business literature for many years. A famous example is the Hirsch-Herfindahl Index. Its background includes contributions from such notables as Claude Shannon and Edward H. Simpson. The Simpson index was introduced in 1949 by Edward H. Simpson to measure the degree of concentration when individuals are classified into types (Simpson 1949) [58]. The same index was rediscovered by Orris C. Herfindahl in 1950, as per his unpublished doctoral dissertation, “Concentration in the U.S. Steel Industry” at Columbia University [51]. The square root of the index had already been introduced in 1945 by the economist Albert O. Hirschman (Hirschman 1945) [31]. As a result, the same measure is usually known as the Simpson index in ecology, and as the Herfindahl index or the Herfindahl-Hirschman index (HHI) in business literature.

The Shannon index has been a popular diversity index in the ecological literature, where it is also known as Shannon's diversity index, the Shannon-Wiener index, the Shannon-Weaver index and Shannon entropy. The measure was originally proposed by Claude Shannon to quantify the entropy (uncertainty or information content) in strings of text (Shannon 1949) [57].

The Herfindahl Index, which measures both industrial concentration and corporate diversification, started by taking the form:

$$I = \sum_{i=1}^{n} P_i w_i \tag{5}$$

where P_i is the share of either the ith firm (in the case of industry concentration) or the ith industry (in the case of industry diversification within the firm), w_i is an assigned weight, and n the number of firms or products (Jacquemin and Berry 1979) [37]. Herfindahl's contribution to the measure was "the suggestion that the share of each firm be weighted by itself," thereby rendering:

$$H_c = \sum_{i=1}^{n} P_i\, P_i \tag{6}$$

The two equations above (Equations 5 and 6) produce measures that increase when industry or firm concentration increases. So, consequently these measures decrease when diversification increases. In fact, in order to show the Herfindahl Index as a measure that *increases* with corporate diversification, the measure is rewritten as, what I will refer to as H_d, denoting Herfindahl diversity measure:

$$H_d = \left(1 - \sum_{i=1}^{n} P_i^2\right) \tag{7}$$

Essentially,

$$H_d = (1 - H_c) \tag{8}$$

The Shannon index has also been a popular diversity index in the ecological literature, where it is also known as Shannon's diversity index, the Shannon-Wiener index, the Shannon-Weaver index and the Shannon entropy. The measure was originally proposed by Claude Shannon to quantify the entropy (uncertainty or information content) in strings of text. (Shannon 1949) [57]

The Shannon entropy measure is also an inverse measure of concentration. Therefore, similar to the measure from Equation 7 above, this entropy measure increases with diversification. It is Shannon entropy that I use as the entropy measure for liquidity in this dissertation. The entropy measure weights each P_i by the logarithm of $1/P_i$:

$$E = \sum_{i=1}^{n} P_i \ln \frac{1}{P_i} \tag{9}$$

It is the contention of this dissertation that greater trading diversity means greater liquidity. Thus, the measures calculated by Equations 7 and 9 (H_d and E, respectively) *increase* with increasing diversification and therefore with increasing liquidity. For example, consider two hypothetical corporate bonds, *Liq* and *Not_Liq*. For a given time period, t, 90% of the total trading volume in each bond is accounted for by six trades.

- *Liq*: All six trades account for 15% each of the trading volume in period *t*, and
- *Not_Liq*: One trade accounts for 80% of the trading volume in period *t*, while the other 5 account for 2% each.

Assume that the remaining 10% of trading volume in both corporate bonds is evenly divided at 1% each for another 10 trades.

The largest six trades in each issue account for 90% of the trading volume. However, corporate bond *Liq* exhibits much more diverse trading, where corporate bond *Not_Liq* exhibits much more concentrated trading. The central expectation of this dissertation is that a higher entropy measure (technically a higher inverse measure, H_d or E) equates to higher liquidity by showing a greater diversity of trading.

Chapter 8 Methodology

Correlation Matrix

Table 2 below is the correlation matrix for the variables employed in developing the model.

Table 2 Correlation Matrix
This matrix was created using the Spearman method in R.

	vol.trd.ge1m	age	amt.out.m	rating	coupon	init.mat	E	vol.trd.le100k.m	dum.dec	dum.sngl	dum.onrun
vol.trd.ge1m	1.00000	-0.25085	0.56320	-0.00448	-0.09393	-0.12131	0.39718	0.41107	-0.01938	-0.04042	0.13145
age	-0.25085	1.00000	-0.30673	-0.03935	0.43830	0.41326	-0.16184	-0.14725	0.00022	0.07708	-0.24955
amt.out.m	0.56320	-0.30673	1.00000	0.04398	-0.07831	-0.13991	0.39222	0.44278	0.00405	-0.07603	0.09558
rating	-0.00448	-0.03935	0.04398	1.00000	-0.26325	0.01478	-0.00385	0.07133	-0.00028	-0.12772	-0.01994
coupon	-0.09393	0.43830	-0.07831	-0.26325	1.00000	0.29693	-0.20472	-0.15465	-0.00930	0.09722	-0.07044
init.mat	-0.12131	0.41326	-0.13991	0.01478	0.29693	1.00000	-0.45421	-0.20158	-0.00695	-0.02290	-0.10734
E	0.39718	-0.16184	0.39222	-0.00385	-0.20472	-0.45421	1.00000	0.52610	0.00682	-0.03490	0.07315
vol.trd.le100k.m	0.41107	-0.14725	0.44278	0.07133	-0.15465	-0.20158	0.52610	1.00000	0.00031	-0.07480	0.03707
dum.dec	-0.01938	0.00022	0.00405	-0.00028	-0.00930	-0.00695	0.00682	0.00031	1.00000	-0.00597	-0.00106
dum.sngl	-0.04042	0.07708	-0.07603	-0.12772	0.09722	-0.02290	-0.03490	-0.07480	-0.00597	1.00000	-0.22247
dum.onrun	0.13145	-0.24955	0.09558	-0.01994	-0.07044	-0.10734	0.07315	0.03707	-0.00106	-0.22247	1.00000

The top row variable is the independent variable, ***vol.trd.ge1m***. This is the variable representing liquidity which is negatively correlated with a bond issue's age, in months, as shown by the variable ***age***, in the following row. The negative correlation between liquidity and a bond issue's age follows the basic intuition that older bonds are less liquid; however, the correlation is not very strong at -0.25. The highest correlation in the matrix is between independent variable and the variable showing the amount of the issue outstanding in the secondary market, ***amt.out.m***, at 0.56. Again this follows basic intuition in that those corporate bond issues with greater amounts outstanding should be more liquid, all else being equal. The variable ***rating***, as discussed in the "Credit Rating" subsection earlier, is an ordinal variable re-engineered to map higher numbers to higher Moody's ratings. The correlation matrix shows no correlation between liquidity and credit rating. The variables, coupon, for coupon size, and init.mat, for initial maturity at issuance, are two bond characteristic variables designed to capture clientele effects that might impact liquidity.

The variable for the entropy measure is denoted simply as ***E***. This variable was the subject of the "Entropy Measure" section. The entropy measure used in this dissertation follows the formula of the index that Claude Shannon pioneered to quantify the uncertainty or information content in strings of text. Shannon (1949) Therefore, as herein written, ***E*** is an inverse measure of trading concentration in a specified bond issue over a specified period. That is to say that it is a measure of trading dispersion in which higher values equate to higher dispersion. And as I have applied it, higher dispersion means higher liquidity. So in summary, I propose that high values of ***E*** mean that trading concentration is low, therefore liquidity is high. Hence, high ***E*** shows high liquidity, and low ***E*** shows low liquidity.

The variable for the volume of trading in small trades is ***vol.trd.le100k.m***, which stands for volume of trades less than or equal to $100,000. This variable is for the total volume of small trades for the month and is scaled in this study to be in millions of dollars. The reason that this variable is theoretically important relates back to the entropy of the iceberg discussed earlier in the “Iceberg Analogy”. When the iceberg is floating in the ocean it is going through progressive stages of the entropy process. It is melting and this is a one-way process. The smaller pieces of ice and water coming off the iceberg do not re-aggregate into larger pieces or return to increase the mass of the iceberg, therefore if one measured the smaller pieces of ice and water coming off the iceberg one should observe that the volume of melted iceberg should be ever increasing and as such should indicate the iceberg’s stage of entropy. Indeed, Figure 8 below lends empirical support to the volume of small trades increasing as liquidity decreases.

The upper graph in Figure 8 plots the average turnover ratio for large trades, in the first 24 months of a corporate bond’s life; also shown is a fitted smooth curve with a standard error band. The shape of this curve demonstrates the steep initial decline in liquidity that this dissertation contends is generalizable to nearly all fixed income issues. A notable exception would be convertible bonds which are an equity hybrid giving them a much different liquidity profile which is why they are not included in the sample. The shape of this curve is remarkably robust. This was determined by dividing the data into five subsets, representing the different economic cycles that occurred over the course of the study period, and re-fitting the curve to each period. The shape of the curve remained substantially the same in each instance. This consistency through changing economic cycles may suggest that the entropy process is largely unaffected by general market conditions. During the 99-month time period of the study, the five distinct periods observed were (1) the normal period before the GM/Ford crisis -

January 2003 to March 2005, (2) the crisis period that was the GM/Ford Crisis - March 2005 to January 2006, (3) the following normal period before the Subprime Mortgage Crisis - January 2006 to July 2007, (4) the crisis period that was the Subprime Mortgage Crisis - July 2007 to January 2009, and (5) the normal period from then to the end of the study - January 2009 to March 2011 (timeline adapted from Friewald et al. 2012) [27].

One possible explanation for this robustness in the pattern of early liquidity, in spite of differing economic climates, may be due to self-selection. The possibility must be recognized that a corporation would not bring a bond issue to market unless there was some expectation that the issue would trade well, at least initially. Such considerations would also naturally guide the size of the issue that a given firm might select to bring to market. Therefore, the specific firm effects that lead firms to choose to issue debt in the corporate bond market may be the same effects responsible the similar trading patterns of new issues.

The lower graph in Figure 8 plots the average turnover ratio for small trades, in the first 24 months of a corporate bond's life; also shown is a fitted smooth curve with a standard error band.

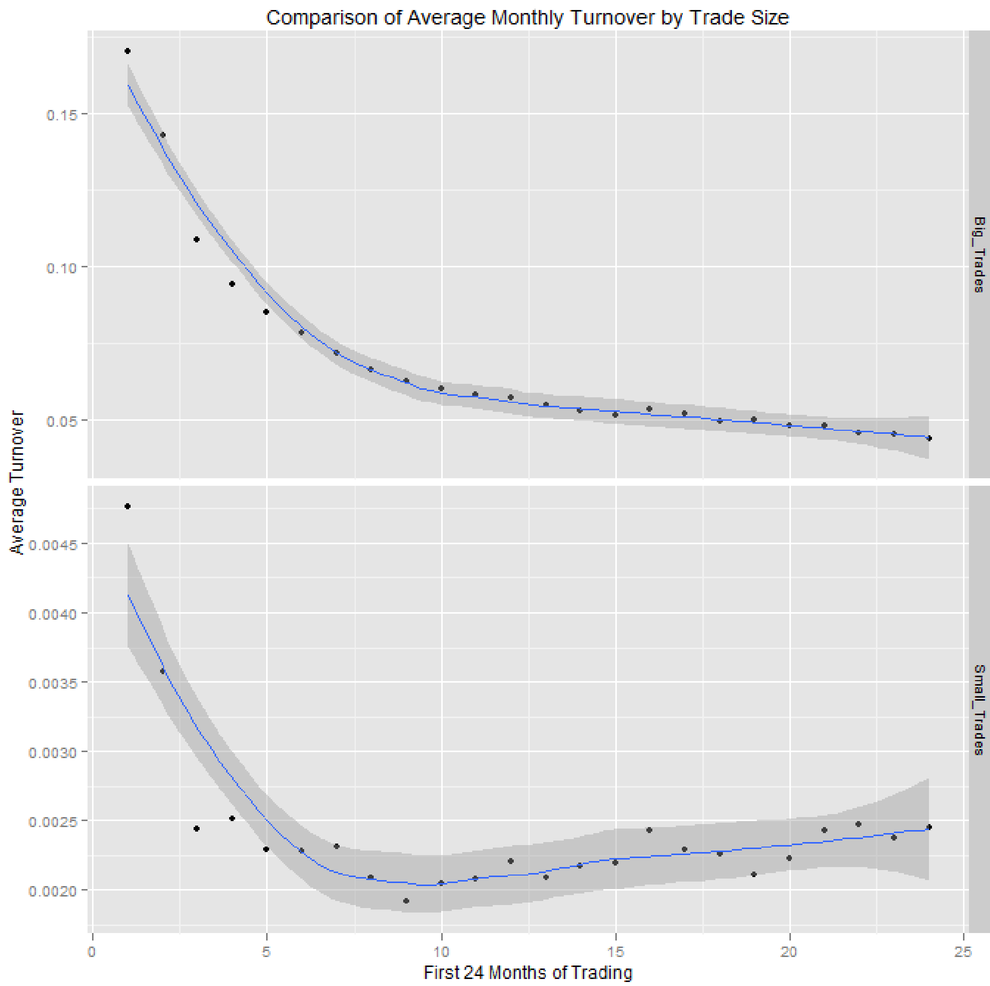

Figure 8 First 24 months of trading

This figure shows two graphs that plot average monthly issue turnover for large trades (upper graph) of $1 million or more and small trades (lower graph) of $100,000 or less, during the first 24 months of trading in the secondary market for the bond issues in the study. Both plots display a smooth curve fitted using the lowness algorithm along with a standard error band. It should be noted that, just before the 10th month, the negative slope of the curve in the upper graph becomes more gradual and steady, where the slope of the curve in the lower graph changes from negative to positive.

Considering both the upper and lower graphs, the shape of the curve was substantially unchanged for the first 10 months of a corporate bond's life, on average, for big trades, no matter which cyclic period was being observed.

It should also be noted here that the appearance of the curve for large trades closely resembles the entropy curve found in nature, particularly with respect to the discontinuity of slope. By this I referred to the initial steep decline to an area in the curve where the slope changes to a more gradual, nearly monotonic decline in turnover. This area is found just prior to corporate bonds becoming 10 months old.

The lower graph in Figure 8, the average turnover ratio curve for small trades, does not maintain its shape when fitted to subsets of the data reflecting different economic cycles. This is why the data points here are so jittery. In spite of greater variance, by the 10th month of a corporate bond's life, it seems clear that the slope of turnover in small trades changes from negative to positive, in general. This is a departure from the behavior of the curve showing turnover for large trades (which, again, becomes monotonically negative, albeit with less severe slope), and hence may lend support to the alternate of *H5- Increasing trading volume occurring in small transactions is consistent with an increase in Liquidity.*

The remaining three variables in the correlation matrix are the dichotomous (dummy) variables, (1) ***dum.dec***, (2) ***dum.sngl***, and (3) ***dum.onrun***. These variables are set to one "1" if for (1) the bond-month observation is in the month of December, for (2) the bond-month observation refers to a corporate bond that is the only (single) issue from that issuer in the market/sample, and for (3) the bond-month observation refers to a corporate bond that is the latest issue in the market/sample from an issuer that has other similar issues in the market/sample. Otherwise, the value is set to zero "0".

The variable ***dum.dec*** was created as one of a set of 11 dichotomous variables used to specify the 12 months of the year in order to test for seasonality in liquidity. The variable was retained as the effect of a bond-month being a December month demonstrated a significantly negative effect on liquidity.

The variable ***dum.sngl*** was created to test claims in prior literature that bonds from issuers who come to the debt market with multiple issues enjoy greater liquidity in the secondary markets.

The variable ***dum.onrun*** was created to test the on-the-run phenomenon.

