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Three Essays on Liquidity Shocks and Their Implication for Asset Pricing and Valuation Models

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THREE ESSAYS ON LIQUIDITY SHOCKS AND THEIR IMPLICATION FOR ASSET PRICING AND VALUATION MODELS

by

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The main objective of my three essays is to incorporate liquidity shocks and the linkages between the liquidity condition of financial markets into asset pricing and valuation models. The first essay focuses on the liquidity adjusted capital asset pricing model, while the second and the third essays examine the popular asset valuation model called the Fed model.

The first essay investigates the pricing of the commonality risk in the U.S. stock market by using a more comprehensive market illiquidity measure that can reflect the liquidity condition of different asset markets. This measure is given by the yield difference between commercial paper and treasury bill. In addition, consistent with the definition of commonality risk, I form portfolios based on the sensitivity of each stock's illiquidity to the market-wide illiquidity. Using monthly data from January 1997 to December 2016 and the conditional version of the Liquidity-adjusted Capital Asset Pricing Model (LCAPM) estimated by the Dynamic Conditional Correlation approach, I find a significant commonality risk premium of 0.022% and 0.014% per year for 12-month and 24-month holding periods, respectively. This premium estimate is significantly higher than those found using the market illiquidity measure and estimation procedures from previous studies. These findings provide evidence that a security's easiness in terms of tradability at times of liquidity dry up is extremely important. It is also higher than the excess return associated with other forms of liquidity risk. In addition, the paper finds a variation in the

estimated commonality risk premium over time, with values being higher during periods of market turmoil. Moreover, estimating the LCAPM with the yield difference between commercial paper and treasury bill as a measure of market illiquidity performs better in predicting returns for the low commonality risk portfolios.

The second essay examines the inflation illusion hypothesis in explaining the high correlation between government bond yield and stock yield as implied by the Fed model. According to the inflation illusion hypothesis, there is mis-pricing in the stock market due to the failure of investors to adjust their cash flow expectation to inflation. This led to a co-movement in stock yield and government bond yield. I use the Gordon Growth model to determine the mis-pricing component in the stock market. In the next step, the correlation between bond yield and stock yield is estimated using the Asymmetric Generalized Dynamic Conditional Correlation (AG-DCC) model. Finally, I regress this correlation on mis-pricing and two other control variables, GDP and inflation. I use monthly data from January 1983 to December 2016. Consistent with the Fed model, the paper finds a significant positive correlation between the yield on government bonds and stock yield, with an average correlation of 0.942 - 0.997. However, in contrast to the inflation illusion hypothesis, mis-pricing in the stock market has an insignificant impact on this correlation.

The third essay provides liquidity shocks contagion between the stock market and the corporate bond market as the driving force behind the high correlation between the yield on stocks and the yield on government bonds as implied by the Fed model. The idea is that when liquidity drops in the stock market, firms' credit risk rises because the deterioration in the liquidity of equities traded in the stock market increases the firms’ default probability. Consequently, investors’ preferences shift away from corporate bonds to government bonds. Higher

demand for government bonds keeps their yield low, leading to a co-movement of government bond yield and stock yield. In order to test this liquidity-based explanation, the paper first examines the interdependence between liquidity in the stock and corporate bond markets using the Markov switching model, and a time series non-parametric technique called the Convergent Cross Mapping (CCM). In order to see the response of government bond yield and stock yield to liquidity shocks in the stock market, the study implements an Auto Regressive Distributed Lag (ARDL) model. Using monthly data from January 1997 to December 2016, the paper presents strong evidence of liquidity shocks transmission form the stock market to the corporate bond market. Furthermore, liquidity shocks in the stock market are found to have a significant impact on the stock yield. These findings support the illiquidity contagion explanation provided in this paper.

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CHAPTER 1

ILLIQUIDITY CONTAGION AND THE PRICING OF COMMONALITY RISK IN THE U.S. STOCK MARKET: EVIDENCE FROM THE DYNAMIC CONDITIONAL CORRELATION (DCC) MODEL

1.1. Introduction

This chapter investigates the pricing of commonality risk in the U.S. stock market. According to the Liquidity-adjusted Capital Asset Pricing Model (LCAPM) developed by Acharya and Pedersen (2005), the commonality risk is the risk that investors face when holding an asset that becomes illiquid when the overall market is illiquid. The current literature, however, shows that the commonality risk has an insignificant premium. For example, Acharya and Pedersen (2005) find a premium of 0.076% per year. Hagströmer, Hansson, and Nilsson (2013), who estimate the conditional version of the LCAPM, find a premium of 0.020%-0.036% per year. These authors argue that the commonality risk premium is the least important component of the total illiquidity premium. Lee (2011) applies the LCAPM to data from developed and emerging economies and finds that the commonality risk premium is insignificant not just in the U.S, but also in other developed countries.

The purpose of this chapter is to challenge the above findings and provide more accurate evidence on the significance of the commonality risk. I modify the testing procedures used in the previous literature in three ways. First of all, I use a more comprehensive market illiquidity measure that can reflect the liquidity condition of different assets. The common feature of the above-mentioned studies is that the overall market illiquidity is measured by the average illiquidity of all the stocks. This measure of market illiquidity, however, is subject to a measurement problem because it includes only equities. The fundamental assumption of the Capital Asset Pricing Model (CAPM) is that investors hold a portfolio that includes all traded financial assets. This "market portfolio," of course, is impossible to measure (Fama & French, 2004). This paper contributes to the commonality risk literature by implementing a market illiquidity measure that is a better representative of the liquidity condition of different asset classes. Specifically, the illiquidity of the market portfolio is broadly measured by the yield difference between the three-month Asset Backed Commercial Papers (ABCP) and the three-month U.S. treasury bill. Frank, Hesse and González-Hermosillo (2008) show that this spread has a high correlation with the liquidity condition in other financial markets such as the bond market, the stock market, and also the funding liquidity condition of banks.

Secondly, the previous studies mentioned above form portfolios based on the illiquidity of each stock, which contrasts the definition of commonality risk. Anderson, Binner, Hagströmer, and Nilsson (2013) argues that commonality risk premium estimate from stocks sorted based on their illiquidity reflects compensation for the level of illiquidity instead of the systematic co-movement between the illiquidity of a given stock and the market illiquidity. Consistent with the definition of commonality risk, I form portfolios based on the sensitivity of each stock's illiquidity to the overall market illiquidity.

The third modification I propose is to use the conditional second moments estimated from the Dynamic Conditional Correlation (DCC) model to capture the dynamics of the commonality risk. As argued by Adrian and Franzoni (2009), an econometric model that fails to mimic the investors' learning process of time-evolving risk may lead to inaccurate estimates of the betas. Simin (2008) also argues that the conditional versions of asset pricing models have better predictive performance. Hagströmer et al. (2013) implement a multivariate GARCH model with BEKK representation to construct time varying risk premium in a LCAPM. However, as argued by Engle and Kroner (1995), the DCC model has a computational advantage over the BEKK model because it only requires the estimation of univariate GARCH processes to parameterize the covariance equations.

The major finding of this study is that estimating the LCAPM by using a more comprehensive measure of market illiquidity yields a significant commonality risk premium. In particular, the estimated commonality risk premium ranges between 0.013% to 0.022% per year for the period from January 1997 to December 2016. This is markedly higher than the premium estimated under the approaches of Acharya and Pedersen (2005) and Hagströmer et al. (2013). In addition, the paper finds a significant variation in the commonality risk premium over time with the premium being higher during periods of economic crisis such as the Dot-com Crash and the Great Recession. Finally, the LCAPM with the broader measure of market illiquidity performs better in predicting the average return for the low commonality risk portfolios considered in the study.

The reminder of the chapter is organized as follows. Section 1.2 presents the theoretical framework of the study and the procedures to parameterize the model to obtain the commonality risk premium. Section 1.3 provides the detailed rationales for the market illiquidity measure used in the study. Data descriptions and the estimation results follow. Some robustness tests are also provided at the end of the section. Lastly, section 1.4 concludes the chapter and offers further discussions.

1.2. Data and Methodology

1.2.1. The Liquidity Adjusted CAPM (LCAPM)

Acharya and Pedersen (2005) relax the assumption of a frictionless world in the standard market Capital Asset Pricing Model (CAPM) and introduce the Liquidity adjusted CAPM (LCAPM). They argue that trading securities involve a cost that varies randomly over time. Assuming a stochastic liquidity cost (per share cost of selling), the LCAPM can be expressed as:

$$E_t(r_{t+1}^i - c_{t+1}^i - r^f) = \frac{Cov_t(r_{t+1}^i - c_{t+1}^i, r_{t+1}^m - c_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)} E_t(r_{t+1}^m - c_{t+1}^m - r^f), \tag{1}$$

where r_t^i is the return on stock *i*, c_t^i is the illiquidity of each stock measured as percent per dollar, r_t^m is the market return, r^f the risk free rate, and c_t^m is the illiquidity of the market. Equation (1) states that the conditional net excess return (excess return adjusted for illiquidity cost) of a security *i* is a function of the conditional net market return. Let $\lambda_t \equiv E_t(r_{t+1}^m - r^f - c_{t+1}^m)$ and expanding the covariance term in (1) results in:

$$E_t(r_{t+1}^i - c_{t+1}^i - r^f) = \lambda_t \frac{Cov_t(r_{t+1}^i, r_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)} + \lambda_t \frac{Cov_t(c_{t+1}^i, c_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)} - \lambda_t \frac{Cov_t(r_{t+1}^i, c_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)} - \lambda_t \frac{Cov_t(c_{t+1}^i, r_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)} \tag{2}$$

Equation (2) can be rewritten in the form of traditional risk betas as follows:

$$E_t(r_{t+1}^i - c_{t+1}^i - r^f) = \lambda_t \beta_t^1 + \lambda_t \beta_t^2 - \lambda_t \beta_t^3 - \lambda_t \beta_t^4 \tag{3}$$

Equation (3) states that in addition to the usual market beta $\beta_t^1 \equiv \frac{Cov_t(r_{t+1}^i, r_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)}$, there are three additional sources of risk that can be interpreted as different forms of illiquidity risk. The term $\beta_t^3 \equiv \frac{Cov_t(r_{t+1}^i, c_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)}$ represents the risk factor due to the return sensitivity to the market wide illiquidity and $\beta_t^4 \equiv \frac{Cov_t(c_{t+1}^i, r_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)}$ is the liquidity sensitivity of a security to the market return. In this chapter, the focus is on $\beta_t^2 \equiv \frac{Cov_t(c_{t+1}^i, c_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)}$, which is known as the commonality risk. It is the risk of holding a stock that becomes illiquid when the market is illiquid. It entails a premium because investors have to be compensated for holding illiquid assets at times of distress.