Mann–Whitney–Wilcoxon rank-sum test

In order to make assertions about the on-the-run phenomenon and its behavior, it is incumbent on this dissertation to verify the existence of the on-the-run phenomenon in the sample data. The Mann–Whitney–Wilcoxon rank-sum test is used to verify the existence of the on-the-run phenomenon in the sample data. This is a non-parametric statistical test and, as such, does not require the assumption of normality in the data. The primary assumptions that must be met for validity in this test are that all the observations from both groups are independent of each other and that the responses are ordinal (i.e. one can at least say, of any two observations, which is the greater).

I formed the two groups, for the purpose of this testing, as matched-pairs of corporate bond liquidity observations that are from a common issuer in a common bond-month. The liquidity of the most recent issue from a given issuer is designated with the on-the-run liquidity variable, ***on.liq***, while that for the next most recent issue from the issuer is designated with the off-the-run liquidity variable, ***off.liq***. I named this data set **wilcox.data**. Hence, each observation in **wilcox.data** contains both the on-the-run observed bond liquidity, ***on.liq*** and the off-the-run observed bond liquidity, ***off.liq***, for each issuer, in each month of the study in which said issuer has at least two issues in the sample. The **wilcox.data** data set has 25,894 records. Each record in the data set, used for this test, is unique in its combination of four variables which are 1) month, 2) year, 3) most recent bond issue, and 4) second most recent bond issue; however the two bond issues must come from the same issuer. And, only the two most recent issues from each issuer are used. All other issues are dropped for this test which includes all other outstanding issues that do not meet the above criteria and all outstanding issues from those issuers that have only one issue in the sample.

The following information describes the data. Of the 25,894 records (bond-months) in **wilcox.data**:

- 10,678 (41.2%) have ***on.liq*** values equal to zero.
- 12,329 (47.6%) have ***off.liq*** values equal to zero.
- 8,495 (32.8%) have both ***on.liq*** and ***off.liq*** values equal to zero.
- 3,834 (14.8%) have a positive value for ***on.liq*** while ***off.liq*** is equal to zero.
- 2,183 (8.4%) have a positive value for ***off.liq*** while ***on.liq*** is equal to zero.
- 65 (0.25%) have ***on.liq*** equal to ***off.liq***, when both are positive.
- 7,100 (27.4%) have ***on.liq*** greater than ***off.liq***, when both are positive.
- 4,217 (16.3%) have ***off.liq*** greater than ***on.liq***, when both are positive.

I conducted two tests. The results of the first test, as shown immediately below, shows that the liquidity for on-the-run corporate bonds and off-the-run corporate bonds is significantly different. The null hypothesis of "no difference" interpreted by test software as "no location shift" is rejected in favor of the "Alternate Hypothesis", the means show a difference that is statistically significant.

Wilcoxon signed rank test with continuity correction

- data:wilcox.data$*on.liq* and wilcox.data$*off.liq*
- V = **101574175,** p-value = < 2.2e-16
- Alternative Hypothesis: true location shift is not equal to 0

The result of the second test, as shown immediately below, has equal statistical significance, however this test shows that on-the-run liquidity is significantly greater than off-the-run liquidity. Again, the null hypothesis of "no difference" interpreted by test software as "no location shift" is rejected in favor of the "Alternate Hypothesis"; the mean of ***on.liq*** is greater than that of ***off.liq,*** and that inequality is statistically significant.

Wilcoxon signed rank test with continuity correction

- data:wilcox.data$*on.liq* and wilcox.data$*off.liq*
- V = **101574175,** p-value = < 2.2e-16
- Alternative Hypothesis: true location shift is greater than 0

Therefore, as expected, the on-the-run phenomenon is present in the corporate bond sample data used in this study.

Model Discussion

I develop a regression-based approach to test how well entropy and other predictor variables estimate liquidity, following the series of equations discussed in this section. The initial model for estimating liquidity consistent with the theory of this dissertation and preliminary examination of the data is shown below.

$$\begin{aligned} Liquidity_{i,j} = \beta_0 + \beta_1 amt.out.m_{i,j} + \beta_2(1/age_{i,j}) \\ + \beta_3 rating_{i,j} + \beta_4 coupon_{i,j} + \beta_5 init.mat_{i,j} \\ + \beta_6 E_{i,j} + \beta_7 vol.trd.le100k.m_{i,j} \\ + \beta_8 dum.dec_{i,j} + \beta_9 dum.sngl_{i,j} + \epsilon_{i,j} \end{aligned} \tag{10}$$

Table 3 Regression results for estimating liquidity using Equation 6.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	-2.139e+07	1.237e+06	-17.297	< 2e-16	***
amt.out.m	6.677e+04	3.905e+02	170.993	< 2e-16	***
I(1/age)	1.373e+08	1.074e+06	127.814	< 2e-16	***
rating	-8.754e+05	5.687e+04	-15.394	< 2e-16	***
coupon	3.254e+05	1.216e+05	2.676	0.00745	**
init.mat	1.175e+03	3.549e+01	33.111	< 2e-16	***
E	7.490e+06	1.293e+05	57.924	< 2e-16	***
vol.trd.le100k.m	3.211e+06	6.128e+04	52.392	< 2e-16	***
dum.dec	-5.524e+06	5.140e+05	-10.748	< 2e-16	***
dum.sngl	8.522e+05	4.015e+05	2.122	0.03381	*

--- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

- Residuals standard error: 50402534.5679 on 123183 degrees of freedom
- Multiple R-Squared:**0.4438**
- Adjusted R-Squared:**0.4437**
- F-statistics: **10919.5346** on 9 and 123183 DF. P-value: **0**.

The data used for the above regression, Equation 6, was the full data set describes in Section 7.2, “Data Sample Selection”; the sample size is approximately 123,000 after removing 69 outliers/extreme points.

The variable for age has been transformed in this initial model, Equation 6, because, as discussed earlier, the relationship between age and liquidity is not linear. Using the reciprocal of age provided a better fit than a log-transformation of the *age* variable. To demonstrate the improvement of this non-linear transformation on the age variable, I next show the model without transforming *age* and compare the difference.

In Equation 11 below the *age* variable is not transformed.

$$\begin{aligned} Liquidity_{i,j} = \beta_0 + \beta_1 amt.out.m_{i,j} + \beta_2 age_{i,j} + \beta_3 rating_{i,j} \\ + \beta_4 coupon_{i,j} + \beta_5 init.mat_{i,j} + \beta_6 E_{i,j} \\ + \beta_7 vol.trd.le100k.m_{i,j} + \beta_8 dum.dec_{i,j} \\ + \beta_9 dum.sngl_{i,j} + \epsilon_{i,j} \end{aligned} \tag{11}$$

Table 3 showed a higher coefficient of determination (R-Squared), 0.4437, compared to that shown in Table 4, 0.3797, solely because of the non-linear transformation of the *age* variable. Using the reciprocal of the age in months created a more linear relationship to the variable for liquidity than using the age in months un-transformed.

Table 4 Regression results for estimating liquidity using Equation 7**.**

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	-9.594e+06	1.319e+06	-7.271	3.59e-13	***
amt.out.m	6.503e+04	4.339e+02	149.878	< 2e-16	***
age	-1.492e+05	3.394e+03	-43.970	< 2e-16	***
rating	-8.232e+05	6.025e+04	-13.664	< 2e-16	***
coupon	7.043e+05	1.380e+05	5.102	3.37e-07	***
init.mat	1.420e+03	3.993e+01	35.563	< 2e-16	***
E	8.932e+06	1.386e+05	64.444	< 2e-16	***
vol.trd.le100k.m	3.163e+06	6.472e+04	48.879	< 2e-16	***
dum.dec	-5.194e+06	5.427e+05	-9.570	< 2e-16	***
dum.sngl	2.545e+06	4.246e+05	5.995	2.04e-09	***

--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

- Residuals standard error: 53224627.2936 on 123183 degrees of freedom
- Multiple R-Squared: **0.3797**
- Adjusted R-Squared: **0.3797**
- F-statistics: **8379.3219** on 9 and 123183 DF. P-value: **0**.

However, a general rule for data analysis is that, "…for any strictly positive variable with no fixed upper bound whose values cover two or more orders of magnitude (i.e. powers of 10), replacement of the variable by its logarithm is likely helpful." (Fox and Weisberg, p. 129)[64] The use of logarithms essentially scales down the large values of my dependent variables and spreads them out. Therefore, I take the log of the dependent variable as shown in Equation 8 below and display the estimation results in Table 5.

$$\log(Liquidity_{i,j} + 1) = \beta_0 + \beta_1 amt.out.m_{i,j} + \beta_2(1/age_{i,j}) + \beta_3 rating_{i,j} + +\beta_4 coupon_{i,j} + \beta_5 init.mat.m_{i,j} + \beta_6 E_{i,j} + \beta_7 vol.trd.le100k.m_{i,j} + \beta_8 dum.dec_{i,j} + \beta_9 dum.sngl_{i,j} + \epsilon_{i,j} \quad (12)$$

The logarithmic transformation of the dependent variable in Equation 8 above takes the natural log of the liquidity variable and, because there are zeros in the data, a one is added to the variable before the transformation.

Table 5 Regression results for estimating liquidity using Equation 8.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	7.827e+00	1.663e-01	47.061	<2e-16	***
amt.out.m	6.610e-03	5.252e-05	125.852	<2e-16	***
I(1/age)	7.029e+00	1.445e-01	48.662	<2e-16	***
rating	-2.047e-01	7.649e-03	-26.766	<2e-16	***
coupon	-4.385e-01	1.635e-02	-26.814	<2e-16	***
init.mat	6.143e-05	4.774e-06	12.867	<2e-16	***
E	2.090e+00	1.739e-02	120.163	<2e-16	***
vol.trd.le100k.m	-7.191e-02	8.242e-03	-8.724	<2e-16	***
dum.dec	-1.026e-01	6.913e-02	-1.484	0.138	
dum.sngl	-7.715e-01	5.401e-02	-14.286	<2e-16	***

--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

- Residuals standard error: 6.7794 on 123183 degrees of freedom
- Multiple R-Squared: **0.3593**
- Adjusted R-Squared: **0.3593**
- F-statistics: **7676.0019** on 9 and 123183 DF. P-value: **0**.

Because the R-square is lower than that of the previous model, it is likely that the transformation of the age variable is no longer advisable. Equation 9 maintains the transformation of the dependent variable, from Equation 8, but removes the transformation from the *age* variable, as shown below.

$$\log(Liquidity_{i,j}+1)=\beta_0+\beta_1 amt.out.m_{i,j}+\beta_2 age_{i,j}+$$
$$\beta_3 rating_{i,j}++\beta_4 coupon_{i,j}+\beta_5 init.mat.m_{i,j}+\beta_6 E_{i,j}+ \quad (13)$$
$$\beta_7 vol.trd.le100k.m_{i,j}+\beta_8 dum.dec_{i,j}+\beta_9 dum.sngl_{i,j}+\epsilon_{i,j}$$

The estimation of Equation 9, shown below in table 6, shows some improvement over 0.3593, but, at 0.3931, its R-Squared is still significantly less the 0.4438 estimated earlier for the model in Equation 6, shown in Table 3.

Table 6 Regression results for estimating liquidity using Equation 9.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	5.772e+00	1.636e-01	35.289	< 2e-16	***
amt.out.m	5.158e-03	5.379e-05	95.899	< 2e-16	***
age	-4.071e-02	4.208e-04	-96.750	< 2e-16	***
rating	-1.529e-01	7.469e-03	-20.468	< 2e-16	***
coupon	9.951e-02	1.711e-02	5.815	6.07e-09	***
init.mat	2.114e-04	4.950e-06	42.707	< 2e-16	***
E	2.398e+00	1.718e-02	139.556	< 2e-16	***
vol.trd.le100k.m	-6.331e-02	8.023e-03	-7.891	3.01e-15	***
dum.dec	-4.376e-02	6.728e-02	-0.650	0.515	
dum.sngl	-4.658e-01	5.263e-02	-8.851	< 2e-16	***

--- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

- Residuals standard error: 6.5981 on 123183 degrees of freedom
- Multiple R-Squared: **0.3931**
- Adjusted R-Squared: **0.3931**
- F-statistics: **8865.8035** on 9 and 123183 DF. P-value: **0**.

Changing the transformation function of the dependent variable (and leaving the *age* variable untransformed) proves to be the best solution. Taking the square root of the dependent variable does not require adding one to the dependent variable and provides the model with the best R-Squared. See Equation 10, for the model, and Table 7, for the regression estimation, below.

$$\sqrt{Liquidity_{i,j}} = \beta_0 + \beta_1 amt.out.m_{i,j} + \beta_2 age_{i,j} + \beta_3 rating_{i,j} + \beta_4 coupon_{i,j} + \beta_5 init.mat.m_{i,j} + \beta_6 E_{i,j} + \beta_7 vol.trd.le100k.m_{i,j} + \beta_8 dum.dec_{i,j} + \beta_9 dum.sngl_{i,j} + \epsilon_{i,j} \tag{14}$$

Table 7 Regression results for estimating liquidity using Equation 10.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	5.295e+02	6.990e+01	7.575	3.61e-14	***
amt.out.m	4.088e+00	2.299e-02	177.827	< 2e-16	***
age	-1.686e+01	1.798e-01	-93.743	< 2e-16	***
rating	-7.281e+01	3.192e+00	-22.811	< 2e-16	***
coupon	8.358e+01	7.313e+00	11.429	< 2e-16	***
init.mat	1.143e-01	2.115e-03	54.016	< 2e-16	***
E	9.704e+02	7.343e+00	132.153	< 2e-16	***
vol.trd.le100k.m	1.231e+02	3.429e+00	35.918	< 2e-16	***
dum.dec	-2.823e+02	2.875e+01	-9.817	< 2e-16	***
dum.sngl	6.023e+01	2.249e+01	2.678	0.00741	**

--- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

- Residuals standard error: 2819.8198 on 123183 degrees of freedom
- Multiple R-Squared: **0.5382**
- Adjusted R-Squared: **0.5382**
- F-statistics: **15954.3867** on 9 and 123183 DF. P-value: **0**.

This model, as specified by Equation 10, has the highest R-Squared of all that were tested, at 0.5382.

The best model developed herein and set forth in Equation 10 is the model used from this point forward in this dissertation to present findings and advance theory.

Chapter 9 The Model

The model set forth in Equation 10, the estimation of which is shown in Table 7, of the previous section is the baseline model that I use to explain the on-the-run phenomenon, make assertions about the entropy measure's ability to estimate liquidity, examine the hypotheses of this dissertation, and make the case that the entropy measure should be made a mandatory component of accounting information. The validity of the assumptions about the probability distribution generating the data that justify the use of a parametric model is addressed in the Appendix, which is available upon request. The baseline model explains 54% of the variation in liquidity.

Empirical Results

Single Issues

The low-hanging fruit to be gathered from the model, before any further changes are made for hypothesis testing, is that ***dum.sngl*** is the least significant variable in the model. This is the dichotomous variable that shows the effect on a bond's liquidity due to the circumstance that the bond is issued by an issuer who has no other bond issues in the market/sample (i.e. the bond was issued by a single-issue issuer). Prior literature holds that multi-issue issuers should enjoy greater liquidity, because having multiple issues in the market increases a firm's "visibility" (Chang, Kedia, Wei, and Zhou) [11]. The estimation of the model shown in Table 7, shows that the sign of the effect is positive, which is not consistent with expectation, and the t value is the weakest in the model, at 2.678, therefore, therefore I do not find an effect for the aspect of "visibility " attributable to having additional issues in the corporate bond market.

Hypothesis One

Table 7 shows that the entropy measure, ***E***, has the largest effect size, 970.4, and second highest t value (t-statistic), 132.2. Therefore, $H1_0$ is rejected and I find that the entropy measure adds statistically significant model precision in estimating corporate bond liquidity (i.e. $H1_A$ is accepted).

Hypothesis Two

Table 7 shows that the issue size, ***amt.out***, is significant (in fact, it has the highest t value of the independent variables in the model at 177.8); I reject the null hypothesis, $H2_0$, and find that outstanding issue amount positively affects liquidity.

Hypothesis Three

While bond characteristics coupon size and initial maturity are statistically significant, they have a small effect size when compared with entropy. So again, we reject the null but make the point that it is the entropy measure that has the largest effect size in the model.

Hypothesis Four

To obtain, empirical results for Hypothesis Three, *H3*, utilize two regression models for comparison purposes. The first is a univariate model using the dichotomous (dummy) variable for the on-the-run issues, ***dum.onrun***, as shown in Equation 11 below.

$$\sqrt{Liquidity_{i,j}} = \beta_0 + \beta_1 dum.onrun_{i,j} + \epsilon_{i,j} \tag{15}$$

The second is a modification of the baseline model to include ***dum.onrun***. The modified model is shown in Equation 12 below.

$$\sqrt{Liquidity_{i,j}} = \beta_0 + \beta_1 amt.out.m_{i,j} + \beta_2 age_{i,j} + \beta_3 rating_{i,j} + \beta_4 coupon_{i,j} + \beta_5 init.mat.m_{i,j} + \beta_4 E_{i,j} + \beta_5 vol.trd.le100k.m_{i,j} + \beta_6 dum.dec_{i,j} + \beta_7 dum.onrun_{i,j} + \epsilon_{i,j} \tag{16}$$

The data set for both estimates is modified to exclude the bond-months of corporate bond issues from single-issue issuers (i.e. exclude bond-months where ***dum.sngl*** = 1). Tables 8 and 9, on the following page, show the estimates for both models.

Table 8 Regression results for estimating liquidity using Equation 11.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	2591.73	14.95	173.36	<2e-16	***
dum.onrun	1427.93	29.90	47.76	<2e-16	***

--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

- Residuals standard error: 4174.2742 on 103951 degrees of freedom
- Multiple R-Squared:**0.0215**
- Adjusted R-Squared:**0.0215**
- F-statistics: **2281.0415** on 1 and 103951 DF. P-value: **0**.

Table 9 Regression results for estimating liquidity using Equation 12.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	137.98686	80.10628	1.723	0.085	.
amt.out.m	4.09912	0.02460	166.598	<2e-16	***
age	-18.23785	0.21709	-84.010	<2e-16	***
rating	-58.04140	3.58493	-16.190	<2e-16	***
coupon	134.91854	8.45566	15.956	<2e-16	***
init.mat	0.10524	0.00228	46.147	<2e-16	***
E	915.72977	8.12031	112.770	<2e-16	***
vol.trd.le100k.m	128.26490	3.58336	35.795	<2e-16	***
dum.dec	-279.20466	31.59850	-8.836	<2e-16	***
dum.onrun	362.66486	21.43129	16.922	<2e-16	***

--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
- Residuals standard error: 2857.2934 on 103942 degrees of freedom
- Multiple R-Squared: **0.5416**
- Adjusted R-Squared: **0.5415**
- F-statistics: **13642.7816** on 9 and 103942 DF. P-value: **0**.

Comparing Tables 8 and 9 above with respect to ***dum.onrun*** shows that the baseline liquidity model (without ***dum.sngl***, of course) explains three quarters of the on-the-run phenomenon. The effect size goes from 1,427.9 down to 362.7. And, the t value drops from 47.8 down to 16.9. Therefore, the null hypothesis, $H3_0$, is rejected in favor of an alternate hypothesis which may indicate that the on-the-run phenomenon is simply reflective of the difference in entropy stages of the two bonds.

To further compare the predictive capability of entropy on liquidity versus that of on-the-run status, the model is run with the on-the-run variable, ***dum.onrun***, and without the entropy variable, ***E***. Those results are shown below as Table 10. And, subsequently the model is run with ***E*** and without ***dum.onrun***. And, those results are shown as Table 11.

In comparing the variable coefficients to document the difference in effect size and model R-squares to establish which included variable constructs a model that better explains liquidity, reveals that entropy has nearly double the effect size of the on-the-run status of a corporate bond 470.6 versus 921.9, respectively. Further, the model that employs E (the results of which are shown in Table 10)), proves better at explaining liquidity than the model that employs the on-the-run status variable (the results of which are shown in Table 11, because the former model shows a higher R-Squared value, 0.540 versus 0.486, respectively.

Therefore, this is confirmation that *E* has greater explanatory capability than a corporate bond's status as being on or off the run. In light of E, there is little more information about to be gleaned about the liquidity of a bond by considering the on-the-run effect.

Table 10 Regression results for estimating liquidity using equation 12 excluding the variable for entropy, *E*.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	2,575.0000	81.7200	31.504	< 2e-16	***
amt.out.m	4.7600	0.0253	188.007	< 2e-16	***
age	-13.9700	0.2265	-61.693	< 2e-16	***
rating	-82.8900	3.7910	-21.867	< 2e-16	***
coupon	9.5650	8.8800	1.077	0.28143	
init.mat	-0.0064	0.0022	-2.94	0.00329	**
vol.trd.le100k.m	290.9000	3.4750	83.707	< 2e-16	***
dum.dec	-267.9000	33.4800	-8.004	1.22E-15	***
dum.onrun	470.6000	22.6800	20.75	< 2e-16	***

--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

- Residuals standard error: 3027.035 on 103944 degrees of freedom
- Multiple R-Squared:**0.4855**
- Adjusted R-Squared:**0.4854**
- F-statistics: **12258.8141** on 8 and 103944 DF. P-value: **0**.

Table 11 Regression results for estimating liquidity using equation 12 excluding the variable for on-the-run status, *dum.onrun*.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	254.4000	79.9200	3.184	0.00145	**
amt.out.m	4.0960	0.0246	166.231	< 2e-16	***
age	-19.1700	0.2103	-91.13	< 2e-16	***
rating	-60.5700	3.5870	-16.888	< 2e-16	***
coupon	145.3000	8.4450	17.209	< 2e-16	***
init.mat	0.1047	0.0023	45.874	< 2e-16	***
E	921.9000	8.1230	113.483	< 2e-16	***
vol.trd.le100k.m	126.2000	3.5860	35.179	< 2e-16	***
dum.dec	-280.6000	31.6400	-8.868	< 2e-16	***

- --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
- Residuals standard error: 2861.2129 on 103943 degrees of freedom
- Multiple R-Squared:**0.5403**
- Adjusted R-Squared:**0.5403**
- F-statistics: **15270.4114** on 8 and 103943 DF. P-value: **0**.

Hypothesis Five

For *H5* I look again to the baseline model. The effect size of small trade volume is the third largest in the model and is statistically significant with a t value of 35.9. Therefore, I reject the null hypothesis. This result confirms that small trade volume increases with liquidity, as expected.

Robustness

One of the problems with significance testing with large sample sizes is that even very small effects can become significant. Mark van der Laan and Sherri Rose (2010) states that "We know that for large enough sample sizes, every study—including ones in which the null hypothesis of no effect is true — will declare a statistically significant effect."[61] Thus, as a robustness test I randomly sample from the data set - 4 random samples of 1,000 – and re-test for significance. I use Equation 12 as my model and present the results side-by-side in Table 12.

Table 12 Robustness Checks

This table shows regression results from estimating liquidity using Equation 12 on four different random samples of 1,000 bond-months, to check robustness.

	RobustCk.1	RobustCk.2	RobustCk.3	RobustCk.4
(Intercept)	176.535	98.712	−1002.888	352.793
	(852.087)	(820.975)	(839.039)	(771.351)
amt.out.m	4.108***	4.280***	4.749***	4.583***
	(0.250)	(0.245)	(0.251)	(0.221)
age	−16.845***	−17.415***	−17.953***	−20.237***
	(2.193)	(2.164)	(2.204)	(2.136)
rating	−24.359	−57.561	−12.097	−40.086
	(38.798)	(36.473)	(38.280)	(34.389)
coupon	106.939	131.478	233.633**	93.697
	(88.929)	(83.402)	(89.872)	(79.993)
init.mat	0.086***	0.109***	0.092***	0.099***
	(0.024)	(0.020)	(0.023)	(0.023)
E	741.211***	1032.401***	810.879***	922.245***
	(80.908)	(83.306)	(83.424)	(79.860)
vol.trd.le100k.m	92.999*	−112.826	132.863***	28.142
	(37.384)	(58.592)	(33.191)	(41.392)
dum.dec	−168.539	−274.954	−22.342	−543.309
	(319.090)	(302.655)	(314.742)	(288.113)
dum.onrun	255.190	177.174	280.576	297.453
	(212.266)	(213.562)	(226.154)	(209.307)
R-squared	0.496	0.549	0.575	0.563
adj. R-squared	0.491	0.545	0.572	0.559
p	0.000	0.000	0.000	0.000
F	108.204	133.721	149.112	141.838
N	1000	1000	1000	1000

The four data sets created from randomly sampling 1,000 bond-month observations from the dissertation data set (after having removed those bonds from single-issuers) show that, in tests using smaller sample sizes, many of the variables in a model that explains over 50% of liquidity fail to maintain significance. The variable for the on-the-run effect, *dum.onrun*, is not significant in any of these random robustness tests and neither are the variables for credit rating, coupon size, initial maturity, and seasonality.

The important variables that drive the model are outstanding issue amount, amount of time outstanding in the secondary market, initial maturity (to a very small effect) and entropy (to a very large effect).

Chapter 10 Market Pricing of Liquidity Using Yield to Maturity

It has been widely documented that liquidity can predict future returns on securities. For example, Amihud and Mendelson (1986) [5] predict in their theory that less liquid securities yield higher expected returns. In this chapter of this dissertation, I study the explanatory power of liquidity on yield to maturity by considering the effects of the on-the-run phenomenon and my measure for liquidity, the entropy measure. If indeed the on-the-run effect and the entropy measure are indicators of liquidity, then they should be priced in a competitive market.

In financial markets, competition between investors to buy those securities that generate the greatest net present value allows us to assume that securities, specifically fixed income corporate bonds, are fairly priced by the market at any given point in time. A simple illustration of the mechanism through which this occurs might begin by considering a situation in which investors perceive that a security offers an abnormally good value. Said investors would rush in to buy this bargain. They will stop buying only when the security offers just a normal rate of return. This is the essence of efficient capital markets. In the case of on-the-run bonds, this pricing efficiency must mean that the premium for the greater liquidity must exist because the on-the-run bond must offer some recognizable value to investors that allow them to forgo the higher returns of a similar security that is less liquid. The fact that the on-the-run bond and the off-the-run bond share a common issuer means that many other reasons for the price differential such as information asymmetry or default risk can be ruled out.

It is the theory of this dissertation that debt securities are most liquid at issuance and from that moment forward liquidity normally diminishes gradually over time. In the first chapter of this dissertation, the analogy of the iceberg was used to describe this process. In this chapter, I seek to verify that theory by examining price effects via liquidity effects on yield to maturity. With fixed-income securities yield moves inversely to price, therefore any effect that lowers the yield on a corporate bond raises its price, and vice versa.

In a study of the Treasury bond market, Warga (1992) [63] uses a sample of issues with similar duration ranges to examine the on-the-run phenomenon and finds that on average on-the-run Treasury bonds have a 55 basis point lower yield than off-the-run Treasury bonds. The large number of treasury issues makes it much less difficult to find off-the-run issues that have matching durations to the on-the-run issues. This dissertation studies the on-the-run phenomenon in the corporate bond market, where the smaller number of issues makes it much more difficult to match durations. However, using OLS regression model, I find a 41 basis point difference between on-the-run and off-the-run issues.

A study by Vayanos (2008) [62] cites two hypotheses for the on-the-run phenomenon, "First, on-the-run bonds are more valuable because they are significantly more liquid than their off-the-run counterparts. Second, on-the-run bonds constitute better collateral for borrowing money in the repo market." Further, the Banerjee and Graveline (2013) [8] study also characterizes the on-the-run phenomenon as a liquidity premium reflecting, "the future benefits that long investors attribute to securities that can be sold quickly and with little price impact." But also add that, "short-sellers themselves may also value a liquid security over and above the higher sale price they receive. When closing out a position, short-sellers are required to deliver the specific security that they initially borrowed and sold short. As such, they naturally prefer to use liquid securities that can be bought back easily."

Anecdotal observations of liquidity using yield to maturity data

This section will show figures in which yield to maturity data points will illustrate when bonds are liquid, illiquid and when bonds undergo rapid change from one state to the other. Part of the reason to make such observations is to facilitate the discussion about an important difference between the entropy measure and the price dispersion measure.

The first graph below is included to illustrate that it is possible to observe liquidity via a scatterplot of data points representing the various transactions, the yield to maturities of which are represented on the y-axis, where the x-axis represents time.

The bond issue for which the activity is shown in Figure 9, below, is the Cisco Systems Inc. 5 ¼% debentures due in 2011. This is a large issue, $3 billion in amount outstanding that was issued in 2006. This is a very late corporate bond. One can see that the transactions as plotted seem to form a dark, tight rope or band in the early years, becoming just a bit more frayed in the later years.

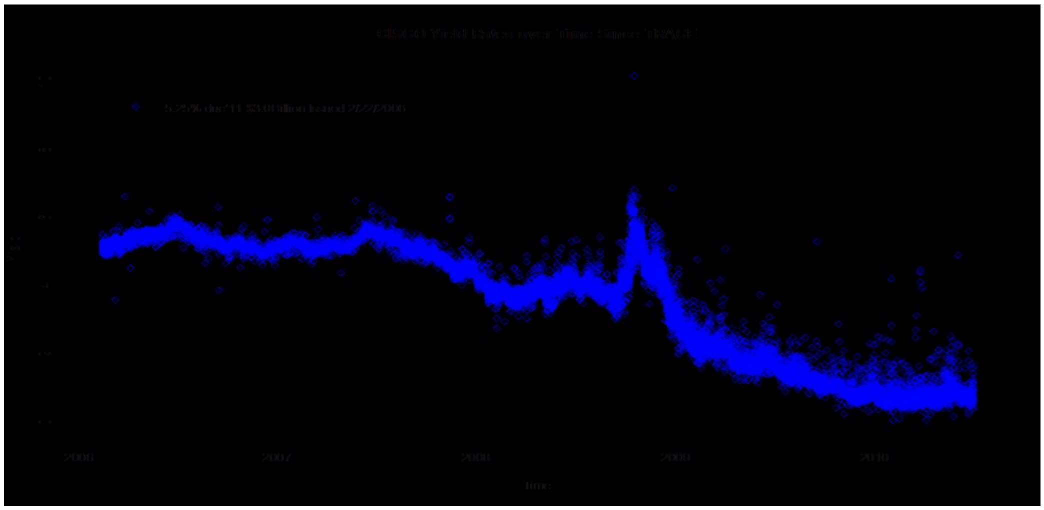

Figure 9 Plot of a very liquid bond

This graph shows an example of a very liquid bond.

In contrast, the Cisco Systems issue in Figure 9 above is observably much more liquid than the Bristol-Myers issue depicted in Figure 10 below.

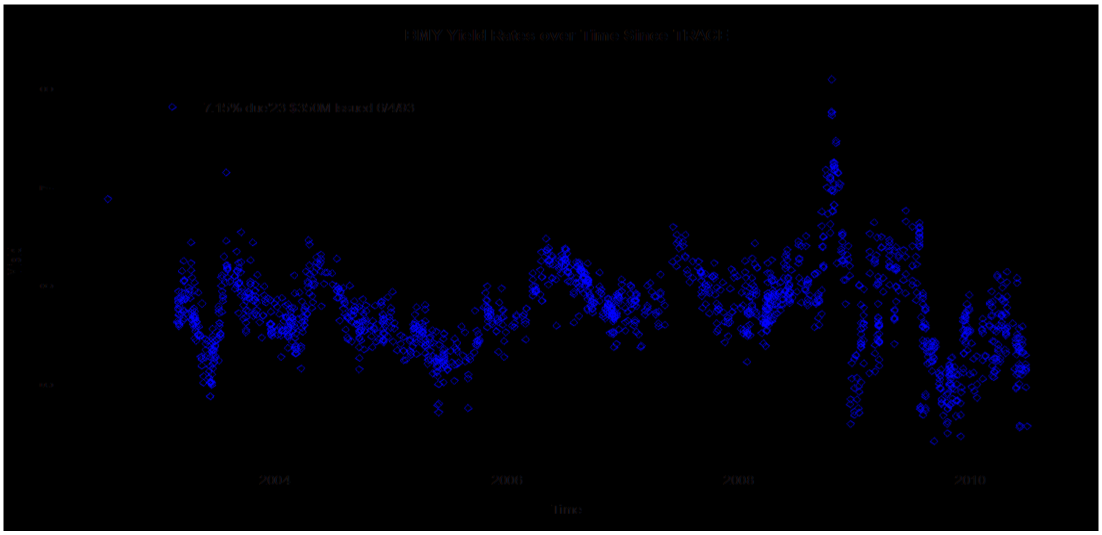

Figure 10 Plot of an illiquid bond

This graph shows an example of an illiquid bond.