The traditional Fama-MacBeth (1973) two-step procedure for testing the significance of risk factors cannot be applied in equation 3. This is because the way the LCAPM is set up. All the factor loadings have the same coefficient, λ_t, which makes it impossible to compute the risk premium associated with each risk beta and test for its significance via the usual two-stage regression. Acharya and Pedersen (2005) and Piqueira (2005) propose an alternative approach. According to these authors, the commonality risk premium, which is the focus of this paper, can be defined as the difference in the expected returns between the highest (H) and the lowest (L) commonality risk portfolios that can be attributed to a difference in β_t^2. Specifically, the difference in the expected return can be expressed as:

$$E_t(r_{t+1}^H - c_{t+1}^H) - E_t(r_{t+1}^L - c_{t+1}^L) = \lambda_t(\beta_t^{H1} - \beta_t^{L1}) + \lambda_t(\beta_t^{H2} - \beta_t^{L2}) - \lambda_t(\beta_t^{H3} - \beta_t^{L3}) - \lambda_t(\beta_t^{H4} - \beta_t^{L4}) \quad (4)$$

The return premium due to the commonality risk is given by the term $\lambda_t(\beta_t^{H2} - \beta_t^{L2})$. Consistent with Acharya and Pedersen (2005), and Hagströmer et al. (2013), λ_t is assumed to be constant across different periods and is estimated by taking the sample average of $r_t^m - c_t^m - r_t^f$.

1.2.2. Calculating the Commonality Risk Premium

To obtain the commonality risk premium $\lambda_t(\beta_t^{H2} - \beta_t^{L2})$, I follow the following four steps:

Step 1: Calculate the illiquidity measure for each stock

Following Acharya and Pedersen (2005), and Goyenko and Ukhov (2009), this study uses Amihud's (2002) illiquidity measure, which defines the illiquidity of stock *i* in month *t* as

$$ILLIQ_t^i = \frac{1}{N_t}\sum_{d=1}^{N_t}\frac{\left|R_{t,d}^i\right|}{V_{t,d}^i} \qquad (5)$$

where N_t is the number of days in month t, $R_{t,d}^i$ is the return on day d in month t, and $V_{t,d}^i$ is the dollar volume on day d in month t. This measure is calculated for each stock i in month t from the daily data and multiplied by 10^6 (Amihud, 2002). A high value of $ILLIQ_t^i$ indicates that the stock price moves a lot in response to little volume change. When a stock is illiquid, the spread between the price the seller is willing to accept (the ask price) and the price the buyer offers (the bid price) is wide, so that the sellers who want to offload their properties quickly have to reduce the price by a large amount. This implies that the ratio of the return to the trading volume will be higher.

To calculate the individual stock illiquidity measure as described in Equation 5, I use daily data on returns and trading volumes from January 1, 1997 to December 31, 2016 obtained from the Center for Research in Security Prices (CRSP) database. The sample includes shares listed on the New York Stock Exchange (NYSE) with a share code of 10 or 11 (ordinary common shares). As suggested by Acharya and Pedersen (2005) and Hagströmer et al. (2013), only stocks with prices in the range from \$5 to \$999 are included in the sample. In addition, dead stocks with less than 12 months of observations are also excluded from the study. There are a total of 458 stocks included in the sample.

However, the LCAPM is specified in terms of dollar cost per dollar invested while the Amihud illiquidity measure is expressed in percent per dollar terms. Acharya and Pederson (2005) suggest the following transformation to normalize the illiquidity measure:

$$c_t^i = \min(0.25 + 0.3 \cdot ILLIQ_t^i \cdot P_{t-1}^m, 30.00)\,, \qquad (6)$$

where P_t^m is the ratio of the capitalizations of the market portfolio at the end of month t and of the market portfolio at the end of a base month, for which I pick July 1998, the last month before the beginning of the housing market bubble (Saxton, 2008). This normalized measure is capped at a maximum value of 30% to ensure that the results are not driven by outliers. According to Acharya and Pedersen (2005), the goal of this transformation is to approximately match the mean and the variance of the effective spread between the transaction price and the midpoint of the prevailing bid-ask quote reported by Chalmers and Kadlec (1998). This spread is considered as the benchmark because it directly measures the extent of illiquidity of a given stock. Chalmers and Kadlec (1998) report that this spread ranges from 0.29% to 3.41% with an average of 1.11% from 1983 to 1992. Acharya and Pedersen (2005) report that their normalized measure has an average of 1.24% and a standard deviation of 0.37%. For the sample period considered in this study, the cross-sectional average illiquidity is 0.531% with a standard deviation of 0.268%, close enough to solve the scale problem.

Step 2: Form the high (H) commonality risk portfolio and the low (L) commonality risk portfolio

I form the portfolios based on the sensitivity of each stock's illiquidity to the market wide illiquidity as in Anderson et al. (2013). This is achieved by regressing the illiquidity of each stock on the market wide illiquidity (c_t^m, which will be defined in the next section) and the market return (r_t^m, served as a control variable) by using 24 month and 36 month formation period:

$$c_t^i = \alpha_0^i + \alpha_1^i c_t^m + \alpha_2^i r_t^m + u_t^i. \tag{7}$$

The estimated α_1^i is the measure of the sensitivity. The individual stocks are ranked based on the sensitivity from the highest to the lowest and put into 10 portfolios.[1] The first portfolio includes

[1] The choice of the number of portfolios is to make use of sufficiently large number of stocks and information set in the determination of the commonality risk premium. In line with this, the first and the tenth portfolios have 45 stocks.

the stocks with the highest commonality risk (the *H* portfolio) while the tenth portfolio has the stocks with the lowest commonality risk (the *L* portfolio). The annualized average illiquidity and return of the 10 portfolios formed based on the sensitivity of each stock's illiquidity to the market wide illiquidity is presented in Table 1.1. It can be seen that the average illiquidity is not monotonic from high commonality risk to low commonality risk portfolios. This supports the argument that forming portfolios by sorting stocks based on their illiquidity cannot fully represent compensation for the co-movement of a given stock's illiquidity and overall market illiquidity.

Table 1.1
Average and Standard Deviation of Portfolio Return and Portfolio Illiquidity

	Average portfolio return	Standard deviation of portfolio return	Average portfolio illiquidity	Standard deviation of portfolio illiquidity
Portfolio 1	1.619	2.173	1.664	1.375
Portfolio 2	1.098	1.511	0.534	0.407
Portfolio 3	1.119	1.509	0.363	0.132
Portfolio 4	1.168	1.522	0.308	0.079
Portfolio 5	1.0002	1.555	0.282	0.036
Portfolio 6	1.082	1.527	0.275	0.033
Portfolio 7	0.865	1.295	0.265	0.014
Portfolio 8	0.958	1.348	0.273	0.024
Portfolio 9	0.734	1.623	0.328	0.088
Portfolio 10	1.541	1.616	1.014	0.492
Cross sectional average	1.119	1.568	0.531	0.268

There are two different portfolio rebalancing processes considered in this study. First, portfolios are rebalanced after the 12-month holding period by using the previous 24 months and 36 months as the formation period. Second, portfolios are rebalanced after the 24-month holding period by using the previous 24 months and 36 months as the formation period. The portfolio returns and illiquidity are calculated for the holding period.

Step 3: Adjusting the Portfolio Illiquidity Measure

As argued by Acharya and Pedersen (2005), Bongaerts et al. (2014), and Lee (2011), illiquidity should be short-lived and less persistent. However, the illiquidity measure (6) usually has a very high serial correlation. Therefore, when computing the illiquidity betas, Acharya and Pedersen (2005) suggest to use the innovations of the portfolio illiquidity instead of the portfolio illiquidity. To compute these innovations, they calculate the portfolio illiquidity as the average of individual stock un-normalized illiquidity, truncated for outliers, in the portfolio:

$$ILLIQ_t^P = \frac{1}{n}\sum_{i=1}^{n}\min\left(ILLIQ_t^i, \frac{30.00-0.25}{0.3\cdot P_{t-1}^m}\right). \tag{8}$$

Then the portfolio illiquidity measure c_t^p is defined as the residual from an AR(2) regression:

$$\begin{aligned} c_t^p = &\left(0.25+0.3\cdot ILLIQ_t^p\cdot P_{t-1}^m\right)\\ &-\left[\hat{a}_0+\hat{a}_1\left(0.25+0.3\cdot ILLIQ_{t-1}^p\cdot P_{t-1}^m\right)+\hat{a}_2\left(0.25+0.3\cdot ILLIQ_{t-2}^p\cdot P_{t-1}^m\right)\right]. \end{aligned} \tag{9}$$

Note that in (9), P_{t-1}^m is used in all the three terms to ensure that the transformation measures only innovations in illiquidity, not changes P_{t-1}^m.

Step 4: Estimate the betas for the high and low commonality risk portfolios in the LCAPM

The time-varying betas, $\beta_t^{H2} \equiv \frac{Cov_t(c_{t+1}^H, c_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)}$ and $\beta_t^{L2} \equiv \frac{Cov_t(c_{t+1}^L, c_{t+1}^m)}{V_t(r_{t+1}^m - c_{t+1}^m)}$ are estimated by the Dynamic Conditional Correlation (DCC) model. The conditional net market return $\lambda_t \equiv E_t(r_{t+1}^m - r^f - c_{t+1}^m)$ is estimated using data on market return, risk free rate and market illiquidity. Multiplying λ_t by $\left(\beta_t^{H2} - \beta_t^{L2}\right)$ yields the commonality risk premium.

<u>1.2.3. The Dynamic Conditional Correlation (DCC) Model</u>

To estimate time-varying betas, the paper implements a multivariate GARCH process estimated by the Dynamic Conditional Correlation (DCC) approach developed by Engle (2002, 2016). This modeling strategy involves two stages. In the first stage, a univariate GARCH model is estimated for each of the four model variables: the return on portfolio (r_t^p), the illiquidity of each portfolio (c_t^p), the market return (r_t^m), and the market wide illiquidity (c_t^m). In the second stage, the transformed residuals resulting from the first stage are used to estimate a conditional correlation estimator. Specifically, it is assumed that those four variables are conditionally multivariate normal with zero expected value and conditional covariance matrix H_t. In the first stage, each of the conditional variances in H_t is estimated by a univariate GARCH model. Let Z_t denote a 4x1 vector of portfolio return, portfolio illiquidity, market return, market illiquidity, and let $Z_t \sim N(0,\ H_t)$, the GARCH model is given by,

$$H_t = diag(\alpha_i) + diag(\varphi_i) o\, Z_{t-1} Z_{t-1} + diag\ (\lambda_t) o\, H_{t-1} \tag{10}$$

where in equation 10, H_t represent the conditional variance, α, φ, and λ are parameter matrices, and o denotes the Hadamard product.

The second stage involves expressing the covariance matrix in H_t as $H_t = D_t \cdot R_t \cdot D_t$, where D_t is a diagonal matrix consisting of the squared root of the conditional variances and R_t is the correlation matrix with ones on the diagonal and the off-diagonal element less than or equal to one in absolute value. Engle (2002) suggests that the off diagonal elements of the correlation matrix can be constructed by estimating another univariate GARCH process. This computational advantage makes the DCC model more attractive than other multivariate GARCH specifications such as the BEKK representation (Engle & Kroner, 1995).

Denote the off-diagonal elements of R_t as $\rho_{ij,t} \equiv \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$, the dynamic correlation between variable i and j. Engle (2002) suggests that the elements of the conditional covariance matrix can be obtained by estimating the following univariate GARCH process, using an exponential smoothing:

$$q_{ij,t} = \bar{\rho}_{ij} + \alpha(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \bar{\rho}_{ij}) + \beta(q_{ij,t-1} - \bar{\rho}_{ij}), \tag{11}$$

where $\bar{\rho}_{ij}$ is the unconditional correlation of the standardized model variables ε_{it}, $\varepsilon_{it} = D_{it}^{-1} Z_{it}$, where the standardization is done by the corresponding conditional variance from the first stage. The resulting second moments from the first and second stages are used to compute the βs in Equation (3).

1.2.4. Principal Component Analysis

Imposing the model implied constraint that the risk premium is the same across all betas on equation 3 yields a net beta, $\beta_t^{net} = \beta_t^1 + \beta_t^2 - \beta_t^3 - \beta_t^4$. The relative importance of the risk betas in the LCAPM can be assessed by constructing factors as a proxy for β_t^{net} using the Principal Component Analysis (PCA) and then comparing the contribution of each risk type. This approach is in the spirit of Connor and Korajczyk (1993) and Lettau and Pelger (2018). Connor and Korajczyk (1993) use PCA to determine the set of factors that can generate asset returns. Lettau and Pelger (2018) extend the standard PCA approach by introducing a penalty term to account for the pricing error and hence differentiate between weak and strong factors.

PCA extracts the common variation in a multivariable data table and expresses this information set as a set of new variables called Principal Components. These components are a linear combination of the model variables (James, Witten, Hastie, & Tibshirani, 2013). The number of principal components is less than or equal to the number of original variables.

The first principal component (PC1) of a set of risk features $\beta_t^1, \beta_t^2, \beta_t^3$ and β_t^4 is the normalized linear combination of the features,

$$PC1 = \phi_{11}\,\beta_{it}^1 + \phi_{21}\,\beta_{it}^2 - \phi_{31}\,\beta_{it}^3 - \phi_{41}\,\beta_{it}^4 \tag{12}$$

that has the largest variance, given the constraint that $\sum_{j=1}^{4} \phi_{j1}^{2} = 1$. The ϕ_{11}.. ϕ_{41} are called the loadings and their sum of squares is equal to one to avoid an arbitrarily large variance. The amount of variation retained by each component is measured by its Eigen values. Similarly, the second principal component (PC2) would be a linear combination of the risk features that has maximal variance out of all linear combinations that are uncorrelated with PC1. Risk features that are correlated with PC1 and PC2 are the most important in explaining the variability in the data set. The contributions of variables in accounting for the variability in a given principal component are expressed in percentages.

1.2.5. Measure of Market Illiquidity

Harrington and Korajczyk (1993) and Damodaran (1999) argue that the betas in the asset pricing model measure the risk added on to a diversified market portfolio. They represent the market component of risk in any investment that affects a large subset or all investments. A market portfolio, on the other hand, includes every traded asset that a marginal investor can hold including fixed income and real assets. Consequently, the measure of the illiquidity of the market portfolio should be a representative of the illiquidity of different asset classes that could constitute a diversified market portfolio. In this regard, taking the average of the liquidity of each stock as a measure of the market illiquidity is highly restrictive because it considers only equities, not a diversified portfolio consisting of other assets. The major problem facing practitioners is that there are no indices that measure a diversified market portfolio. In order to overcome this problem in measuring the market illiquidity, the study uses a measure that is given by the spread between the yield of 3-month Asset Backed Commercial Papers (ABCP) and that of U.S. treasury bill. Frank et al. (2008) showed that this spread has a high correlation with the liquidity condition in other financial markets such as the bond market, the stock market and also the funding liquidity condition of banks. Because of this, the measure can be considered as being a broad representative of the overall liquidity condition.

The widening of the spread between the two yields indicates deterioration in liquidity. Based on the empirical observation during the 2007/08 financial crisis, Frank et al. (2008) argue that falling housing prices led to increased delinquencies on mortgages. Increased delinquencies and defaults on mortgages cause deterioration in the ratings of structured mortgage backed instruments. A wide range of financial institutions hold these mortgage backed securities and are funded through issuance of short term asset backed commercial papers. Because of the deterioration of the ratings of mortgage backed securities and increasing uncertainty with regard to the exposure to and the value of the underlying mortgage backed securities, investors become unwilling to roll over the corresponding asset backed commercial papers. This can be captured by the widening of the spread between the yield of asset backed commercial papers and treasury bill. Moreover, fund managers and investors that held these structured mortgage backed products in their balance sheet were then burdened by increased margin requirements. As a consequence, they attempted to offload the more liquid parts of their portfolios (such as stocks and bonds) to meet these margin calls and also respond to redemptions by investors. This infrequent trading and limited price discovery process eventually caused increased volatility and uncertainty, causing illiquidity spirals.

The data on the two yields are obtained from the St. Louis Fed (FRED) website. The market illiquidity measure is plotted in Figure 1.1. The measured illiquidity is higher during periods that are anecdotally known for higher illiquidity. The blue shaded regions represent some of these known periods such as the Asian Financial Crisis in late 1997, the Russian Default and the Long Term Capital Management crisis in October 1998, the Dotcom crash in May 2000, the Great Recession from December 2007 to June 2009, the August 2010 stock market selloff, and Brexit in June 2016.

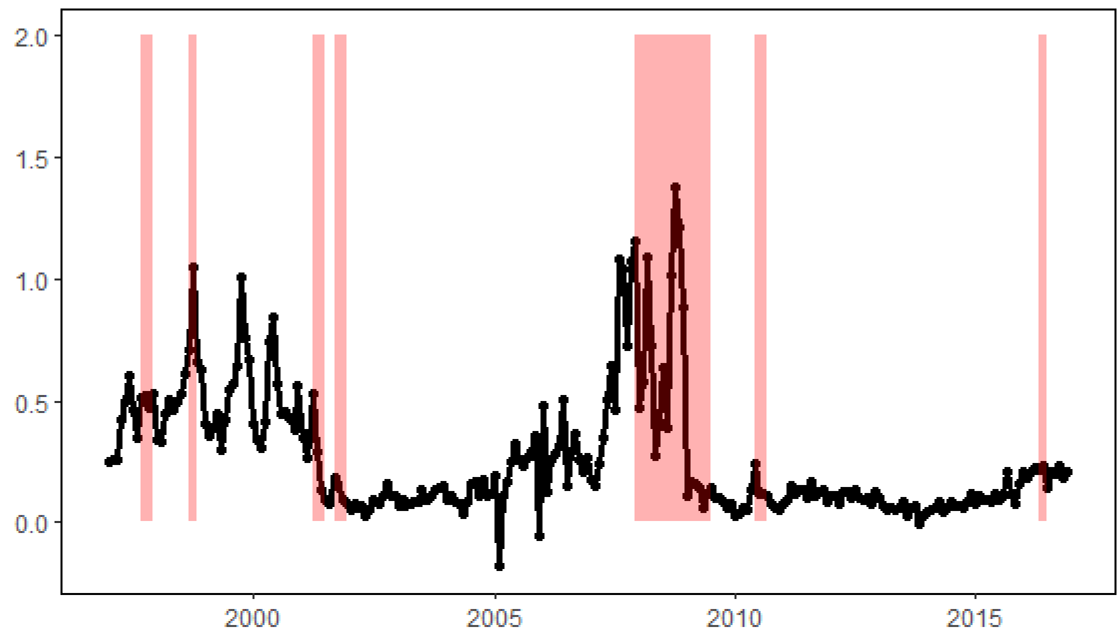

Figure 1.1. Market illiquidity from 1997 to 2016 measured using the yield gap between 3-month asset backed commercial paper and 3-month treasury bills.

For the purpose of comparison, Figure 1.2 presents the market illiquidity measured as the average of the illiquidity of each stock. In contrast to the measure based on the housing market, taking the average of the illiquidity of each stock does not capture some of the well-known liquidity crisis periods like the Great Recession. In addition, the plot in Figure 1.2 unrealistically implies that the illiquidity during the Great Recession period is lower than the illiquidity during the Dot-com crash and the Asian Financial Crisis.