The Bristol-Myers Inc. bond issue, the transactions over time for which are plotted in Figure 10 above, is much smaller than the Cisco Systems Inc. issue, $350 million versus $3 billion, respectively. The Bristol-Myers bond issue has been outstanding in the market for much longer as it was issued in 1993 as compared to 2006 for the Cisco bond issue. One can see that the trading in this issue is not a dark, tight rope. It is more loose, frayed or dispersed in appearance. And as such, shows that the Bristol-Myers bond is observably much less liquid, i.e. illiquid.

Figure 10 below shows that changes in liquidity are also observable in scatter plots. The bond depicted in Figure 10 is issued by Altria Group, Inc. (previously named Philip Morris Companies Inc.). The bonds are the 7 ¾% debentures due in 2027 and were issued in 1997. The bond issue was observably liquid until apparently something happened in early 2008. One can see that the tight, dark rope frayed or dispersed at that point clearly showing that what was once a very liquid issue has suddenly become illiquid, or at least a lot less liquid. The event that caused this was that Altria group Inc. was dropped from the Dow Jones Industrial Average, on February 19, 2008. Losing its status of being a Dow Jones Index company meant that a significant number of index funds stop trafficking in Altria Group, Inc. securities, and thus the bonds became much more illiquid.

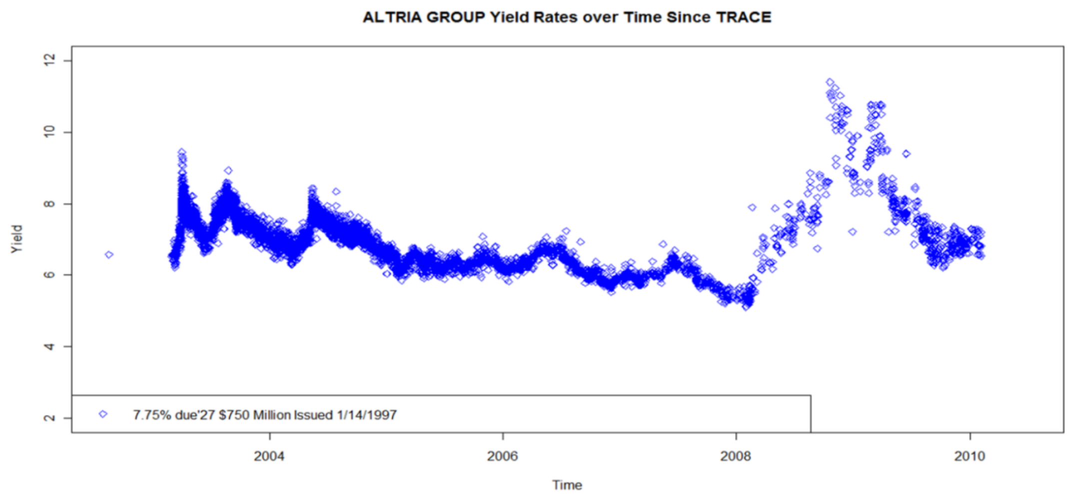

Figure 11 Plot of a liquidity change

This graph shows a change in liquidity.

Further scrutiny of the Altria Group, Inc. bond issue shown above in Figure 11, reveals that after becoming illiquid for time in early 2008 the bond becomes more liquid towards the end of 2008. This is because Altria Group, Inc. came to market at the end of 2008 with a new issue, the 8 ½% debentures due in 2013. The brokerage industry swapped many holders out of the 7 ¾% bonds and into the 8 ½% bonds, retiring nearly all of the outstanding 7 ¾% bonds. Figure 12 below shows the scatterplot of the transaction histories of the two bonds.

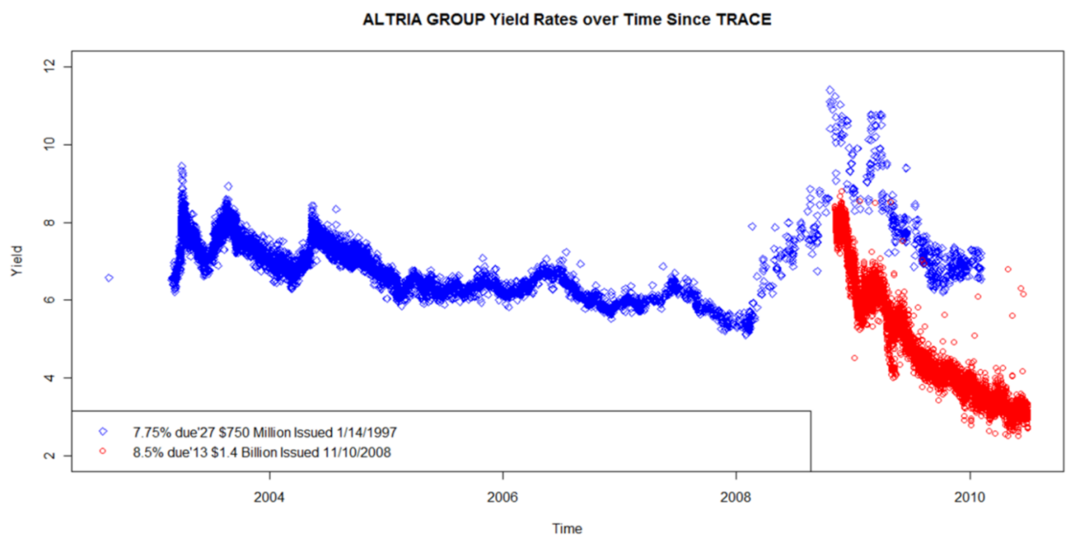

Figure 12 Plot of liquidity effect of new issue

This graph shows the reason for the re-emergence of liquidity in the previous graph: a new bond was issued and the brokerage industry swapped many holders of the old bond (in blue) into the new bond (in red).

From the foregoing scatter plots, it is easy to see how price dispersion could seem like an attractive method for measuring illiquidity. In fact I used the terms, "…frayed or dispersed" to describe the appearance of bond issues that were illiquid. The data points in the illiquid Bristol-Myers bond appeared to have great dispersion. The price dispersion measure is heralded in Jankowitsch et al. (2011) [38] as the premier method for assessing bond liquidity. And while I believe that the price dispersion measure is superior to the measures that came before it, it has two drawbacks that I can discern. The minor concern is that the centeredness variable (i.e. the bond price, which I assume to be at or near the center point of the price dispersion) comes from outside of the data. The centeredness measure is the value of the bond denoted by the price, which is obtained by purchase from a commercial vendor, the Markit Group, Limited. This naturally introduces skewness into any resulting spread measure.

Markit Group's website says that the company arrives at the corporate bond prices that it reports through a combination of consensus data and proprietary models. There is no real information on how they arrive at their pricing. The company is private and has been described as having an almost monopolistic grip on the reporting of credit default swap prices.

Markit Group was co-founded by Rony Grushka, Lance Uggla, and Kevin Gould. Their website claims that they provide transparency to the market, but they themselves are a "London-based black box". It seems that four hedge funds are also co-founders of the company, but Markit refuses to disclose the names of those hedge funds. It does say however, that no one owner has a stake larger than 15%, but won't say who those owners are much less give any ownership percentages. The company is criticized in the media for being "secretive". It has admitted to using a number of "contributors" in arriving at prices.

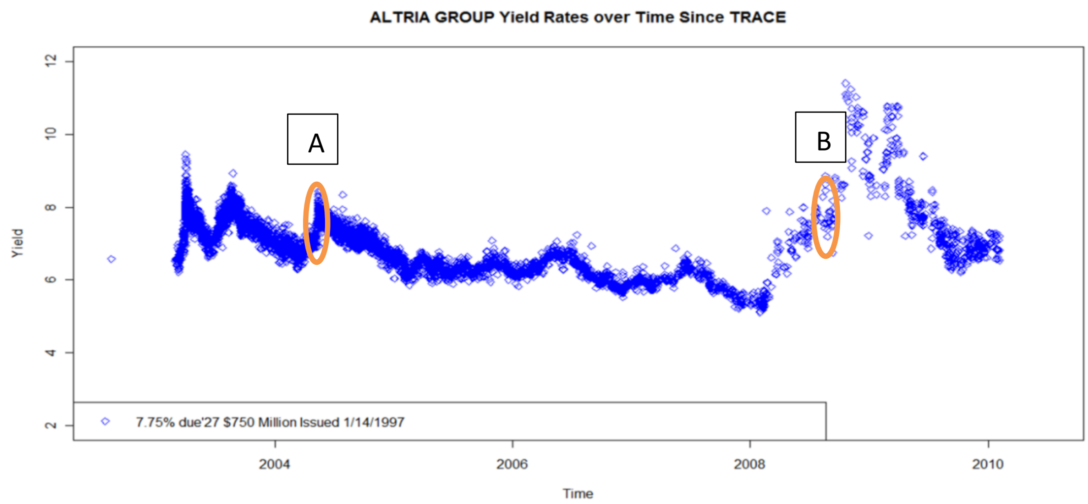

Figure 13 Plot of illiquidity versus price discovery

This is the same scatterplot as displayed Figure 11 reprinted here to point out two specific areas for the discussion on why price dispersion cannot distinguish "illiquidity" from "price discovery".

The skewness in a spread measure such as standard deviation in a situation, where the data are not used to derive the center value, results from the error introduced by the distance of the purchased centeredness value from the true center of the data.[7]

But, the most troubling concern with the price dispersion measure in my opinion is its inability to distinguish "illiquidity" from "price discovery". Figure 12 above is the scatter plot reprinted from Figure 11 with two added objects to help illustrate the point. The two added objects are ovals identifying two areas of the scatterplot for the purpose of comparison. The oval to the left is labeled "A" and the oval to the right is labeled "B". The price dispersion in each of the ovals is similar; however the levels of liquidity are vastly different. This is an example where the price dispersions are

[7] And incidentally, I am not able in this dissertation to compare my entropy measure to the price dispersion measure as set forth in Jankowitsch et al. (2011) [31], because calculating the measure would require purchasing bond price quotes from Markit Group, Limited.

approximately the same; therefore the price dispersion measure would hold that liquidity for the two periods are the same and that would be incorrect. The price dispersion in oval “B” does, in fact, reflect illiquidity, but the price dispersion in oval “A” reflects price discovery. The price dispersion measure is not subject to this type of error. As entropy, at its roots, is measure of concentration, and as such, it delineates the concentration of trading activity found to achieve the given volume level. The remaining sections of this chapter examine on-the-run status and the entropy measure to ascertain liquidity price effects for each as reflected by the variations in the yield to maturity that the market requires.

Liquidity pricing effects

As previously discussed, liquidity effects should be priced by the market. But, changes in the current market price of individual bonds are not directly comparable because of differences in par value, coupon interest rate, and time to maturity. Therefore, bond values will be compared, studied, and analyzed on the basis of yield to maturity in this chapter.

The data set described in chapter 6 is the starting point from which the sample selection process is executed to create the data set used for the analysis of the pricing effects of liquidity. The initial data set contains transaction data on more than 8.7 million bond trades, obtained from TRACE data provided by Wharton Research Data Services (“WRDS”) Merging FISD dataset. In this data set is information for daily transactions on 2,899 bond issues from 745 issuers.

Subsample selection

I compiled the data into monthly statistics such that each resulting observation refers to a particular corporate bond issue within a particular month. I referred to these observations as “bond-months”. Strictly speaking, because there are 2,899 bond issues and 99 months in the study it would be possible to have a maximum of 287,001 bond-months (2,899 multiplied by 99). But, not every bond issue was issued and outstanding for every month of the study, therefore the downloaded sample contains information for only 123,209 bond-months.

Further, because of a multitude of adjustments including 593 issues being dropped from the study due to early retirement of greater than 10% of the outstanding debt and other adjustments as outlined in Table 13 below, the sample before pair matching contains 79,619 bond-months. There are 347 issuers represented in these bond-months. As a result of previous screening, each of these issuers has two or more issues in the remaining sample.

To facilitate a study on the effect of the on the run status of a corporate bond a subsample matched pairs is built using the 79,619 bond-month observations. The pair matching based on the two issues from a common issuer that were closest in time to maturity. Therefore, each of the 347 issuers have two bonds in the resulting sample, an on-the-run bond and an off-the-run bond, for a total of 694 bonds for which there are 17,446 bond months.

Table 13 Sample Selection

This table reports the sample selection process in which 745 firms were identified using the SDC Platinum database that issued bonds during the sample period that were not finance companies, insurance companies, or any type of bank or thrift. The bond issues from those firms that are fixed-rate and not convertible number 2,899. The Total Transactions reported for the selected issues from the selected firms during the study period number 8,775,239. The monthly statistics for each bond are grouped into Bond-Months. Each Bond-Month contains statistics for a particular bond in a particular month. All Bond-Months with that less than 90% of their original issue amount outstanding are removed. Also, to reduce errors in bond information on coupon rates, the top and bottom five percent of coupon values are removed from the sample. Further, those issuers that have only one issue in the market provide no basis to study the on-the-run effect; therefore both the issuer and their single issue are removed from the study. Finally, issues are selected in pairs that are from a common issuer, the closest in maturity of all available pairings, and display the on-the-run effect.

Sample Period: Jan.2003–Mar.2011

	Number of Observations	Number of Issues	Number of Issuers
Total Transactions (daily observations)	8,775,239	2,899	745
Total Transactions (monthly composites)	123,209	2,899	745
Less:			
Issues with < 90% of original amount out	(8,713)	(593)	(120)
Issues Winsorized 5% by Coupon	(7,839)	(217)	(35)
Initial Sample of Bond-Months	106,657	2,089	590
Less:			
Observations with missing data	(12,978)	0	0
Single-issue issuers	(11,918)	(184)	(184)
Issues issued on the same day	(2,142)	(118)	(59)
Sample before pair matching	79,619	1,787	347
Nearest-maturity pairs from the 347 issuers	17,446	694	347
Less:			
Pairs Winsorized 1% by yield-to-maturity	462	80	40
Bond-Months with no on-the-run effect	9,332	138	64
Final Sample	7,652	486	243

From the 17,446 bond-month subset, I winsorize the data by 1% on each end by yield to maturity, age, amount outstanding, months to maturity, initial maturity, and coupon to remove what I saw as obvious errors in the data.

The final step in the selection process is to keep only those bond-months that exhibit the on-the-run effect, the effect I wish to study. The final data sample consists of 7,652 bond-months, representing 486 bonds, from 243 issuers, where each bond-month contains statistics regarding an on-the-run bond and an off-the-run bond from a common issuer in a specific month. Having pair the bonds in this way, before separating into individual observations to create the data set, assures that, not only are the on-the-run bonds and the off-the-run bonds properly designated, but for every month that has statistics for one bond, the other bond from the pairing will have statistics, also.