1.3. Results

The average annual excess return for portfolios formed based on the sensitivity of each stock's illiquidity to the market wide illiquidity is presented in Table 1.1. It can be seen that portfolios which contain stocks whose illiquidity is highly sensitive to the overall illiquidity tend to have higher return than portfolios containing stocks whose illiquidity is less sensitive to the market liquidity condition. In relation to Equation 4, the return of the highest (H) commonality

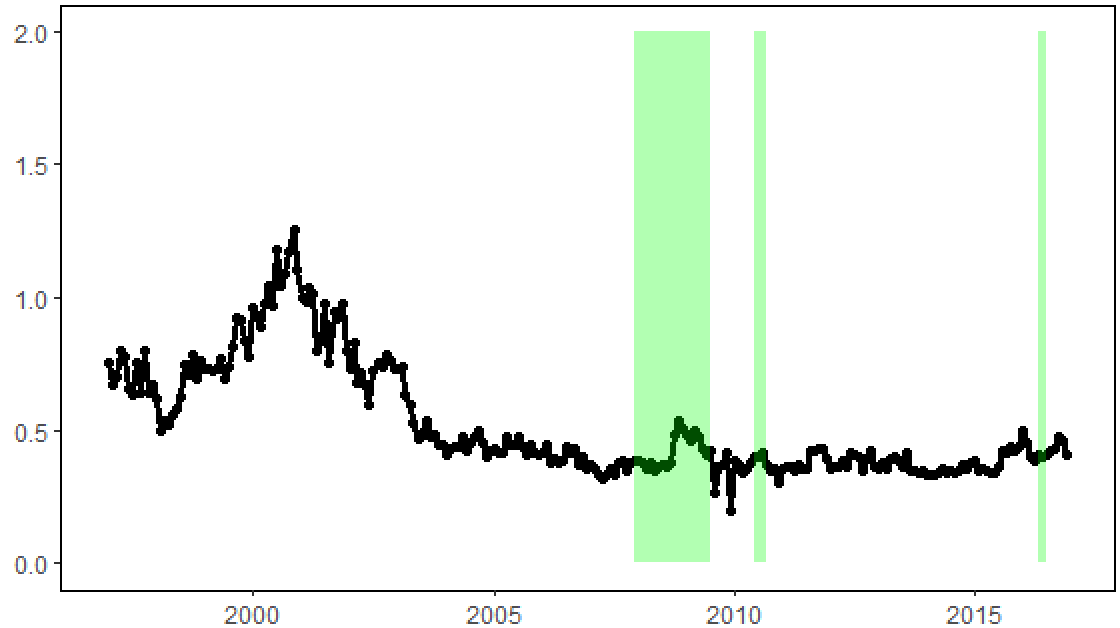

Figure 1.2. Market illiquidity measured as the average of the illiquidity of each stock. The green shaded boxes represent missing low liquidity periods.

risk portfolio, r_t^H and the lowest (L) commonality risk portfolio, r_t^L, are measured by the cross-sectional average of the r_t^i of each stocks in the 1st portfolio and 10th portfolio. Descriptive statistic on the risk price (λ_t), market return, risk free rate, and market illiquidity used in the calculation of the commonality risk premium is presented in Table 1.2.

The main purpose of this chapter is to test the magnitude and significance of the commonality risk premium by using a more comprehensive measure of market illiquidity, and by forming portfolios based on liquidity sensitivity. To make sure that these changes are the reason that alters the commonality risk premium, the paper first estimates the LCAPM with constant beta followed by time varying beta while the market illiquidity is measured as the average of the illiquidity of each stock. This approach is in the spirit of Acharya and Pedersen (2005) and Hagströmer et al. (2013), respectively. The results are presented in the first two columns of panel A of Table 1.3. The findings imply that the difference in the annualized expected returns between portfolio 1 and

Table 1.2
The Average and Standard Deviation of Risk Price, Market Return, Risk Free Rate and Market Illiquidity Used in the Calculation of the Commonality Risk Premium

	Risk price when market illiquidity is measured as the average of the illiquidity of each stock (λ_t)	Risk price when market illiquidity is measured as the spread between the yield on commercial paper and treasury bill (λ_t)	Market return (r_t^m)	Risk free rate (r_t^f)	Market illiquidity measured as the spread between the yield on commercial paper and treasury bill (C_t^m)	Market illiquidity measured as the average of the illiquidity of each stock (C_t^m)
Average	0.433%	0.192%	0.579%	0.149%	0.238%	5.461 x 10^{-17}%
Standard Deviation	4.439%	4.493%	4.421%	0.169%	0.255%	0.063%

portfolio 10 that can be attributed to the difference in their level of commonality risk is nearly zero. These findings imply that commonality risk premium is the least important in its economic significance, which is consistent with Acharya and Pedersen (2005) and Hagströmer et al. (2013).

The above result can be explained by the failure to capture the level of commonality risk when the market illiquidity is measured by taking the average of the illiquidity of each stock. This failure is apparent in Table 1.4, which presents the averages and standard deviations of the four betas in the LCAPM estimated under the Hagstromer et al. (2013) approach. The beta associated with commonality risk (β^2) for portfolio 10 is higher than that of portfolio 1, which contrasts the portfolio formation procedure implemented in this paper.

The result presented in the third column of panel A of Table 1.3 is the core contribution of this chapter. It presents the commonality risk premium when the LCAPM is estimated with time varying betas and the market illiquidity measured as the yield difference between commercial paper and treasury bill. The result reveals that the difference in the annual excess return between

Table 1.3
Commonality Risk Premium Estimates from LCAPM with 24-Month Formation Period

Constant beta LCAPM with the market illiquidity measured as the average of the illiquidity of each stock	Time varying beta LCAPM with the market illiquidity measured as the average of the illiquidity of each stock	Time varying beta LCAPM with the market illiquidity measured as the yield gap between commercial paper and treasury bill
Panel A: 12 month portfolio re-balancing		
-0.00004%	-0.005% (42.015)*	0.022% (12.263)*
Panel B: 24 month portfolio re-balancing		
-0.000008%	-0.013% (42.015)*	0.013% (12.263)*
Panel C: Observations from the Great Recession period dropped		
-0.00002%	-0.061% (44.989)*	0.039% (11.548)*

Numbers in parentheses are t-statistics,* indicates significance at 5%

portfolio 1 and 10 stemming from the difference in their level of commonality risk is 0.022% per year. This estimate is significantly different from zero at the 5% level of significance. It is also significantly higher than the commonality risk premium estimates using the approaches of Acharya and Pedersen (2005), and Hagströmer et al. (2013). The increase in the premium estimate can be explained by using a broader market illiquidity measure that can reflect the liquidity condition of different financial markets.

Using a broader market illiquidity measure captures the true extent of commonality risk better than taking the average of each stock’s illiquidity including the tendency of investors to set their buying strategies based on the prices of other asset classes. As suggested by Cespa and

Table 1.4
Time Series Average of the Four Betas in the LCAPM for 12-Month Holding Period and the Market Illiquidity Measured as the Average of the Illiquidity of Each Stock

	β^1	β^2	β^3	β^4
Portfolio 1	2.664 (1.504)	0.024 (0.013*)	-3.091 (1.861)	0.001 (0.0008*)
Portfolio 2	1.928 (0.777*)	0.037 (0.013*)	-3.091 (1.861*)	0.002 (0.0005*)
Portfolio 3	1.975 (0.643*)	0.005 (0.002*)	0.064 (0.056*)	0.0009 (0.0003*)
Portfolio 4	2.084 (0.808*)	0.005 (0.002*)	0.053 (0.039*)	0.002 (0.001*)
Portfolio 5	2.219 (0.841*)	0.005 (0.002*)	0.086 (0.064)	0.001 (0.0004*)
Portfolio 6	2.373 (0.983*)	0.005 (0.002*)	0.103 (0.085*)	0.0008 (0.0004*)
Portfolio 7	2.473 (0.968*)	0.005 (0.002*)	0.104 (0.108)	0.0008 (0.0003*)
Portfolio 8	2.478 (1.047)	0.006 (0.002*)	0.052 (0.055)	0.0007 (0.0003*)
Portfolio 9	2.799 (1.197*)	0.008 (0.003*)	0.069 (0.097*)	0.002 (0.0007*)
Portfolio 10	2.881 (1.271*)	0.025 (0.009*)	0.359 (0.479)	0.002 (0.0008*)

The numbers in parentheses are standard deviation. * indicates significance at 5%.

Foucault (2014), the advancement in the information technology and the resulting improved access to price information make liquidity suppliers to increasingly rely on the information contained in the prices of other assets. When liquidity drops in other financial markets, investors in the stock market face uncertainty and feel they are exposed to price changes while holding the asset in their inventory. As a consequence, they react by postponing their buying decision or by widening their quotes, which lowers the liquidity of equities traded in the stock market. Accordingly, investors with an intention of selling at times of distress would rather buy stocks with a low risk of becoming illiquid in such times. The results presented in this paper show that this behavior is indeed valued in the stock market.

Another explanation for the increase in the premium estimate is that forming portfolios based on the sensitivity of each stock's illiquidity to overall liquidity condition captures the level of commonality risk better than using the level of illiquidity. Table 1.5 presents the averages and standard deviations of the betas estimated in this approach. Moreover, the time series plots of β^2, the commonality risk beta, for the 1st and 10th portfolio are presented in Figure 1.3. It can be seen that β^2 tends to increase with the level of commonality risk. The difference in β^2 between the highest and the lowest commonality risk portfolios is much higher at times of financial distress such as the dot-com crash (2000-01) and the Great Recession (2007-09).

Table 1.5
Time Series Average of the Four Betas in the LCAPM for 12-Month Holding Period and the Market Illiquidity Measured as the Yield Gap Between Treasury Bill and Commercial Paper

	β^1	β^2	β^3	β^4
Portfolio 1	2.702 (1.186*)	0.006 (0.006*)	0.556 (0.877*)	-0.007 (0.003*)
Portfolio 2	2.317 (1.069*)	0.036 (12.263*)	-2.337 (1.632*)	-0.007 (0.003*)
Portfolio 3	2.363 (0.838*)	0.002 (0.0014*)	0.094 (0.106)	-0.009 (0.004*)
Portfolio 4	2.155 (0.686*)	0.0004 (0.0005*)	0.102 (0.092*)	-0.009 (0.003*)
Portfolio 5	2.163 (0.701*)	0.0001 (0.0002*)	0.075 (0.067*)	-0.009 (0.003*)
Portfolio 6	2.098 (0.781*)	0.0003 (0.0004)	0.078 (0.064*)	-0.006 (0.002*)
Portfolio 7	2.275 (1.049*)	-0.0002 (0.0003)	0.083 (0.068*)	-0.005 (0.003*)
Portfolio 8	2.292 (0.938*)	-0.0004 (0.0005)	0.0725 (0.058*)	-0.007 (0.003*)
Portfolio 9	2.389 (1.112*)	0.003 (0.002*)	0.099 (0.123)	-0.013 (0.006)
Portfolio 10	2.825 (1.485*)	-0.006 (0.008)	0.041 (0.036*)	-0.009 (0.005*)

The numbers in parentheses are standard deviation. * indicates significance at 5%.