To be concise, the observation unit is a bond-month and what a bond-month is can be explained the observed trading characteristics of a specific bond in a specific month. To make this data set, I put the statistics for two bonds in a month before I broke that month into two bond-months. This was done to ensure that there exited an on-the-run bond-month for every off-the-run bond-month in the final sample. At the end, there were 7,652 bond-months for the yield to maturity part of the study

Variables

The variables created and available for use in this chapter of the study are listed and briefly defined in Table 14 below. The yield to maturity variable, ***ytm***, is being introduced at this point in this dissertation in order to study pricing effects and will be the dependent variable in the forthcoming regression models. Yield to maturity is the anticipated annual rate of return for a bond if it is held until the maturity date. It does not correspond to the rate earned on the bond over any intermediate period. The calculation of yield to maturity takes into account the current market price, par value, coupon interest rate and time to maturity. One specific assumption in the calculation of yield to maturity is that all coupons are reinvested at the same rate. This assumption is understood and generally accepted by investors and trading parties in bond transactions.

Table 14 Description of Variables

This table presents the descriptions and definitions of the variables in the analysis.

Variable	Definition
ytm	The average yield to maturity or internal rate of return earned by investors who bought the bond in the given month.
age	The number of months since the bond was issued.
amt.out	The amount of the issue outstanding, in millions.
init.mat	The initial maturity of the bond issue, in days, i.e. the number of days between the issue date and maturity.
E	The entropy for the bond issue in the given month.
mth.2.mat	The number of months until the bond matures from the given month.
rating	Categorical variable for the Moody's rating, configured such that higher values coincide with higher ratings. Range is 1:20.
px	The average bond price for the month.
riskfr	WRDS - Interest Rates (Federal Reserve, H15 report) reported for monthly AAA bond yield as risk-free rate.
vol.le100k	Volume of trades that are less than or equal to $100,000 in face amount.
coupon	The coupon rate for the bond, also called stated rate or contract rate.
maturity	The date the bond issue matures.
dum.onrun	Dummy variable equal to one if the bond is the newer bond used in this database created from match-paired issues and zero if the older bond.
dum.a	Dummy variable equal to one if the Moody's rating is single A 1, 2 or 3 and zero otherwise.
dum.baa	Dummy variable equal to one if the Moody's rating is Baa 1, 2 or 3 and zero otherwise.
dum.ba	Dummy variable equal to one if the Moody's rating is Ba 1, 2 or 3 and zero otherwise.
dum.b	Dummy variable equal to one if the Moody's rating is single B 1, 2 or 3 and zero otherwise.
dum.c	Dummy variable equal to one if the Moody's rating is C and zero otherwise.
dum.dec	Dummy variable equal to one if the given month is the month of December and zero otherwise.

The risk-free rate is typically defined as the market interest rate for an investment with *certain* cash payments. To the extent that expected cash flows from an investment are less certain, the market requires a risk premium. The effect of liquidity on this risk premium is the subject of this chapter.

Most of the other variables that will be used for modeling in this chapter were previously introduced in earlier chapters, with the exception of the variable for the risk-free rate, ***riskfr***.

And, as this risk-free rate floor is not constant from month-to-month, it is included in all models herein of yield to maturity, as a control. Usually in academic literature, the risk-free rate is taken from the market rates of Treasury bonds, however, since the Treasury index in the WRDS database do not cover the full time period of the study, I used the AAA corporate bond interest rate index as quoted in the Federal Reserve, H15 report.

Fortunately, there is support in prior literature for using the highest quality corporate bond rate instead of the Treasury bond rate as the risk free rate for corporate bonds. In the book Credit Risk Management (Saunders and Allen 2010, pp.74) [56], the authors note that, "the specification of the risk-free rate can be troublesome. Duffee (1998) finds that changes in credit spreads are negatively related to changes in risk-free interest rates for lower credit quality bonds. Although Treasury yields are typically used to measure the risk-free rate, it may be more appropriate to use the highest quality corporate bond yield as the benchmark default-free rate. Part of this stems from the asymmetric tax treatments of corporate and Treasury bonds. Bohn (2000b) claims that use of a default-free (corporate bond) rate is more appropriate."

Table 15 Description of Variables (continued)

This table reports the descriptive statistics for the variables in the analysis.

Variable	min	max	range	median	mean	std.dev
ytm	1.12657	12.17974	11.05317	5.90076	5.75101	1.70165
age	1	228	227	52	61.13382	45.81706
amt.out	5	2500	2495	350	433.2738	320.6851
init.mat	1093	36515	35422	7305	7615.301	4923.055
E	0	6.30323	6.30323	1.92416	1.85363	1.46931
mth.2.mat	10.24342	1132.151	1121.908	150.7895	189.3695	147.1715
rating	3	20	17	13	12.72347	2.63927
px	56.66808	143.2079	86.53977	103.8451	103.335	10.17792
riskfr	4.49045	6.28136	1.79091	5.33095	5.31687	0.35313
vol.le100k	0	75.889	75.889	0.4315	1.40417	3.25512
coupon	3.375	8.5	5.125	6.375	6.31808	1.04249
dum.onrun	0	1	1	0.5	0.5	0.50003
dum.a	0	1	1	0	0.34449	0.47523
dum.baa	0	1	1	0	0.45818	0.49828
dum.ba	0	1	1	0	0.08782	0.28305
dum.b	0	1	1	0	0.05071	0.21941
dum.c	0	1	1	0	0.00078	0.02799
dum.dec	0	1	1	0	0.0886	0.28419

Table 15 above is a continuation of the description of the variables from Table 14 that reports the descriptive statistics of the variables calculated and available for this subsample.

Description of the bond maturities at issuance for the sample data

In this subsection the initial maturities of the corporate bond issues in the observed bond-months for the data sample used in this part of my analysis, specifically regarding yield to maturity, are described. Figure 14 shows a bar plot of the time to maturity (in days), at the time of issuance, for the bond issues in the 7,652 bond-months in this data sample.

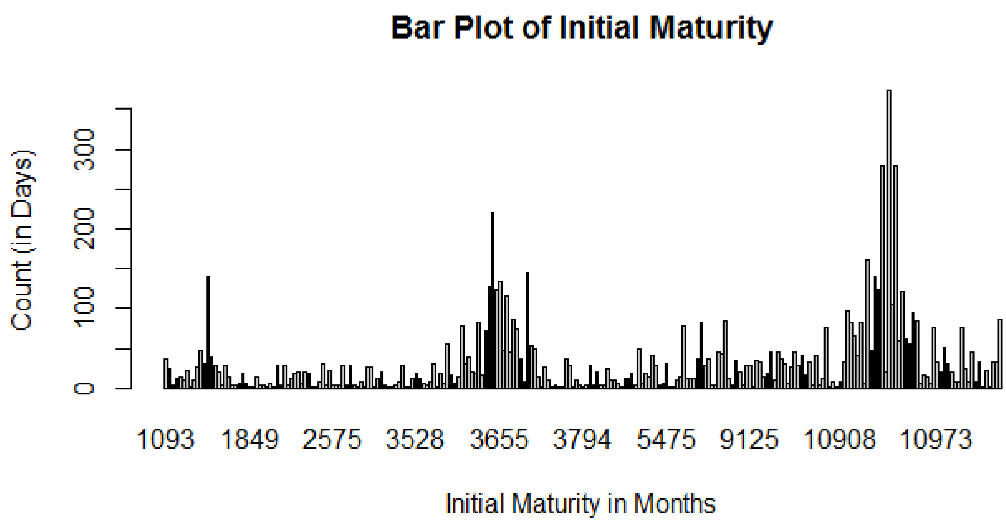

Figure 14 Bar plot of initial maturities

This figure shows a bar plot of the number of bond-month observations (out of a total of 7,652) segmented by the bond issue's initial maturity (in days).

The first spike in Figure 14 represents 5-year maturities; the second spike represents 10-year maturities; the tallest spike represents 30-year maturities; and the raised spike in between the 10- and 30-year spikes represents the 20-year maturities.

Table 16 below supplements the graphic in Figure 14 by showing a more discreet breakdown of the bond-month observations into 5-, 10-, 20-, and 30-year categories.

Table 16 Bond-month observations segmented by maturity

This table shows the number of bond-month observations for four initial maturity categories.

Count of Bond-Month Observations by Maturity

Five-Year	Ten-Year	Twenty-Year	Thirty-Year
522	2,052	399	3,009
6.82%	26.82%	5.21%	39.32%

Table 17 Correlation Matrix

This table reports the correlation matrix, using the “Pearson" method, of the variables available for the analysis. The yield-to-maturity variable, *ytm,* is the dependent variable used in the models.

	ytm	age	amt.out	init.mat	E	mth.2.mat	rating	px	riskfr	vol.le100k	coupon	dum.onrun
ytm	1	0.258	-0.057	0.467	-0.273	0.433	-0.455	-0.560	0.388	-0.106	0.484	-0.122
age	0.258	1	-0.151	0.449	-0.022	0.183	-0.106	0.054	-0.067	-0.050	0.425	-0.363
amt.out	-0.057	-0.151	1	-0.055	0.295	-0.013	0.066	0.117	-0.027	0.285	0.079	0.078
init.mat	0.467	0.449	-0.055	1	-0.486	0.961	0.004	-0.047	0.081	-0.179	0.412	-0.181
E	-0.273	-0.022	0.295	-0.486	1	-0.528	0.026	0.109	-0.064	0.496	-0.148	0.067
mth.2.mat	0.433	0.183	-0.013	0.961	-0.528	1	0.038	-0.068	0.110	-0.181	0.321	-0.086
rating	-0.455	-0.106	0.066	0.004	0.026	0.038	1	0.280	0.015	0.035	-0.367	0
px	-0.560	0.054	0.117	-0.047	0.109	-0.068	0.280	1	-0.358	-0.030	0.285	-0.003
riskfr	0.388	-0.067	-0.027	0.081	-0.064	0.110	0.015	-0.358	1	-0.093	0.036	0
vol.le100k	-0.106	-0.050	0.285	-0.179	0.496	-0.181	0.035	-0.030	-0.093	1	-0.105	0.077
coupon	0.484	0.425	0.079	0.412	-0.148	0.321	-0.367	0.285	0.036	-0.105	1	-0.138
dum.onrun	-0.122	-0.363	0.078	-0.181	0.067	-0.086	0	-0.003	0	0.077	-0.138	1

Table 17 above contains the correlation matrix, using the “Pearson” method for the variables described in Tables 14 and 15. With respect to the dependent variable, ***ytm***, the signs of most of the correlations are as expected. For example, the variable ***age*** is positively correlated with ***ytm***. The positive relationship means that age has a negative effect on bond value i.e. bond price. This relationship reflects the fact that bond yield to maturity and bond price are inversely related. Therefore, the longer a bond issue has been free to trade in the secondary market, which is to say the more seasoned the issue, with all else being equal, the higher the yield to maturity the market will require. And hence, the value of a bond becomes lower as it ages.

So it follows that, given the previous discussion, yield to maturity, ***ytm***, and bond price, ***px***, are negatively correlated. Additionally, the two variables that directly indicate higher bond liquidity, which are the on-the-run status dummy variable, ***dum.onrun***, and the entropy measure, ***E***, are also negatively correlated with ***ytm***. This relationship is consistent with expectation, as the theory of this dissertation and prior academic literature hold that liquidity enhances bond value, and should therefore reduce the market yield required. The amount outstanding, ***amt.out***, is also negatively correlated with ***ytm***, and it is the theory of this dissertation that this is a second-order effect as result of larger outstanding bond issue amounts contributing to greater liquidity. Likewise, because I find (as discussed in earlier chapters) that small trade volume correlates positively with liquidity, it is consistent that the variable for the volume of trades less than or equal to $100,000 in face amount, ***vol.le100k***, negatively correlated with ***ytm***.

The variables for risk-free rate, ***riskfr***, initial maturity, ***init.mat***, and the number of months until maturity, ***mth.2.mat***, are all positively correlated with ***ytm*** as expected. The risk-free rate is such because it is the base or floor rate, on to which all other risk factors are added. As for initial maturity and the number of months until maturity, both indicate longer payback periods which subject the investor to more risk, which is priced.

Creditworthiness is reflected in the variable, ***rating***. Please refer to Table 1 in Chapter 6 for the index of numerical values that correspond to the Moody's ratings used to create this variable. Also note that variables possible values, numbers 1 through 20, have been organized in such a way that the numbers are increasing with higher bond ratings. Higher bond ratings reflect lower risk which is consistent the negative correlation to ***ytm*** i.e. lower required rate of return from the market.

The strongest correlation in Table 17 between any of the independent variables used to explain yield to maturity in the next section is that between ***E*** with ***amt.out***, at 0.295. However, since this correlation is not very large and with the others being significantly smaller, multicollinearity is not a problem here or in the models employed in the upcoming section.

Modeling yield to maturity to analyze the price effect of liquidity

The first of four models used to estimate yield to maturity is Equation 17 below. I consider this equation/model as basically a univariate regression of the on-the-run status variable, ***dum.onrun***, on yield to maturity, because functionally the risk-free rate adjusts the floor for the intercept. The intercept, β_0, plus the product of the coefficient, β_1, multiplied by the risk-free rate is the common floor value that moves each month for the every bond observation in that month. Therefore, the model in Equation 17 may be interpreted as a univariate model with a non-stationary intercept, varying month-to-month for a cross-section of the entire bond sample. The single variable within each cross-section is the on-the-run status of the bonds. The results for the model in

Equation 17 are presented in Table 18 under "Model 1" and serve as a basis to compare to the Warga (1992) [63] findings in the treasury bond market.

$$ytm_{i,j} = \beta_0 + \beta_1 riskfr_{i,j} + \beta_2 dum.onrun_{i,j} + \epsilon_{i,j} \qquad (17)$$

The second of the four models used to estimate yield to maturity is Equation 18 below. This model adds the variables ***age*** and ***E***, in order to compare on the run status to entropy. The variable ***age*** accompanies the variable ***E*** in being added to the model because it is the theory of this dissertation that entropy is a natural, evolutionary process that occurs over time, making age a significant factor in the interpretation of entropy.

Consider heart rate in humans and liken its development over time to that of entropy. A healthy baby up to the age of a one-year-old has a resting heart rate in the range of 100 to 160 beats per minute (bpm). A healthy young adult at the age of 21 or older has a resting heart rate in the range of 60 to 100 bpm. It would not be possible to tell if a patient is healthy or in crisis based on heart rate unless you also know that person's age. However, if you do know that person's age, their resting heart rate is a significant independent predictor of mortality — even in healthy people in good physical condition[8]. Similarly, entropy is a much more powerful predictor variable in

[8] "If you have two healthy people," says lead author of a study published in 2013, Dr. Magnus Thorsten Jensen, a researcher at Copenhagen University Hospital Gentofte, "exactly the same in physical fitness, age, blood pressure and so on, the person with the highest resting heart rate is more likely to have a shorter life span." (Jensen, Suadican, et. al. 2013) [31] The foregoing prediction about life span would not be good without controlling for age, just as a prediction about yield effect would be lacking without same.

light of age. The results for the model in Equation 18 are presented in Table 18 under "Model 2".

$$ytm_{i,j} = \beta_0 + \beta_1 riskfr_{i,j} + \beta_2 dum.onrun_{i,j} + \beta_3 age_{i,j} + \beta_4 E_{i,j} + \epsilon_{i,j} \tag{18}$$

The third of the four models used to estimate yield to maturity is Equation 19 below. Equation 19 includes the variable for the amount outstanding, ***amt.out***, to test whether the intuitive appeal of larger issues being more liquid (basically on the supposition that larger issues have more holders and size matters) holds up in empirical testing. The results for the model in Equation 19 are presented in Table 18 under "Model 3".

$$ytm_{i,j} = \beta_0 + \beta_1 riskfr_{i,j} + \beta_2 dum.onrun_{i,j} + \beta_3 age_{i,j} + \beta_4 E_{i,j} + \beta_5 am\ \ .out_{i,j} + \epsilon_{i,j} \tag{19}$$

And, the fourth of the four models used to estimate yield to maturity is Equation 20 that follows. The spinal model includes the variable for credit risk, ***ratings***, to control for the large impact that default risk carries in asset pricing. As stated earlier, the closer a bond comes to default, the more it will trade like equity.

$$ytm_{i,j} = \beta_0 + \beta_1 riskfr_{i,j} + \beta_2 dum.onrun_{i,j} + \beta_3 age_{i,j} + \beta_4 E_{i,j} + \beta_5 amt.out_{i,j} + \beta_6 rating_{i,j} + \epsilon_{i,j} \tag{20}$$

The results

The results of the regression analysis for the four models are presented below in Table 18.

As a result of the analysis reported under Model 1, where Warga (1992) [63] finds a 55 basis point yield advantage for on-the-run treasury bonds over off-the-run treasury bonds, I find a 42 basis point advantage (lower yield) for on-the-run corporate bonds over off-the-run corporate bonds, which is consistent with the existence of the on-the-run phenomenon being present in the corporate bond market.

As a result of the analysis reported under Model 2, in the presence of the entropy measure, the on-the-run status of a corporate bond loses size effect and significance. The size effect of ***dum.onrun*** is reduced from 42 basis points to just 2 basis points, and statistically the variable goes from a very significant t-value of -11.72 to a very insignificant -0.051. Here the entropy measure completely dominates the on-the-run status of a corporate bond as a measure liquidity. Similar to the findings in the early chapters of this dissertation, there is no on-the-run phenomenon in the light of a properly tuned liquidity measure.

The findings that ensue from the analysis reported under Model 3 revealed that, counter to my intuition, the outstanding amount of a corporate bond issue has almost no impact on pricing, at a mere 4/100 of a basis point.

As a result of the analysis reported under Model 4, I find that default risk, ***rating***, and liquidity, ***E***, are extremely close in impact on pricing for corporate bonds, with an advantage of slightly less than two basis points for liquidity. This constitutes an unexpectedly good finding for the entropy measure, a model with a high adjusted R-square of 0.48.

The remaining sections of this chapter seek to offer validity and robustness to my findings thus far.

Table 18 Market Pricing of Liquidity

This table reports the results of four OLS models for which the dependent variable is bond yield-to-maturity and show that, when considering just the risk-free rate and the on-the-run status of the corporate bond, the on-the-run bond would average a 42 basis point advantage in value. However, when controlling for liquidity, using entropy combined with the age of the issue and its current outstanding amount, the on-the-run attribute loses significance.

	Model 1				Model 2				Model 3				Model 4			
Variable	Estimate	t value	Pr(>|t|)		Estimate	t value	Pr(>|t|)		Estimate	t value	Pr(>|t|)		Estimate	t value	Pr(>|t|)	
(Intercept)	-3.9922	-14.86	<2e-16	***	-4.38271	-17.19	<2e-16	***	-4.5680	-17.891	<2e-16	***	-1.0160	-4.432	9.45e-06	***
riskfr	1.8716	37.2	<2e-16	***	1.8867	40.45	<2e-16	***	1.8933	40.73	<2e-16	***	1.912	47.941	<2e-16	***
dum.onrun	-0.4158	-11.7	<2e-16	***	-0.0181	-0.05	0.61		-0.0195	-0.56	0.58		-0.0878	-2.91	0.00363	**
age					0.0103	26.75	<2e-16	***	0.0107	27.62	<2e-16	***	0.0089	26.486	<2e-16	***
E					-0.2795	-24.29	<2e-16	***	-0.3048	-26.1	<2e-16	***	-0.2983	-29.767	<2e-16	***
amt.out									0.0004	7.4	<2e-16	***	0.0005	11.039	<2e-16	***
rating													-0.2803	-52.356	<2e-16	***
N	7,652				7,652				7,652				7,652			
Adj. R^2	0.166				0.29				0.295				0.4808			

Standardizing regressor units

Two coefficients in the same model can be directly compared only if the regressors are measured in the same units. In order to compare the effects of regressors measured in different units, standardized estimates are calculated for the coefficients of Model 4 in Table 18.

Standardized estimates are defined as the estimates that result when all variables are standardized to a mean of 0 and a variance of 1. Standardized estimates are computed by multiplying the original estimates by the sample standard deviation of the regressor variable and dividing by the sample standard deviation of the dependent variable.

Table 19 Regression coefficients in terms of standard deviation

This table shows the calculated standardized estimates for Model 4 in Table 18 above. Standardized estimates are computed by multiplying the original estimates by the sample standard deviation of the regressor variable and dividing by the sample standard deviation of the dependent variable.

Variable	Original Estimate	Std. Dev. of Regressor	Std. Dev. of Response Var.	Standardized Estimate
riskfr	1.91200	0.35313	1.70165	0.39678
dum.onrun	-0.08780	0.50003	1.70165	-0.02580
age	0.00890	45.81706	1.70165	0.23963
E	-0.29830	1.46931	1.70165	-0.25757
amt.out	0.00050	320.68510	1.70165	0.09423
rating	-0.28030	2.63927	1.70165	-0.43475

Standardized estimates show that ***dum.onrun*** is still very minor in effect size when compared with ***E***. However, standardization also shows that ***E*** is not quite as powerful in effect size as ***rating***. Rather than being equal in effect, now ***E*** is roughly

60% of the ***rating*** effect. But, because the rating variable is ordinal and not continuous, the distance between the ***ratings*** intervals is itself arbitrary. Therefore, I argue that both are quite excellent predictor variables, putting liquidity much higher in importance than previously thought.

Cross-validation

Cross-validation is a statistical technique for estimating the performance of a predictive model. In the preceding analysis, most compelling findings are found in the later models, Model 3 and Model 4.

Table 20 Cross-Validation Score Comparison

This table reports the results of cross validation analysis. Cross validation techniques center on not using the entire data set when building a model. Some cases are removed before the data is modeled; these removed cases are often called the testing set. Once the model has been built using the cases left (often called the training set), the cases which were removed (testing set) can be used to test the performance of the model on the "unseen" data (i.e. the testing set).

The k – fold method randomly removes k – folds for the testing set and models the remaining (training set) data. Here the commonly accepted (Harrell, 1998) 10 – fold application is used.

Prediction error below refers to the discrepancy or difference between a predicted value (based on the model) and the actual value, hence the lower the "Average corrected measure of prediction error across all folds", the more accurate, or better, the model.

Statistical software used to perform cross validation is the Data Analysis And Graphing ('DAAG') package (Maindonald & Braun, 2011) in R.

Cross Validation Results
Linear Model 3 (with ***dum.onrun***) $ytm = \beta_0 + \beta_1 riskfr + \beta_2 age + \beta_3 amt.out + \beta_4 dum.onrun$ Average corrected measure of prediction error across all folds = 2.23

Linear Model 3 (with ***E***ntropy)

$$ytm = \beta_0 + \beta_1 riskfr + \beta_2 age + \beta_3 amt.out + \beta_4 E$$

Average corrected measure of prediction error across all folds = 2.04

Fitted Linear Model 4 (with ***dum.onrun***)

$$ytm = \beta_0 + \beta_1 riskfr + \beta_2 age + \beta_3 amt.out + \beta_4 rating + \beta_5 dum.onrun$$

Average corrected measure of prediction error across all folds = 1.68

Fitted Linear Model 4 (with ***E***ntropy)

$$ytm = \beta_0 + \beta_1 riskfr + \beta_2 age + \beta_3 amt.out + \beta_4 rating + \beta_5 E$$

Average corrected measure of prediction error across all folds = 1.51

Table 20 above is a ten-fold cross-validation assessment of how well my analysis regarding the effect the liquidity variables have on yield to maturity will generalize to an independent sample. The technique is predicated upon not using the entire data set when building a model. Some cases are removed before the data is modeled; these removed cases are often called the testing set. Once the model has been built using the cases left (often called the training set), the cases which were removed (testing set) can be used to test the performance of the model on the "unseen" data (i.e. the testing set). [9]

Harrell, Margolis et al. (1998) [29] endorses a tenfold method as sufficient. The meaning of tenfold is to divide the data into 10 sets, using 9 of the data sets to train the model and then test the model on that 10th data set, which was held out.

The results of cross validation analysis as shown in Table 20 revealed that, with respect to Model 3, the entropy measure improves the accuracy of the model over that

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[9] [The statistical software package that I used is available in R. It is the Data Analysis And Graphing ('DAAG') package (Maindonald & Braun, 2011) [44]].

of the on the run status dummy, with an average error of 2.03 versus 2.23, respectively. And with respect to Model 4, the entropy measure again improves the accuracy of the model over that of the on the run status dummy, with an average error of 1.51 versus 1.68, respectively. The entropy measure is a better predictor of yield to maturity as per this ten-fold cross validation analysis. I find identical rankings that are also non-zero and positive differences, in the bootstrap analyses (for which the results are shown later in the chapter) where the averages are those for over 7,600 folds.

Residual Sum of Squares, AIC, and F-Test Measures

Table 21 below reports the results of three goodness of fit measures, the residual sum of squares, the Akaike Information Criterion (AIC), and the F-test value of each predictor variable run in a simple regression. The results for each predictor variable are largely consistent across these three measures namely, the credit risk variable, rating, is substantially superior using goodness of fit measures, but with regard to the entropy measure and the on the run dummy variable, the entropy measure's goodness of fit proves it to be a much better explanatory variable than the on the run status of a corporate bond.

Table 21 RSS, AIC and F-test goodness of fit measures

This table reports Residual Sum of Squares (RSS), also known as the Sum of Squared Errors of prediction (SSE), which is a measure of the discrepancy between the data and an estimation model. A small RSS indicates a tight fit of the model to the data. This table also reports the Akaike Information Criterion (AIC) is a measure of the relative goodness of fit where again a smaller value indicates a better fit. Lastly, this table reports the F-test value of each predictor variable run in a simple regression, where now the value is larger if the null hypothesis is not true.

	Df	Sum of Sq	RSS	AIC	F value	Pr(>F)	
riskfr	1	3342	18812.4	6887.3	1359.03	< 2.2e-16	***
age	1	1477.6	20676.8	7610.4	546.7	< 2.2e-16	***
amt.out	1	72.2	22082.2	8113.6	25.01	5.83E-07	***
rating	1	4577.4	17577	6367.6	1992.23	< 2.2e-16	***
dum.onrun	1	330.7	21823.8	8023.5	115.91	< 2.2e-16	***
E	1	1647.7	20506.7	7547.2	614.68	< 2.2e-16	***

Bootstrap analysis

The next four tables, Table 22 through Table 25, demonstrate similar findings to the cross validation analysis as Models 3 and 4 perform much better including the entropy measure and excluding the on-the-run status variable than vice versa.

Table 22 (1 of 4) Bootstrap analysis one

This table reports the results, for the first of four models, of the *K* – fold cross validation for the generalized linear model where *K* is set to the number of cases (rows), and then a complete Leave One Out Cross Validation (LOOCV) is done. In the LOOCV, one case is *left out* as the testing set and the rest of the data is used as the training set. This process is repeated so that each case is given a chance as the testing case. The Akaike Information Criterion (AIC) is a measure of the relative goodness of fit of the model and the delta shows (first) the raw cross-validation estimate of prediction error and (second) the adjusted cross-validation estimate. The adjustment is designed to compensate for the bias introduced by not using leave-one-out cross-validation (as the method shown here is leave-one-out cross-validation, the two numbers are essentially the same.)

Linear Model 3 (with ***dum.onrun***)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-5.763	-0.734	0.045	0.803	7.089

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-5.26E+00	2.65E-01	-19.8577	< 2e-16	***
riskfr	1.96E+00	4.84E-02	40.4802	< 2e-16	***
age	1.03E-02	4.04E-04	25.4977	< 2e-16	***
amt.out	-1.29E-05	5.38E-05	-0.2388	0.81126	
dum.onrun	-7.27E-02	3.66E-02	-1.9847	0.04721	*

--- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 2.223788)

Null deviance: **22154.4217** on **7651** degrees of freedom.

Residual deviance: **17005.3103** on **7647** degrees of freedom.

AIC: **27838**

Number of Fisher Scoring iterations: **2**

K: 7652

delta: 2.22541013715225 2.22540993612674

Table 23 (2 of 4) Bootstrap analysis two

This table reports the results, for the second of four models, of the K – fold cross validation for the generalized linear model where K is set to the number of cases (rows), and then a complete Leave One Out Cross Validation (LOOCV) is done. In the LOOCV, one case is *left out* as the testing set and the rest of the data is used as the training set. This process is repeated so that each case is given a chance as the testing case. The Akaike Information Criterion (AIC) is a measure of the relative goodness of fit of the model and the delta shows (first) the raw cross-validation estimate of prediction error and (second) the adjusted cross-validation estimate. The adjustment is designed to compensate for the bias introduced by not using leave-one-out cross-validation (as the method shown here is leave-one-out cross-validation, the two numbers are essentially the same.)

Linear Model 3 (with ***E***ntropy)

Deviance Residuals:

Min	**1Q**	**Median**	**3Q**	**Max**
-5.391	-0.711	-0.033	0.673	7.535

Coefficients:

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	-4.58E+00	2.54E-01	-18.084	< 2.2e-16	***
riskfr	1.89E+00	4.65E-02	40.749	< 2.2e-16	***
age	1.08E-02	3.62E-04	29.802	< 2.2e-16	***
amt.out	3.99E-04	5.40E-05	7.401	1.50E-13	***
E	-3.05E-01	1.17E-02	-26.176	< 2.2e-16	***

--- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 2.04197)

Null deviance: **22154.4217** on **7651** degrees of freedom.

Residual deviance: **15614.9483** on **7647** degrees of freedom.

AIC: **27185**

Number of Fisher Scoring iterations: **2**

K: 7652

delta: 2.04352956760732 2.04352937844071

Table 24 (3 of 4) Bootstrap analysis three

This table reports the results, for the third of four models, of the K – fold cross validation for the generalized linear model where K is set to the number of cases (rows), and then a complete Leave One Out Cross Validation (LOOCV) is done. In the LOOCV, one case is *left out* as the testing set and the rest of the data is used as the training set. This process is repeated so that each case is given a chance as the testing case. The Akaike Information Criterion (AIC) is a measure of the relative goodness of fit of the model and the delta shows (first) the raw cross-validation estimate of prediction error and (second) the adjusted cross-validation estimate. The adjustment is designed to compensate for the bias introduced by not using leave-one-out cross-validation (as the method shown here is leave-one-out cross-validation, the two numbers are essentially the same.)

Fitted Linear Model 4 (with ***dum.onrun***)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-5.81	-0.632	0.088	0.736	6.251

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.67053	0.241121	-6.9282	4.61E-12	***
riskfr	1.97849	0.042069	47.0291	< 2.2e-16	***
age	0.00845	0.000353	23.9458	< 2.2e-16	***
amt.out	0.000109	4.68E-05	2.3256	0.02007	*
rating	-0.28227	0.005655	-49.9184	< 2.2e-16	***
dum.onrun	-0.14029	0.031825	-4.408	1.06E-05	***

--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 1.677408)

Null deviance: **22154.4217** on **7651** degrees of freedom.

Residual deviance: **12825.4628** on **7646** degrees of freedom.

AIC: **25681**

Number of Fisher Scoring iterations: **2**

K: 7652

delta: 1.67889045522018 1.6788902722796

Table 25 (4 of 4) Bootstrap analysis four

This table reports the results, for the fourth of four models, of the K – fold cross validation for the generalized linear model where K is set to the number of cases (rows), and then a complete Leave One Out Cross Validation (LOOCV) is done. In the LOOCV, one case is *left out* as the testing set and the rest of the data is used as the training set. This process is repeated so that each case is given a chance as the testing case. The Akaike Information Criterion (AIC) is a measure of the relative goodness of fit of the model and the delta shows (first) the raw cross-validation estimate of prediction error and (second) the adjusted cross-validation estimate. The adjustment is designed to compensate for the bias introduced by not using leave-one-out cross-validation (as the method shown here is leave-one-out cross-validation, the two numbers are essentially the same.)