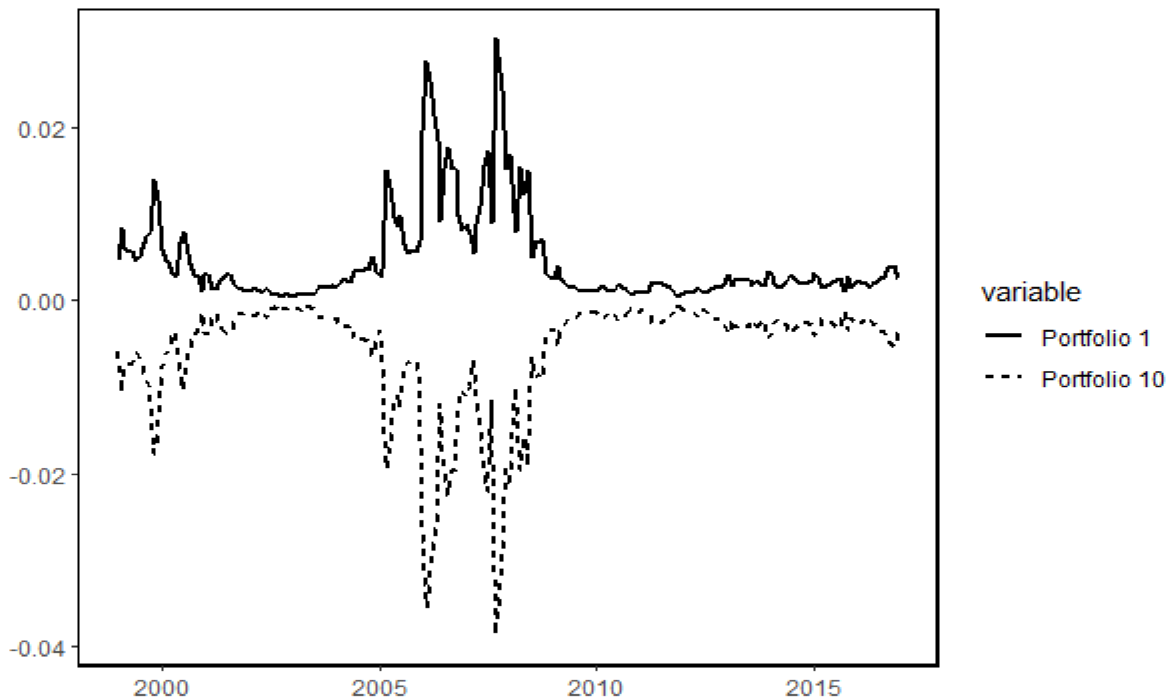

Figure 1.3. Time varying commonality risk beta plots of portfolio 1 and portfolio 10 for 12-month holding period with the market illiquidity measured as the yield gap between commercial paper and treasury bill.

In order to give further insight on the significance of the 0.022% estimate, I presented the premium for the other two forms of liquidity risk in Table 1.6. A noticeable finding is that unlike previous studies, the premiums for both the risk due to the correlation between stock return and market illiquidity, and the risk due to the correlation between stock illiquidity and market return are found to be less than the commonality risk premium. Specifically, the excess return associated with the correlation between stock illiquidity and market return disappears under the 12-month portfolio formation case. The time series plots of the betas associated with the risk due to the correlation between stock illiquidity and market return are plotted in Figure 1.4. It can be seen that the β^4 for portfolio 10 is lower than the β^4 for portfolio 1 for the majority of the sample period. In the LCAPM, the interpretation of this finding is that portfolio 1 has stocks that become less illiquid when the market return is low than portfolio 10, leading to a discount. The implication is that there

Table 1.6
Premium Estimates for the Risk Due to the Correlation Between Stock Illiquidity and Market Return and for the Risk Due to the Correlation Between Stock Return and Market Illiquidity

	Premium for the risk due to the correlation between stock illiquidity and market return	Premium for the risk due to the correlation between stock return and market illiquidity
12-month holding period with market illiquidity measured as the yield gap between treasury bill and commercial paper	-1.283% (10.316*)	-0.007% (16.747*)
24-month holding period with market illiquidity measured as the yield gap between treasury bill and commercial paper	0.283% (11.128*)	0.0008% (19.449*)

The number in parentheses is standard deviation, * indicates significance at 5% level.

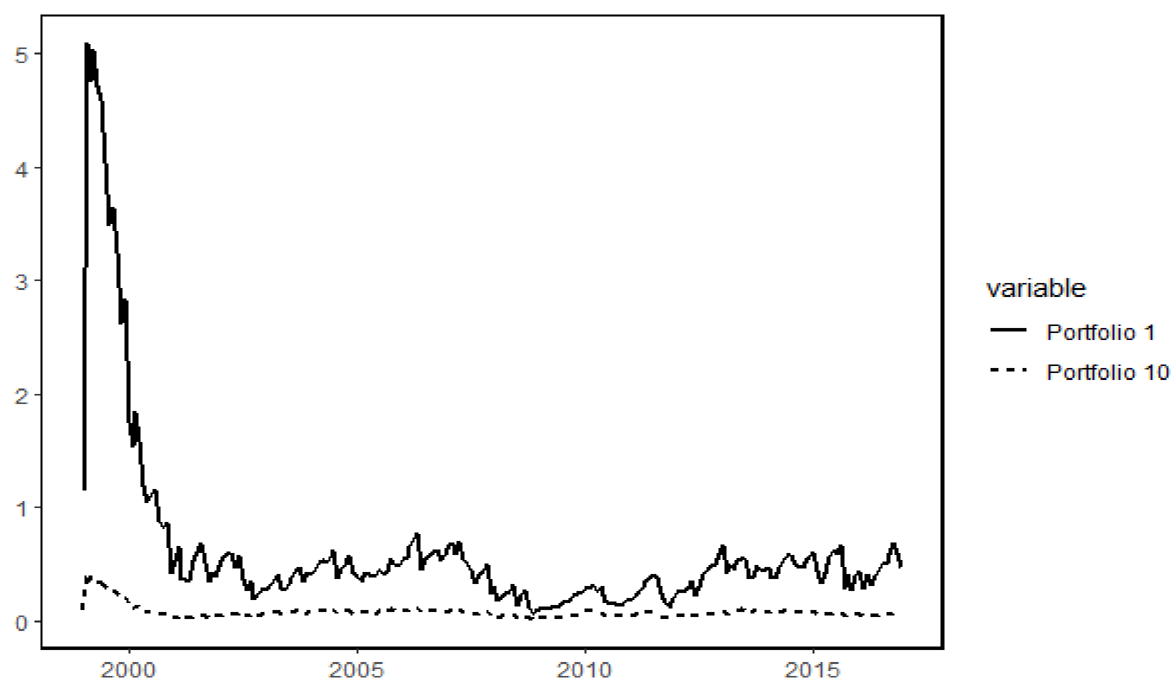

Figure 1.4. Time varying beta plots of portfolio 1 and portfolio 10 for the risk due to the correlation between stock illiquidity and market return (β^4) for 12-month holding period with the market illiquidity measured as the yield gap between commercial paper and treasury bill.

is no difference in the excess return between high and low commonality risk portfolios that emanates from the correlation between their illiquidity and the market return.

The 0.022% commonality risk premium found in this chapter is also higher than the premium for the risk due to the correlation between stock return and market illiquidity. This finding is not surprising because as can be seen from Figure 1.5, the highest commonality risk portfolio (portfolio 1) has a lower level of risk due to the correlation between stock return and market illiquidity than the lowest commonality risk portfolio (portfolio 10). The interpretation is that portfolio 10 has stocks whose return become low when the market is illiquid than portfolio 1. Hence, portfolio 10 is riskier in terms of holding stocks with a low return at times of illiquidity. As a result, it can be argued that forming portfolios based on the sensitivity of each stock's

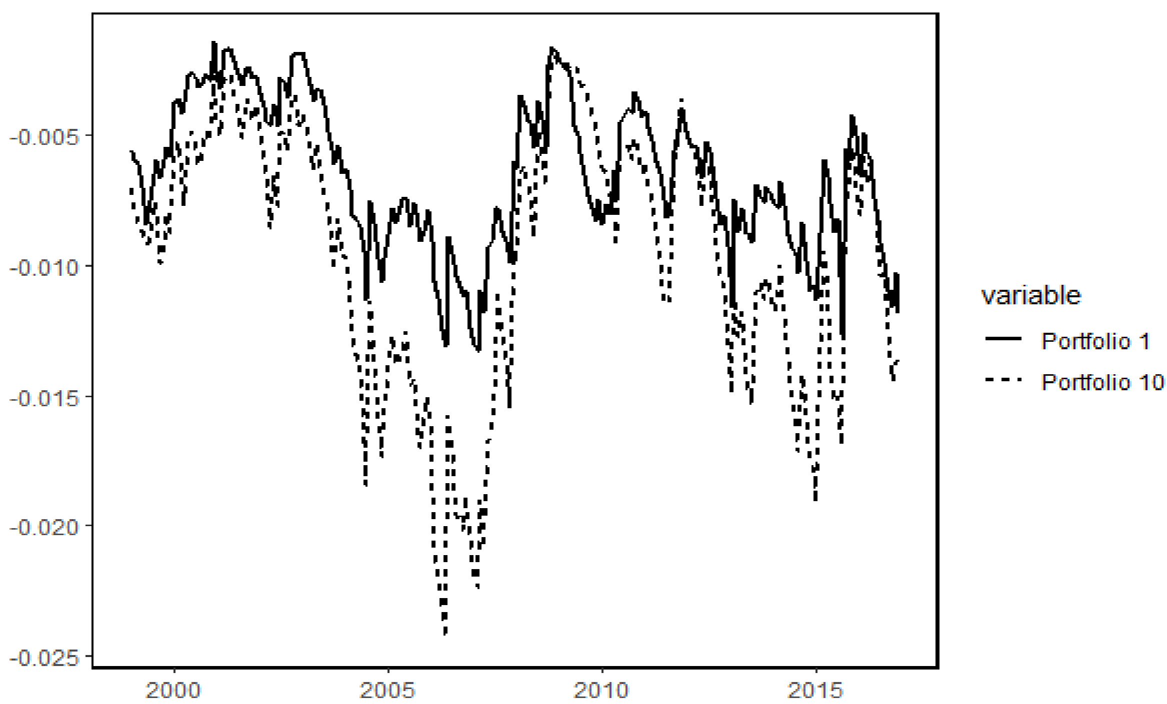

Figure 1.5. Time varying beta plots of portfolio 1 and portfolio 10 for the risk due to the correlation between stock return and market illiquidity (β^3) for 12-month holding period with the market illiquidity measured as the yield gap between commercial paper and treasury bill.

illiquidity to the market wide illiquidity loosely captures the risk due to the correlation between stock return and market illiquidity.

The time series plot of the commonality risk premium under the broader market illiquidity measure is presented in Figure 1.6. A noticeable finding is that there is a significant variation in the estimated risk premium over time, justifying the implementation of the conditional version of LCAPM. The variation is especially bigger during the pre-2007/08 financial crisis period. In addition, the commonality risk premium tends to be higher at times of financial distress than in periods of tranquility. The premium estimate is higher during the Dot-Com recession (2001) and the Great Recession period (2007-09). For instance, it reaches 0.043% during the 2000 Dot-com crash, and peaks at 0.149% in the 2007/08 Great Recession era. This finding is consistent with Hagströmer et al. (2013).