Fitted Linear Model 4 (with ***E***ntropy)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-5.71	-0.6	0.05	0.64	6.48

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-1.10E+00	2.28E-01	-4.8326	1.37E-06	***
riskfr	1.91E+00	3.99E-02	47.9915	< 2.2e-16	***
age	9.21E-03	3.12E-04	29.5074	< 2.2e-16	***
amt.out	5.11E-04	4.64E-05	11.0117	< 2.2e-16	***
rating	-2.80E-01	5.35E-03	-52.2537	< 2.2e-16	***
E	-3.00E-01	1.00E-02	-29.974	< 2.2e-16	***

--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 1.504845)

Null deviance: **22154.4217** on **7651** degrees of freedom.

Residual deviance: **11506.0455** on **7646** degrees of freedom.

AIC: **24851**

Number of Fisher Scoring iterations: **2**

K: 7652

delta: 1.5062071658841 1.50620699964935

Chapter 11 Accounting Implications, Part 1: Asset Valuation

The demand for financial reporting

The 18th century Industrial Revolution stimulated the formation of capital markets and the separation of owners and managers. With this separation came the opportunity for "moral hazard", hidden behavior by managers to act in their own interests at the expense of the owners. This, in turn created a market for independent auditors, voluntarily hired by some to provide a way to check on management's performance with the owner's resources. And, the publicly owned corporation survived for well over a century without any requirements except the financial reporting rules of the stock exchanges.[10] But when the market crashed in 1929, Congress became convinced that it was due in part to the lack of meaningful reporting requirements to protect creditors and investors. Further, they believed economic conditions would not improve until the public regained confidence in the financial markets. So Congress passed the Securities Act of 1933 and the Securities Exchange Act of 1934 to address these concerns. The Securities Exchange Act of 1934 created U.S. Securities and Exchange Commission (SEC) and it was given responsibility for establishing financial reporting standards and began issuing standards in 1937.

Since that time accounting standard setting has experienced a series of growing pains and changes in authoritative bodies. With the blessings of the SEC, the American Institute of Certified Public Accountants (AICPA) formed the Committee on Accounting Procedures (CAP) in 1939 to lead in the establishment of accounting rules. The CAP was replaced by the AICPA's Accounting Principles Board (APB) in 1959.

[10] The New York Stock Exchange was established in 1792 for the trade of ownership shares.

Then, due to mounting criticism over the dual responsibility of the AICPA to form of accounting rules and to form auditing standards and practices, the APB was replaced. In 1973, and independently funded full-time standard-setting organization called the Financial Accounting Standards Board (FASB) was established.

The mission of the FASB was to develop standards that would best serve the decision-making needs of investors and creditors. Reporting requirements under U.S. Generally Accepted Accounting Principles (GAAP) and the capital markets they served both grew significantly in the last quarter of the 20th century (Adapted from Imhoff 2003) [36]

Despite the continuous development and refinements in GAAP during the 30 years following WWII, a new wave of high-profile business scandals ensued. Accounting and auditing often cited for failing to prevent these problems. By the end of the 1970s accounting and was under attack for failing to satisfy the needs of investors and creditors. A major criticism during this period was GAAP's inability to provide relevant and reliable information in periods of significant price change.

Therefore, by 1980, there were established two main requirements for setting new accounting standards. First, the FASB is obligated to consider the costs and benefits of its standard. And, second, the objective of accounting policy decisions is to produce information that is both relevant and reliable (FASB, 1980, SFAC No. 2) [9].

It is my purpose in this two part discourse on accounting implications to make the case for the entropy measure becoming a reporting requirement as, at least, a footnote addendum to the balance sheet items “Marketable Securities” and “Securities Held for Sale”.

Footnote reporting of entropy

It is my proposal that, each time a firm uses "fair value" reporting of either asset or liability fixed-income values, there be a table in the footnotes to the balance sheet that report the weighted average entropy measure for the assets subject to this reporting. The firm need not be burdened with granular itemizing. The benefit of the entropy measure is that aggregate entropy and changes seen by investors in aggregate entropy convey sufficient information to effect the actions of decision-makers.

Manager Incentives

Within the US financial reporting environment, we have increasingly provided managers with incentives to manage earnings and to delay and/or conceal bad news. For better or worse, most cash bonus plans as well as most stock option plans or stock awards plans are based on accounting results. This has made the financial statements the focal point of management's wealth maximization strategy. So while the financial reporting process is providing investors and creditors with GAAP-based reports on the entity's performance, it is also impacting the current and future wealth position of its managers. (Adapted from Kirkpatrick 2009) [41]

Empirical evidence in support of managers to succumbing to incentives to mislead users of financial statements can be found in prior literature cited in Chapter 2 where banks and insurance companies concerned about having to mark asset values to market prices in times of financial crisis manipulate the level I[11] input data to window dress their companies. Even observed transaction prices can be altered and used to obscure financial asset values, at the discretion of management. Huizinga (2009) [35] finds "that banks, and especially distressed banks, use discretion in the classification of (debt) securities so as to inflate the value of these securities. Our results provide several pieces of compelling evidence that banks' balance sheets offer a distorted view of the financial health of the banks, especially for banks with large exposures..."

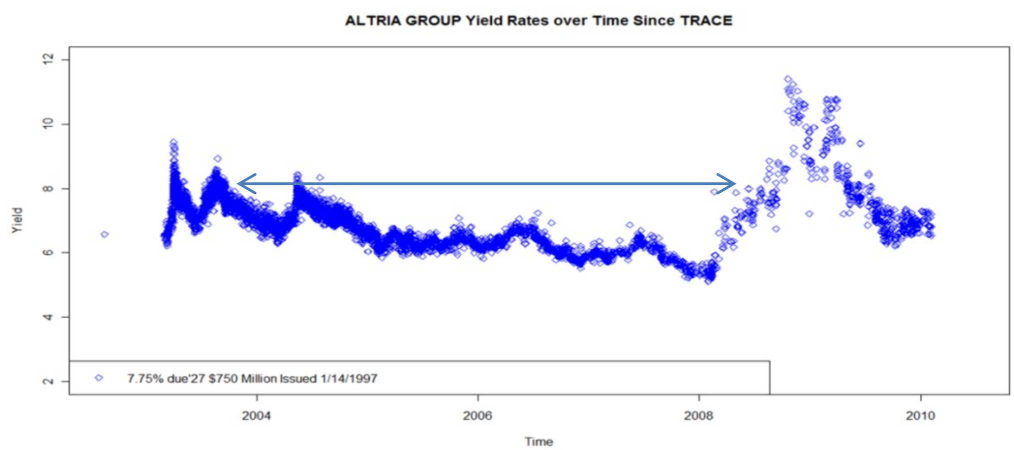

Figure 15 Plot of de-listing event

This figure shows the trade activity of Altria Group 7 ¾% bonds before and after Altria Group, Formerly Philip Morris was removed from the Dow Jones Industrials on February 19, 2008. The double-headed arrow points to two identical price prints that come at times when market liquidity for this bond is vastly different.

[11] SFAS 157 provides a hierarchy of three levels of input data for determining the fair value of an asset or liability.
Level 1 is quoted prices for identical items in active, liquid and visible markets such as stock exchanges.
Level 2 is observable information for similar items in active or inactive markets, such as two similarly situated buildings in a downtown real estate market.
Level 3 are unobservable inputs to be used in situations where markets don't exist or are illiquid such as the present credit crisis. At this point fair market valuation becomes highly subjective.

Under the current reporting rules, the Altria Group bond shown above could have identical fair value, Level 1 input, market values shown in assets on a balance sheet. However, I submit that the net realizable value from the market environment on the left would be substantially higher than that on the right. While it is not possible to observe the counter-factual, i.e. it is not possible, for example, to go back and affect a $1million bond sale in each of the markets in existence at each end of the line segment, the yield to maturity analysis done in Chapter 10 indicates that for each entropy measure point the market on the left is greater (more liquid) than the market on the right, the yield will be 26 basis points lower. The lower yield means better price and as this price difference is virtually the same (26 basis points) for a single increment change in Moody's rating The market from which an observed market price is derived is as relevant as a difference in credit rating.

Relevance of the entropy measure

In addition to the evidence that entropy is as relevant as credit worthiness, the actions of the FASB lend relevance to the need as a way for investors and creditors to discern the quality of reported fair values. The initiative to create levels of input in the first place indicates the need to solve a problem. I simply put forth the entropy measure as a better solution.

Referring again to Figure 15, both fair value prices can be said to come from arguably active markets. But which market was more active, more liquid and how much more? What is certain is that not all Level 1 inputs "are created equal." This single categorical variable (Level 1) is not sufficiently informative to be useful to decision makers and, further, does too little to dissuade the abuses of managers.

The entropy measure is a continuous variable, ranging from 0 to over 6 in the study's sample making it quite sensitive to differences in liquidity and changes in liquidity environments. It also provides a way to quantify these effects.

Reliability of the entropy measure

The entropy measure is calculated from publically available TRACE data making it quite tractable and difficult for managers to misrepresent. The audit community should have no problem verifying reports. Therefore, management incentives to bias and introduce measurement error are effectively countered.

The two main criteria for standard-setters, relevance and reliability, are satisfied by the entropy measure.

Liquidity risk on par with default risk

A recent study by He and Xiong (2012) [30], citing Longstaff (2005) [43] and Chen (2007) [12], points out that the yield spread, "of a firm's bond issue, above the risk-free interest rate, directly determines the firm's debt financing cost and is often referred to as its credit spread. And, it is widely recognized that the credit spread reflects not only a default premium determined by the firm's credit risk but also a liquidity premium due to illiquidity of the secondary debt market." And, results in this dissertation set forth above clearly demonstrate that liquidity risk is just as important to bond value as credit risk. However, there is no vehicle in GAAP to convey information to investors on this critically important aspect of risk. Again, the entropy measure, ***E***, is a tractable measure that quantifies this liquidity risk that I believe has not been proposed or examined in prior literature. The next chapter makes the case for the entropy measure from the standpoint of principal, as opposed to rule satisfaction, in that standard-setters should consider the ability of the item to make a difference in decisions of financial statement users. Toward that end, I turn to the consideration of assessing risk.

Chapter 12 Accounting Implications, Part 2: Risk Assessment

I personally feel that nothing is more relevant about a return than the risk borne to achieve it.

To further investigate the usefulness of the entropy measure, the discussion now turns to how entropy values can be used in the assessment of portfolio risk. A premise central to this discussion is that each corporate bond has two aspects. The first being the “pure debt” piece and the second is the “equity component” piece which constitutes an implied put to the equity holders Merton (1974) [47]. The Alexander et al. (2000) [2] paper reports that “for investment-grade bonds, the put is out-of-the-money and generally has a negligible impact on the price of the bond in its returns…(however) A bond that poses enough default risk … is in a considerably different situation. For this bond the put is at least near-the-money and has a significant influence on the bond’s market price.” When the put becomes near-the-money, the bond trades more like equity. In fact the study by Jiang and Wang (2012) [39] shows that trading on the piece that is a short position in a put option (on the issuer’s equity) has become a viable hedge fund strategy, known as “a ‘loan-to-own’ strategy, whereby a hedge fund acquires the debt of a distressed borrower with the intention of converting the acquired position into a controlling equity stake upon the firm’s emergence from Chapter 11.” Because the equity piece can have a large effect on a corporate bond when the implied put is near-the-money, I limit my theory and conclusions to only those corporate bonds that are not near defaulting and, as such, have at most small influences from the equity component.

The entropy measure measures liquidity. Liquidity differences are reflected in yield differences. The question how these differences should behave in bonds with equivalent credit risk has been the subject of trading strategies in both practice and in academic theories.

Discourse on Yield Convergence

The Banerjee and Graveline (2013) [6] study poses an example of a corporate bond strategy, the underlying assumptions for which, are not consistent with a central theory of this dissertation.

> EXAMPLE: *Suppose that a liquid security trades for* \$100,000, *and an otherwise equivalent but less liquid security costs* \$99,850. *Prices are expected to converge at the end of the period so that the price premium for the liquid security is \$100,000 −\$99,850 = \$150 relative to its illiquid counterpart. Suppose that it costs \$200 more to borrow the liquid security for the period than it does to borrow the illiquid one. Finally, assume that each outstanding unit of the liquid security is borrowed and sold short once, so that the aggregate proportion of long positions relative to short positions is two to one.*

The example above casually makes the assumption that the prices of the on-the-run and the off-the-run bond will converge at the end of the period. It is the position of this dissertation that this convergence should not be taken for granted and is, in fact, unlikely, unless it is a one period maturity situation.

The first reason that this would be unlikely is rooted in efficient markets theory. The weak level of efficient markets theory holds that, in competitive markets, today's price must already reflect the information in past prices. Thereby, securities will be fairly priced and security returns will be unpredictable whatever information you consider. It seems that in much the same way that nature abhors a vacuum, efficient markets theory abhors a pattern. Because trading based on patterns would lead to easy profits and, in efficient markets, easy profits don't last; all of the information in regard to the normal erosion of liquidity must be reflected in the current bond price. A definite pattern of on-the-run bond and off-the-run bond price convergence in a predictable period for trading should not exist.

The second reason that such a price convergence should not take place is the theory that liquidity is guided by the principles of entropy. Entropy curve shown earlier in the upper graph of Figure 8 displays the rate at which entropy/liquidity diminishes over time. The graph shows that entropy, and hence liquidity, starts out high when a bond first issued and free to trade in the secondary market. And, from this high level, the initial rate of decline is very steep until a "kink" point is reached where the rate of decline settles into a lesser almost asymptotic slope.

In theory, two curves with two different starting points in time should not overlap given their shape until possibly when liquidity is zero for both.[12] However, fully convergence should not be necessary for a convergence strategy to work. As long as

[12] Unlike curves that are truly asymptotic, which don't actually reach zero before infinity, the entropy measure does achieve a zero value.

two securities move toward convergence, i.e. closer in value, that should be sufficient to create a profit opportunity.

Lessons from Long Term Capital Management

The strongest empirical evidence of the failure of price convergence as a trading strategy is the failure of Long Term Capital Management (LTCM). The 1998 failure of LTCM is said to have nearly blown up the world's financial system. Indeed Jorion (2000) [40], reports that, "the fund's woes threaten to create major losses for Wall Street lenders. LTCM was so big that the Federal Reserve Bank of New York took the unprecedented step to facilitate a bailout of a private hedge fund out of fear that a forced liquidation might ravage world markets."

A hedge fund is a private partnership fund that can take a long or short positions in various markets and is accessible only to large investors. Hedge funds are not regulated by the Securities and Exchange Commission and therefore can be quite leveraged and highly risky. The core strategy of LTCM is described as "convergence arbitrage" trading, the objective of which is to try to take advantage of small price differences among closely related securities (Adapted from Jorion 2000 [40]). An example cited in the literature is to compare, for instance, "an off-the-run Treasury bond yielding 6.1% versus 6.0% for the more recently issued on the run Treasury bond. The yield spread represents some compensation for liquidity risk." The strategy, over a year, was to take a long position in the off-the-run bond and a short position in the on-the-run bond. The expected return was an extra 10 basis points for every dollar invested. LTCM believed that the two bonds must converge to the same value. The hedge fund had to use leverage in order to take large positions in hopes of making large profits from such small price differences. LTCM was able to obtain unusually attractive financing that allows them to control about $1.25 trillion in principal transactions. Because of the reputation of its founders and the belief that the trade positions seemed to be offsetting and were therefore hedged, the fund was considered a "safe" investment.

In the beginning the convergence arbitrage strategy worked very well. In 1995 and 1996, the fund returned over 40%, after fees. But, shortly thereafter, LTCM faltered, losing over half of its value within six months, and eventually failed.

The core strategy of LTCM was fundamentally flawed likely because of the failure to fully appreciate the implications of efficient markets theory combined with a misunderstanding of the behavior of liquidity. The contribution of this dissertation is in the understanding, measurement and prediction of liquidity.

The Russian Crisis is often referred to as the cause of LTCM's financial downfall. However, the Russian Crisis was merely a trigger and indirect factor for LTCM's collapse. It is the premise of this dissertation that during periods of crisis the demand for liquidity rises sharply and it is this rush to liquidity combined with the core strategy of LTCM that dealt the lethal blow to the firm.

By taking a long position in the off-the-run bond, LTCM was taking a long position in a low entropy bond. Similarly, their short position in the on-the-run bond was a short position in a high entropy bond. Remembering that new issue bonds start with high entropy/liquidity and the rate of decline is quite steep initially and that seasoned issues have already been through the steep entropy/liquidity phase, so their rated decline is much less steep, it becomes evident why the convergence arbitrage strategy holds such appeal. It seems obvious that the bond that is falling faster in entropy/liquidity/price would have to be moving closer to the similar bond that is falling at a slower rate. In essence, the faster bond is catching up to the slower bond effectively causing a convergence. And, this “convergence”, which is part of the name of the strategy, should be exploitable for trading gains with little to no risk. The “little to no risk” contributes the other part of the name "arbitrage" meaning that this profit should be available without regard to the direction of the overall market. If the market is up, being both long and short would mean that the losses on one position would be largely offset by the gains in the opposite position. And, if the market is down the positions still largely offset one another. Theoretically, that leaves the combined profit or loss to be determined by how one price moves in relationship to the other. Therefore, if the two prices move closer together there is a gain and if they moved further apart there is a loss, in this stated strategy.

In order to test the effectiveness of the strategy, I use the yield to maturity histories of the bonds in the entire, initial sample, over eight one-year periods[13] (reset at the same time each calendar year). My method was to identify a subset of bond issues for which I could find beginning of period values and end of period values. From this subset I

[13] I reset the bond portfolios each April because the last month of observations for the study was March 2011.

sorted the bond issues into quintiles according to beginning entropy values. The top 10th in entropy values became the High Entropy Portfolio and the bottom 10th in entropy values became my Low Entropy Portfolio. Portfolios are equally weighted.

Equation 21 on the following page is used to calculate returns for each portfolio in each time period and the results for the strategies are shown in Table 26.

$$Return_t = \frac{P_t + C - P_{t-1}}{P_{t-1}} \tag{21}$$

In Equation 21, $Return_t$ is the bond return for the one-year holding period ending at time t, P_t is the bond price at time t, P_{t-1} is the bond price one year before time t, and C is the coupon rate of the bond.

The formula in Equation 21 above assumes that sale and buy prices are “clean”, meaning net of accrued interest, which is the way prices are reported in TRACE. In some databases, bond prices are “dirty”, meaning they include accrued interest and the above formula would have to be modified appropriately. [14]

Table 26 on the following page reports returns for the portfolio strategies in each time period. Note that, in addition to the single-period “buy and hold” strategies for the low and high entropy portfolios under "Long Strategy Returns", the "Low Entropy Portfolio" and the "High Entropy Portfolio", respectively, there are the "Spread Strategy Returns" which is the same "arbitrage convergence strategy" used by LTCM. In this strategy, the long position is taken in low liquidity bonds (determined by off-the-run bonds for LTCM and by the low entropy quintile bonds in this study), and a short position is taken in high liquidity bonds (determined by on-the-run bonds for LTCM and by the high entropy quintile in this study).

[14] Equation 21 slightly differs from bond return formulae found in prior literature. For example, Asquith, Au, Covert, and Pathak (2012) [6] set forth a correction of the bond return formula from Bessembinder, Maxwell, Kahle, and Yu’s (2010) as Return = (Sale price – buy price + sale accrued interest – buy accrued interest + coupons paid) / (buy price + buy accrued interest) from which I make the simplifying assumption that the holding period is exactly one year. In this way, I can cancel out “sale accrued interest – buy accrued interest” as summing to zero. However, this simplifying assumption only ameliorates the numerator. The denominator should include adding “buy accrued interest”, but does not. The difference will make the return derived from Equation 21 lower than it should be by a negligible amount.)

Table 26 Trading Strategy Returns

This Table reports the performance of three trading strategies, over 8 one-year holding periods. The first one-year holding period ends in March 2004 and the last ends in March 2011. The first trading strategy is a "Long Strategy" that selects the bonds in the sample available for the designated "Holding Period" having Entropy values in the lowest quintile as the "Low Entropy Portfolio". The second trading strategy is also a "Long Strategy", but now selects the bonds in the sample available for the designated "Holding Period" having Entropy values in the highest quintile as the "High Entropy Portfolio". Portfolio returns are a calculated using Equation 21. And, the third trading strategy is a "Spread Strategy" that takes a long position in the "Low Entropy Portfolio" concurrently with a short position in the "High Entropy Portfolio". Of the 8 holding periods in the study, 5 are during normal periods and 3 are during crisis periods (that are the GM/Ford and Subprime Crises, identified under "Holding Period"). The crisis periods coincide with negative returns in the spread strategy.

Holding Period 12 months ending		Long Strategy Returns: Low Entropy Portfolio	Long Strategy Returns: High Entropy Portfolio	Spread Strategy Returns: Long Position = Low Entropy Short Position = High Entropy Portfolio		
Mar-04		0.10799	0.10468	0.00332	33	basis point GAIN
Mar-05		0.11605	0.07287	0.04319	432	basis point GAIN
Mar-06	GM/Ford Crisis	0.01899	0.04313	-0.02413	241	basis point LOSS
Mar-07		0.10882	0.08694	0.02188	219	basis point GAIN
Mar-08	Subprime Crisis	0.00620	0.04500	-0.03880	388	basis point LOSS
Mar-09	Subprime Crisis	-0.04674	0.00299	-0.04973	497	basis point LOSS
Mar-10		0.23896	0.15301	0.08595	859	basis point GAIN
Mar-11		0.08810	0.08011	0.00799	80	basis point GAIN

The results in Table 26 give testimony to the importance of ***E***, the entropy measure, and provide an explanation of what happened to LTCM. The spread strategy returns are calculated by summing the low entropy portfolio return minus the high entropy portfolio return, see Equation 22 below.

$$\begin{aligned} &Spread\ Strategy\ Return_t \\ &\quad = Low\ Entropy\ Return_t \\ &\quad - \ High\ Entropy\ Return_t \end{aligned} \tag{22}$$

More specifically, the solution for Equation 22 is accomplished using the variables as presented in Equation 23 below.

$$\begin{aligned} &Spread\ Strategy\ Return_t \\ &\quad = \frac{LEP_t + LEC - LEP_{t-1}}{LEP_{t-1}} \\ &\quad - \frac{HEP_t + HEC - HEP_{t-1}}{HEP_{t-1}} \end{aligned} \tag{23}$$

In Equation 21, *Spread Strategy Return*$_t$ is the return for holding simultaneously a long position in the low entropy portfolio and a short position in the high entropy portfolio, for the one-year holding period ending at time t, LEP_t is the average bond price for the low entropy portfolio at time t, LEP_{t-1} is the average bond price for the low entropy portfolio one year before time t, LEC is the average coupon rate in the low entropy portfolio, HEP_t is the average bond price for the high entropy portfolio at time t, HEP_{t-1} is the average bond price for the high entropy portfolio one year before time t, and HEC is the average coupon rate in the high entropy portfolio.

The study by Asquith et al. (2012) [7] describes the market for borrowing corporate bonds using a comprehensive dataset from a major lender and find that the cost of borrowing corporate bonds is comparable to the cost of borrowing equity, between 10 and 20 basis points per year. Factors that increase borrowing costs are percentage of inventory lent, loan size, and rating. Trading strategies based on cost or amount of borrowing do not yield excess returns. I do not model these costs in Equation 23 as they affect all time periods equally and, therefore, do not change relative outcomes.

In Table 26, take note that three of the one-year holding periods occur in times of crisis. In each case the resulting return is a loss. This is because in times of crisis liquidity become scarce i.e. demand for liquid securities rises and the greater demand elicits higher prices. Therefore, the spread relationship goes in the opposite direction exhibiting divergence rather than the expected convergence. The higher entropy bond goes away from his normal pattern of a steep decline because in crisis periods such bonds are in demand. Meanwhile, the low entropy bond has weaker than normal demand therefore its decline in liquidity is exacerbated. It is the theory of this dissertation that LTCM's performance mirrors that in Table 26 where the beginning years were normal periods, so the price convergence strategy worked, but when the Russian Bond Default brought about a crisis period similar to the GM/Ford and Subprime crisis years in the sample period, the spread between prices became larger instead of smaller.

The LTCM "arbitrage convergence" strategy was not an arbitrage at all, but rather a highly risky, one-directional bet. Therein lays the value of the entropy measure as a tool for risk assessment. The aggregate entropy of any particular bond portfolio reflects the implied bet on the upcoming state of nature. Making entropy available to decision-makers informs their choices with respect to the risk held in the financial assets of the firm. It is incumbent on any prudent investor to understand the risks to which managers are subjecting the assets of the firm in order to generate returns.

Chapter 13 Conclusion

I investigate the on-the-run phenomenon and I find that this anomaly is caused by differences in liquidity. Although an on-the-run bond can be virtually identical to an off-the-run bond in default risk, cash flows, and time to maturity, the on-the-run bond is always the newer bond and that alone is enough to give it a liquidity advantage. This liquidity advantage translates into a yield advantage i.e. a price advantage. The bond with the greater liquidity is the bond with greater value in the market, *ceteris paribus*.

My major contribution is that I show that liquidity is related to entropy. Therefore, I have developed an entropy measure, based on Shannon entropy that shows bond issues normally progress through stages of entropy as they become seasoned. Essentially, I have quantified liquidity with a single, tractable value that I call the "entropy measure" or simply ***E***.

Empirically, I use the entropy measure to explain the on-the-run phenomenon and I use it to explain the behavior of bond returns during "credit crunches". The full model developed in Chapter 8, Equation 10 of this dissertation explains 54% of the variation in liquidity; the entropy measure is the largest, most significant component of that model. And, in Chapter 12, Table 26, I show that portfolios constructed using corporate bonds ranking in high in entropy (in the top 10% according to ***E***) show superior performance in financial crisis periods. However, the opposite is true during normal times, where portfolios ranking low in entropy (in the bottom 10% according to ***E***) outperform the market. Therefore, the aggregate entropy of any bond portfolio is a critical determinant in risk exposure to upcoming market conditions.

Theoretically, an investor with perfect information about upcoming economic conditions could not utilize that information to maximum effect without being aware of the entropy of the assets available for selection. Similarly, the entropy measure is useful to hedging operations, providers of credit, and regulators. Consider, for example, a situation in which a creditor observes that the entropy of a debtor's bond assets show a sharp decrease from one accounting period to the next, this could mean that this debtor sold off liquid assets to possibly realize gains and maybe replaced them with cheaper illiquid assets. Entropy could be used for contracting purposes to prevent eroding of net realizable value.

Further evidence of the importance of the entropy measure is the finding that a single point move in ***E*** has the same effect on the yield to maturity of a corporate bond as incremental change in Moody's rating. Chapter 10, Table 18, Model 4 shows a change in yield to maturity of nearly 30 basis points for each.

Imhoff (2003) [36] makes the point that in order to achieve orderly capital markets around the world corporations must provide investors and creditors with relevant, reliable and timely information. The entropy measure allows for better assessment of asset values and risk factors that are essential components in the flow of information to capital market participants.

Toward that end, the FASB, while maintaining that the function of accounting is not to provide estimates of equity value, SFAC No. 1, paragraph 49 [9] clearly suggests a concern with demands by lenders for assessing a firm's collateral in times of financial difficulty and for assessing liquidity and solvency. Holthausen and Watts (2001) [32] supports this interpretation that the balance sheet still consists mostly of individual, separable assets and liabilities just as it did prior to the Securities Acts. The FASB's reintroduction of market value accounting is clearly intended to apply to individual assets, not for the firm. Therefore, standard-setters should recognize the entropy measure as a very important input for assessing the value of fixed-income assets.

Additionally, the entropy measure satisfies the principles-based criterion which holds that any change in accounting standards is to be dependent upon the ability of the item to make a difference to the decisions of financial statement users. (Holthausen and Watts 2001) [32]

Hence, the entropy measure should be included in financial statements.

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Appendix

Validity Tests for Statistical Procedures

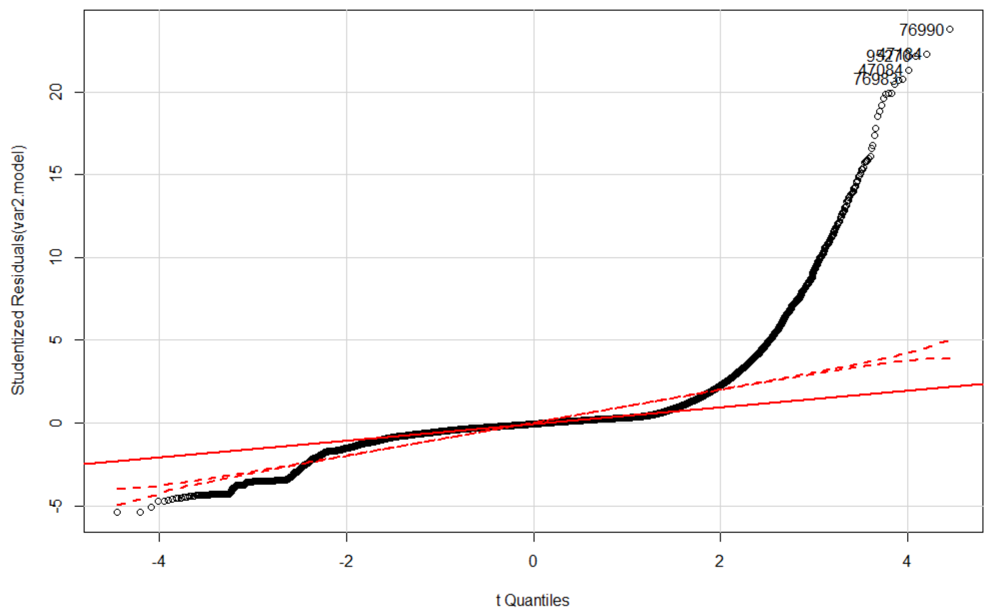

Figure 16 reports the Q-Q plot for the residuals of Model 10 in Chapter 8 modeled in R. A Q-Q plot is a quantile plot comparing two distributions. The first is the distribution of the actual residuals that is compared to the expected normal distribution. The graph plot is then examined visually to check for departures. The departures are where the thick black lines leaves the straight red line that represents normality. It is only at the right end that shows a large departure. The middle 4 quantiles appear normal indicating a “T” distribution which is not bad as the conclusions that are valid under the assumptions of normality are statistically valid here. The “T” distribution looks like a normal distribution with steeper side slopes and hence “fatter” tails.

The purpose of the plot is to check how close the points adhere to the target line. The manner of any deviation from the line is worth commenting on, if it consists of something more than random wobbles. Specific departures indicate skewness, heavy or light tails, and possible extreme values. The departure from Normality is not always as clear as it might seem in the examples, even though the populations being sampled are known not to be Normal. If samples are small (less than a benchmark of 20), then only gross departures from Normality, will be detected. This is no bad thing, since only gross departures from Normality will have a radical effect on the statistical procedures that you are likely to encounter. This sample however is quite large.

Heavy tailed populations present particular problems of identification. The Q-Q plots of the samples can exhibit skewness (if only one of the tails manages to be represented in the sample) or straight down the line Normality (if neither of the tails is represented in the sample). Even though the tails are "heavy" in relation to a Normal population (with the same mean and standard deviation) the probability of sampling a representative in the tail is nevertheless extremely small. The sample size has to be large if we are to be assured of representatives in both tails, and hence of witnessing the *S* shape Q-Q plot. Not only is the sample size here quite large, but the histogram of Studentized error shows both tails.

Therefore, based on the descriptions in DeCarlo (1997) [21] the statistical procedures employed herein should be sound.

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Convertible Bond Broker/Trader — New City, NY
Phoenix Securities,
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Convertible Bond Trader — New York, NY
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PUBLICATIONS

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