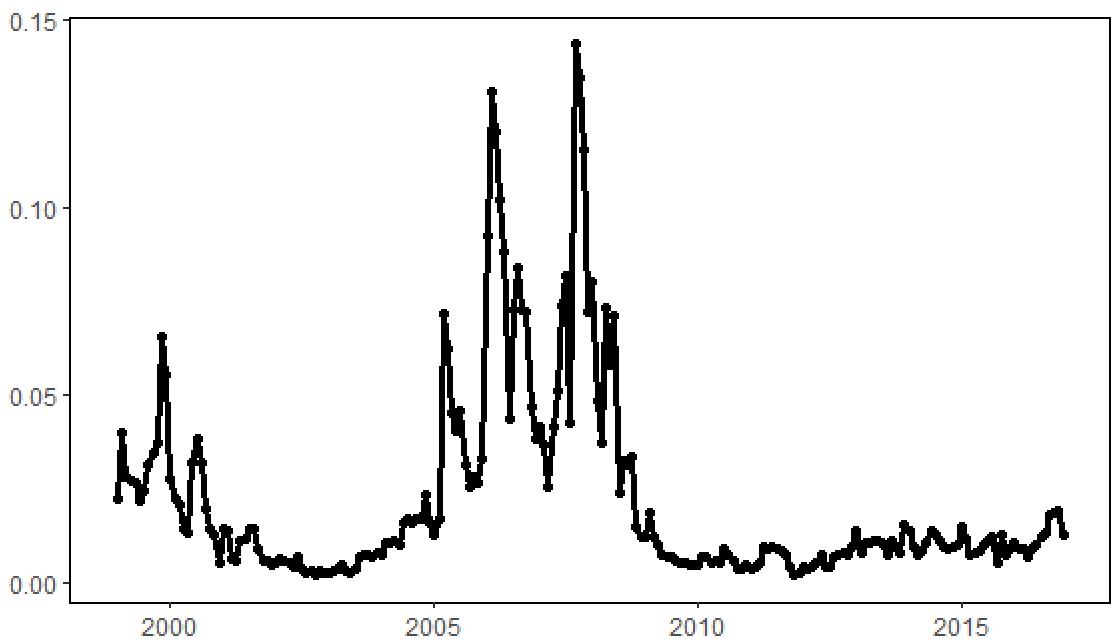

Figure 1.6. Time varying commonality risk premium estimate from January 1998 to December 2016 12-month holding period with the market illiquidity measured as the yield gap between commercial paper and treasury bill.

To check the robustness of the above results, the LCAPM is re-estimated with a longer holding period. The above findings were based on 12-month portfolio re-balancing. However, to maximize returns, investors might be interested in longer holding periods. In line with this, the three versions of the LCAPM are estimated with a 24-month holding period. The results presented in Table 1.3 panel B show similar findings as the 12-month holding period. The excess return difference between high and low commonality risk portfolios disappear in estimating both the constant beta and time varying beta LCAPM with the market illiquidity measured as the average of the illiquidity of each stock. However, estimating the LCAPM with time varying betas and a broader market illiquidity measure increases the premium by a significant margin to 0.013% per year. The averages and standard deviations of the betas estimated under this approach are presented in Table 1.7. In addition, the plots of β^2 for the 1st and 10th portfolios are presented in Figure 1.7. In line with the 12-month holding period result, β^2 is higher for the high commonality risk portfolio (the 1st). Consistent with the 12-month holding period, the commonality risk premium under the 24-month holding period is also higher than the premium for the risk due to the correlation between stock return and market illiquidity. However, it is found to be less than the premium for the risk due to the correlation between stock illiquidity and market return as was presented in Table 1.6.

The plots of the betas for the other two forms of liquidity risk in Figures 1.8 and 1.9 imply similar trends. In contrast to the 12-month holding period, the highest and the lowest commonality risk portfolios capture the variation in the risk due to the covariance between stock illiquidity and market return, and the risk due to the covariance between stock return and market illiquidity under the 24-month holding period. It can be seen in Figure 1.8 that portfolio 1 has become riskier than portfolio 10 in terms of containing stocks that become illiquid when the

Table 1.7
Time Series Average of the Four Betas in the LCAPM for 24-Month Holding Period and the Market Illiquidity Measured as the Yield Gap Between Treasury Bill and Commercial Paper

	β^1	β^2	β^3	β^4
Portfolio 1	2.636 (1.069*)	0.005 (0.006*)	0.487 (0.804)	-0.008 (0.003*)
Portfolio 2	2.636 (1.069*)	0.005 (0.006*)	0.487 (0.804)	-0.008 (0.003*)
Portfolio 3	2.406 (0.796*)	0.0001 (0.0001*)	0.119 (0.106)	-0.012 (0.004*)
Portfolio 4	2.176 (0.924*)	0.005 (0.0001*)	0.107 (0.095*)	-0.008 (0.004*)
Portfolio 5	2.260 (0.924*)	8.755×10^{-5} (0.0001*)	0.107 (0.095*)	-0.009 (0.003*)
Portfolio 6	2.321 (1.048*)	0.0001 (0.0002)	0.095 (0.085)	-0.006 (0.003*)
Portfolio 7	2.271 (0.919*)	0.0001 (0.0002)	0.091 (0.074*)	-0.007 (0.003*)
Portfolio 8	2.195 (0.909*)	-8.726×10^{-5} (0.0001*)	0.031 (0.023*)	-0.008 (0.003*)
Portfolio 9	2.356 (1.157)	0.003 (0.004)	0.079 (0.115*)	-0.009 (0.005*)
Portfolio 10	2.602 (1.471)	-0.002 (0.002)	0.139 (0.096*)	-0.006 (0.003*)

The number in parenthesis is standard deviation. * indicates significance at 5% level.

market return is low. Additionally, Figure 1.9 also indicates that portfolio 1 is also riskier than portfolio 10 in terms of containing stocks with a lower return at times of market-wide illiquidity. These two cases can explain the slight decrease in the commonality risk premium under a 24-month holding period from a 12-month holding period as some of the excess return difference between portfolio 1 and portfolio 10 is captured by their difference in terms of the other two forms of liquidity risk in addition to the commonality risk.

As a further robustness check, the three versions of the LCAPM are estimated after dropping observations from the Great Recession period. This is to check if the baseline results are driven by having a long period of liquidity crisis in the dataset. As can be seen from the results presented in Table 1.3 panel C, the commonality risk premium is smaller when the

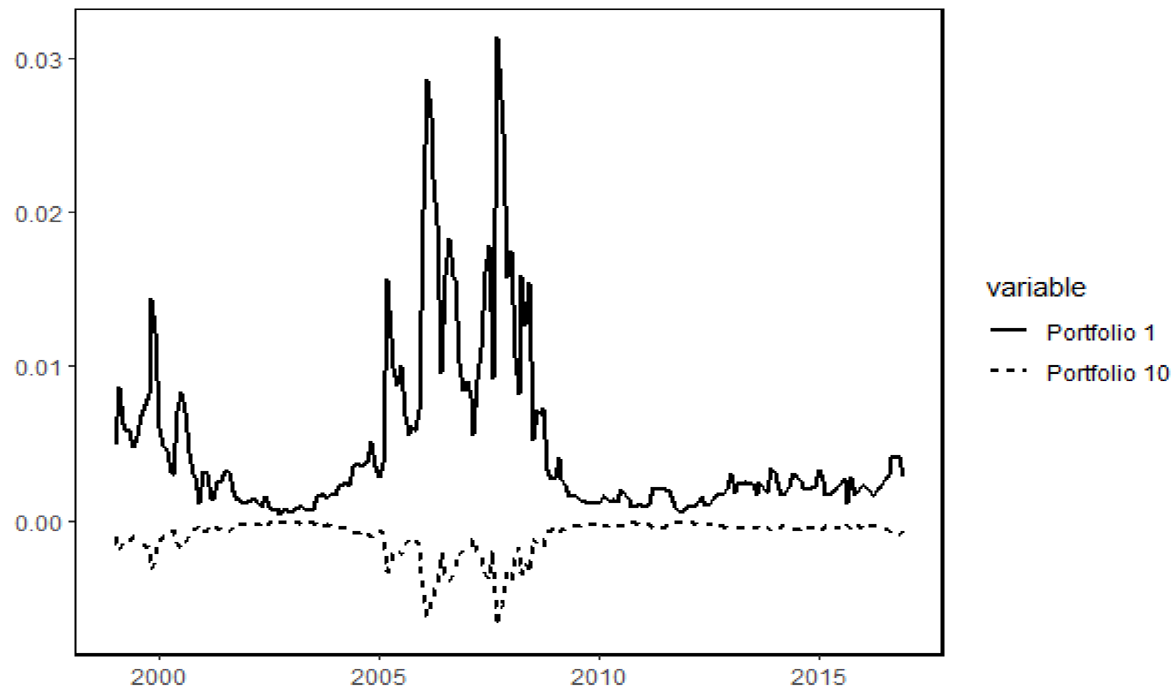

Figure 1.7. Commonality risk beta (β^2) plots of portfolio 1 and portfolio 10 for 24-month holding period with the market illiquidity measured as the yield gap between commercial paper and treasury bill.

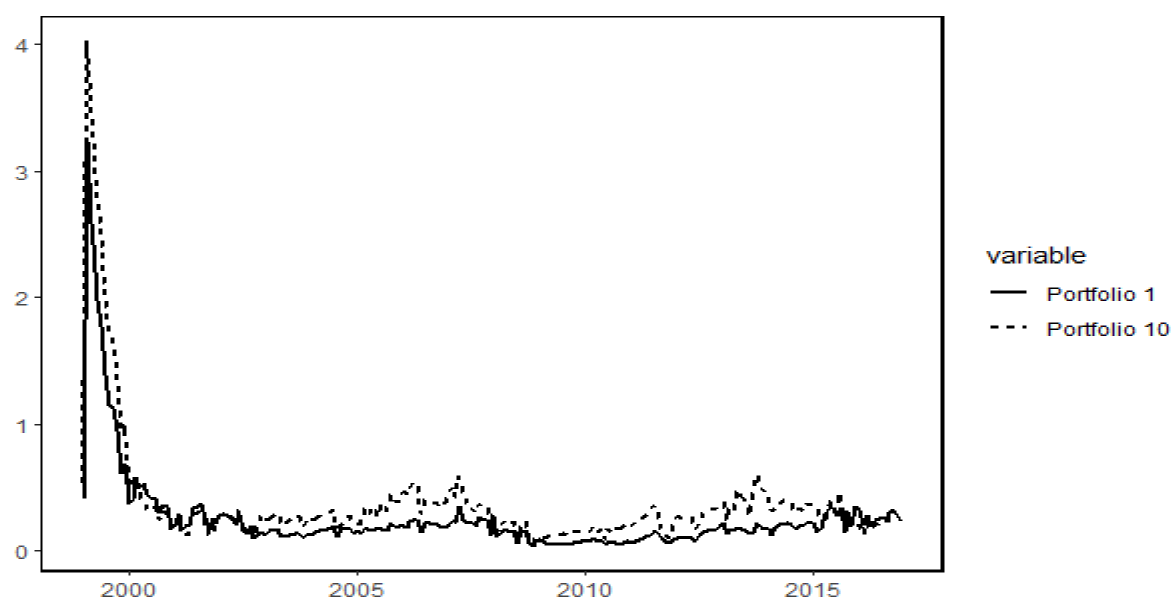

Figure 1.8. Time-varying beta plots of portfolio 1 and portfolio 10 for the risk due to the correlation between stock illiquidity and market return (β^3) for 24-month holding period with the market illiquidity measured as the yield gap between commercial paper and treasury bill.

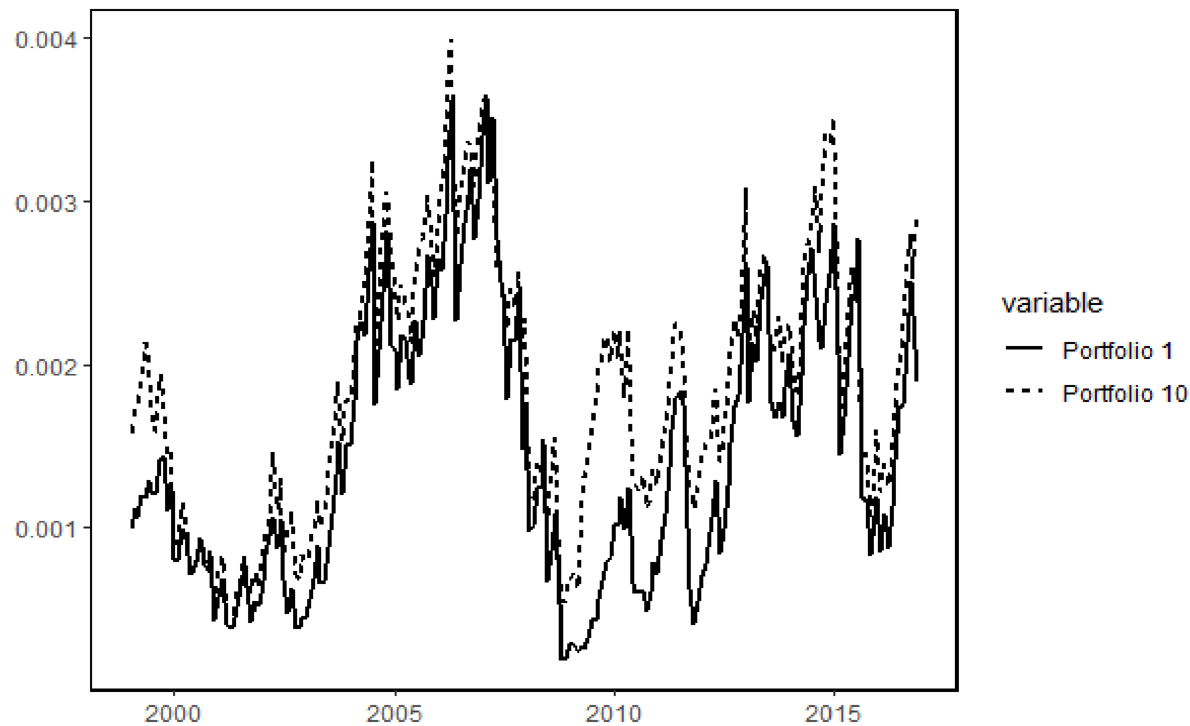

Figure 1.9. Time-varying beta plots of portfolio 1 and portfolio 10 for the risk due to the correlation between stock return and market illiquidity (β^4) for 24-month holding and formation period with the market illiquidity measured as the yield gap between commercial paper and treasury bill.

LCAPM is estimated with the market illiquidity measured as the average of the illiquidity of each stock. This finding is consistent with the baseline results. When the broader measure of market illiquidity is used with the time-varying beta LCAPM, the premium increases to 0.039% per year. In addition, the three versions of LCAPM are also estimated by increasing the portfolio formation period from 24 month to 36 months. The results presented in Table 1.8 remain consistent with the baseline findings.

As outlined in section 1.2.4, this chapter also implements a Principal Component Analysis (PCA) to compare the relative importance of the three liquidity related risks. The eigenvalues and the proportion of variances retained by each principal component are presented in Table 1.9. The first two eigenvalues together account for 86.047% of the variation. Hence, the relative importance of the three liquidity risk betas is compared based on their contribution to the first

Table 1.8
Commonality Risk Premium Estimates from LCAPM with 36 Months Formation Period

Constant beta LCAPM with the market illiquidity measured as the average of the illiquidity of each stock	Time varying beta LCAPM with the market illiquidity measured as the average of the illiquidity of each stock	Time varying beta LCAPM with the market illiquidity measured as the yield gap between commercial paper and treasury bill
Panel A: 12 month portfolio re-balancing		
-0.052%	-0.012% (41.366)*	0.026% (11.385)*
Panel B: 24 month portfolio re-balancing		
-0.001%	-0.051% (41.366)*	0.018% (11.385)*
Panel C: observations from the Great Recession period dropped		
-0.0002%	-0.014% (42.138)*	0.055% (10.487)*

Numbers in parenthesis are t-statistics, * indicates significance at 5%.

Table 1.9
The Eigenvalues and the Proportion of Variances Retained by the Principal Components

	Eigenvalue	Variance Percent	Cumulative Variance
PC1	1.832	45.809%	45.809%
PC2	1.609	40.238%	86.047%
PC3	0.369	9.231%	95.278%
PC4	0.188	4.721%	100.00%

(PC1) and second (PC2) principal components. The plot of a share of the contribution by each risk type to the first and second principal components is presented in Figures 1.10 and 1.11, respectively. It can be seen that out of the three types of liquidity risk, commonality risk (β^2) has the second most contribution (8%) to PC1 next to the risk due to the covariance between asset return and market illiquidity (β^4). In terms of contribution to PC2, commonality risk also contributes the second most (43%) by any liquidity related risk type. These findings underline the significance of the commonality risk implied above based on the risk premium comparison.

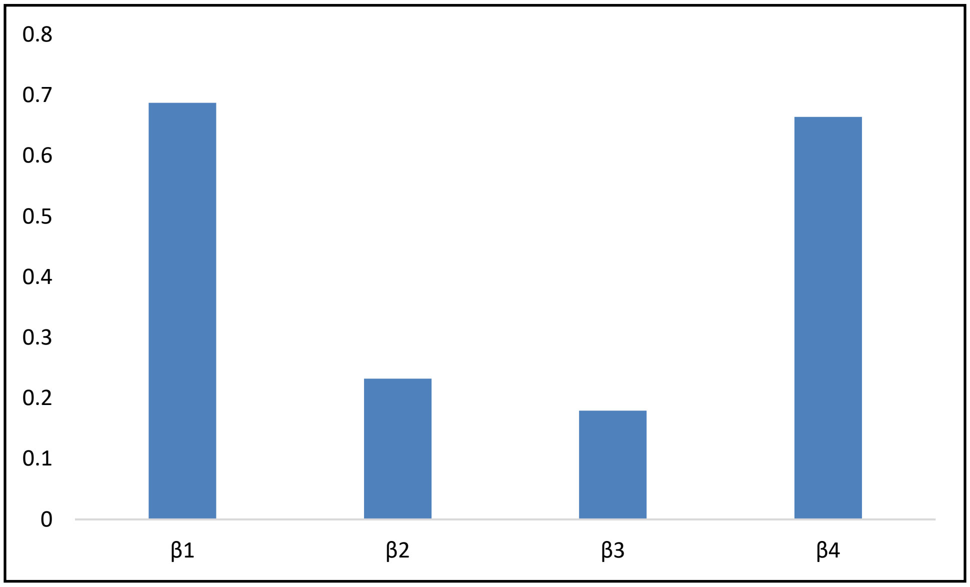

Figure 1.10. Contribution to the first principal component by the four risk betas.

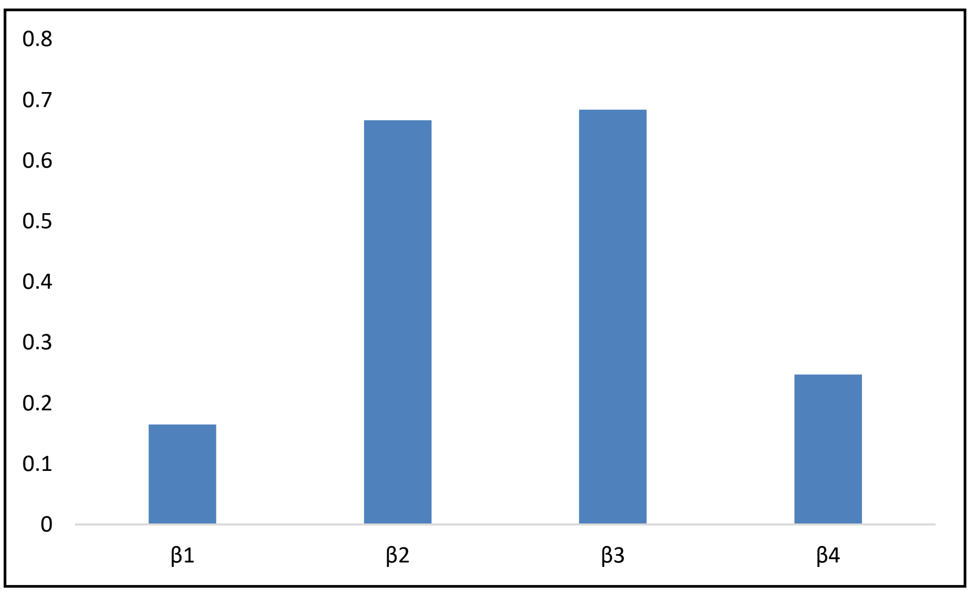

Figure 1.11. Contribution to the second principal component by the four risk betas.

Finally, I assess the predictive performance of the two versions of time-variant beta LCAPM. In the first case, the market illiquidity is measured as the average of the illiquidity of each stock. This is in the spirit of Acharya and Pedersen (2005) and Hagströmer et al. (2013). Secondly, the market illiquidity is measured as the yield difference between commercial paper and treasury bill. In both cases, 12-month portfolio rebalancing period is considered. Equation 3 is used to undertake the prediction. First, the betas are estimated from the DCC model and then used in the equation along with the return for each of the 10 portfolios. Portfolio returns are predicted using the fixed rolling window estimation in the spirit of Simin (2008). In this process, out of the total observations, 140 are used as the training data to estimate the model in each window and then the next 141th observation is used for prediction. This process is repeated until we have a forecast for the entire out of sample observations. The prediction performances are evaluated by Root Mean Squared Error (RMSE). Table 1.10 presents the RMSE for the 10 portfolios. It can be noticed that measuring the market illiquidity broadly as the yield difference between commercial paper and treasury bill improves the prediction performance of the LCAPM

Table 1.10
Root Mean Squared Error (RMSE) for Portfolio Return Prediction

Portfolios	Root Mean Squared Error (RMSE) for LCAM with a broader Market Illiquidity measure	Root Mean Squared Error (RMSE) for LCAPM with market illiquidity measured as the average of the illiquidity of each stock
1	6.325	5.099
2	4.773	4.006
3	4.925	3.865
4	4.567	3.762
5	4.113	3.934
6	3.785	3.928
7	3.751	4.562
8	3.651	4.456
9	3.501	4.707
10	4.683	5.861

for the low commonality risk portfolios. However, the LCAPM with the market illiquidity measured as the average of the illiquidity of each stock performs better in predicting the returns of the high commonality risk portfolios.

CHAPTER 2

INFLATION ILLUSION AND THE FED MODEL

2.1. Introduction

This chapter examines the empirical application of the Fed model and the inflation illusion hypothesis. The Fed model has been the leading practitioners' model used for valuation of equities. It postulates that treasury bond yield and stock yield are highly correlated and the two tend to be equal in the long run. This proposition can be seen on Figure 2.1 which presents the plots of 10-year government bond yield and stock yield

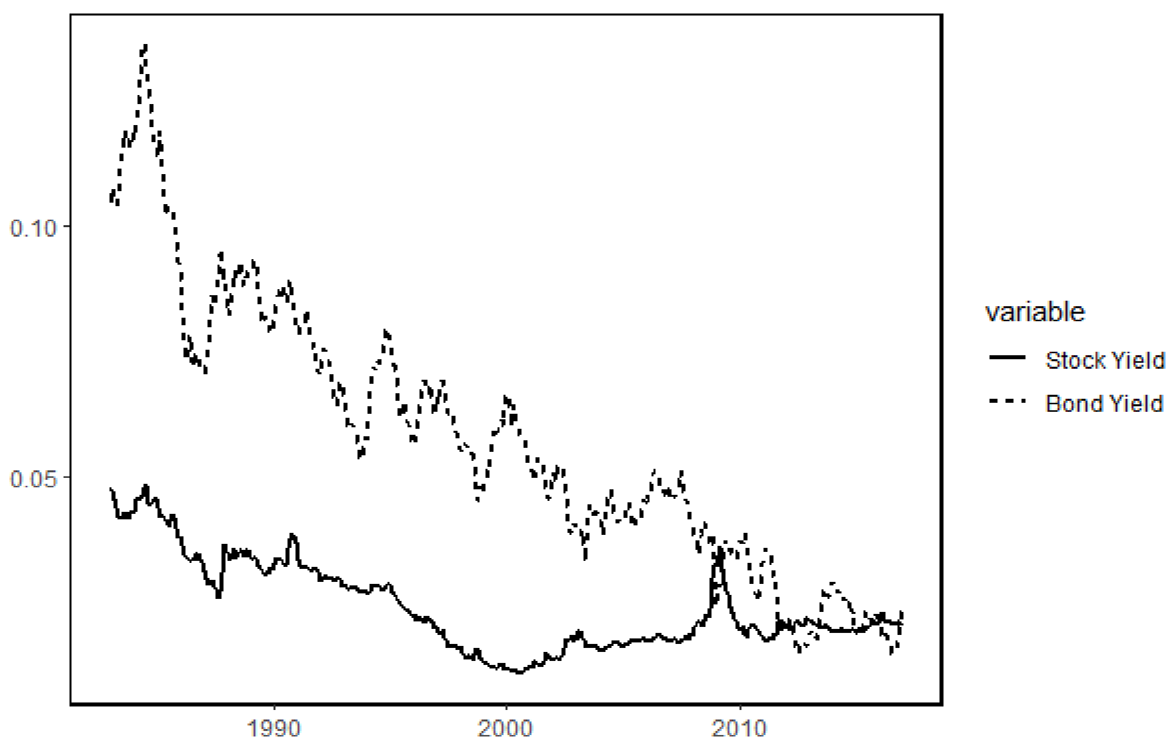

Figure 2.1. The time series plots of 10-year government bond yield and stock yield as measured by dividend price ratio.

series for the sample period January 1983 to December 2016. Previous studies—such as explain the high bond yield-stock yield relationship implied by the Fed model. The argument is Campbell and Vuolteenaho (2004) and Bekaert and Engstrom (2010)—resort to the inflation illusion hypothesis, originally introduced by Modigliani and Cohn in 1979 to that stock market investors are subject to inflation illusion, but not bond market investors. Stock market investors, it is hypothesized, fail to understand the effect of inflation on dividends. Thus when inflation rises, nominal interest rate increases in the bond market, which are used by stock market participants to discount unchanged expectations of future cash flows. The dividend-price ratio in the stock market (stock yield), then, co-moves with the nominal bond yield simply because stock market investors irrationally fail to adjust the dividend growth to inflation.

A study by Campbell and Vuolteenaho (2004) argues that inflation illusion is a major phenomenon driving the relationship between stock yield and inflation. The authors argue that about 80 percent of the mis-pricing in the stock market is inflation related. Similarly, Asness (2003) shows that the Fed model can be used as a descriptive tool to explain the tendency of investors to change current market price to earning ratio depending on nominal interest rate. The inflation illusion hypothesis is also supported by Ritter and Warr (2002). The authors argue there are two forms of inflation related mis-pricing. The first form is when investors discount real cash flows using nominal rates while the second form is failure to take into account the capital gain that occurs when inflation deteriorates the real value of firms' liability. According to their study, inflation related mis-pricing can explain the substantial under valuation of equities during the 1980s and the following correction in the 1990s. Furthermore, the paper by Ritter and Warr (2002) also shows that during periods of low inflation, mis pricing in the stock market tends to be low.

The above studies overlook two variables that determine the value of any stock: news about cash flows and news about the discount rate. According to the inflation illusion hypothesis, stocks are overvalued when inflation is low. This is because, when inflation decreases, bond market participants decrease nominal interest rates. This lower interest rate is used to discount unchanged expectation about future cash flows leading to higher prices. On the other hand, stocks are undervalued when inflation is high due to higher interest rate and unchanged expectation about future cash flows.

This argument, however, is misleading in the context of news about cash flows and news about the discount rate. First, low inflation might indicate a strength of the economy and hence signals good news about future stream of cash flows. This would increase the market value of stocks and future investment opportunities, leading to over-valuation of stocks. Secondly, it is also possible that low inflation might signal that policy makers are going to increase the interest rate in an attempt to prevent deflation or attain their inflation target (news about the discount rate). This could lead to decrease in the market value of stocks and hence undervaluation of stocks. These two cases make the validity of the inflation illusion hypothesis highly questionable and cast series doubt on the previous studies that support it.

The major contribution of this chapter is incorporating these news variables in testing if inflation related mis pricing can explain the high correlation between stock yield and treasury bond yield. The test is undertaken in two stages. First, a decomposition of stock return into news about cash flows and news about the discount rate is used along with the Gordon Growth model to determine mis-pricing in the stock market. Secondly, a dynamic regression model is used to examine the impact of mis pricing on the correlation between stock yield and government bond yield. This correlation is estimated by the Asymmetric Generalized Dynamic Conditional Correlation (AG-DCC) model.

The empirical findings of this chapter demonstrate that there is a significant positive correlation between treasury bond yield and stock yield. This is in line with the argument of the Fed model. Using monthly data from January 1983 to December 2016, I show that there is little variation in the estimated correlation over time with an average correlation of 0.942 - 0.997. In addition, the chapter also finds that mis-pricing in the stock market is insignificant in affecting the correlation between treasury bond yield and stock yield, leading to the rejection of the inflation illusion hypothesis.

The remainder of this chapter is organized as follows. Section 2.2 presents the Gordon Growth model and unexpected stock return decomposition used to determine mis-pricing in the stock market. It also discusses the AG-DCC model implemented to model the correlation between stock yield and bond yield. The empirical findings including the impact of mis-pricing on the bond yield-stock yield correlation is reported in section 2.3. Finally, section 2.4 provides concluding remarks.

2.2. Theoretical Framework

According to Campbell and Vuolteenaho (2004), the dividend-price ratio of a given stock can be decomposed into three components. This decomposition is based on the Gordon growth model that express the dividend-price ratio as;

$$\frac{D_t}{P_{t-1}} = R^e - G^e \tag{1}$$

Where D_t is dividend payments and P_{t-1} is the price at time *t-1*, R^e is the excess discount rate, and G^e is the excess dividend growth rate. Following Campbell and Vuolteenaho (2004), this chapter assumes that there are two types of investors in the stock market: rational and irrational investors. This dichotomy implies the objective expectations of rational investors can be distinguished from the subjective expectation of irrational investors. However, equation 1 must hold for both sets of expectations because the dividend price ratio is the same for both types of investors. This can be written as

$$\frac{D}{P} = R^{e,obj} - G^{e,obj} = R^{e,subj} - G^{e,subj} \tag{2}$$

Rearranging and solving for the objective dividend growth will result in,

$$\frac{D}{P} = -G^{e,obj} + R^{e,subj} + (G^{e,obj} - G^{e,subj}) \tag{3}$$

It can be seen from equation 3 that the dividend price ratio has three components: (1) the negative of objectively expected dividend growth, (2) the subjective discount rate, and (3) a mis-pricing term that is due to the difference between the rational and irrational growth forecast (Campbell & Vuolteenaho, 2004). In this chapter, I first estimate the objective dividend growth, and the subjective discount rate. Then, the mis-pricing component is computed as a residual. The theoretical framework for estimating the objective dividend growth and the subjective discount rate are discussed below.

2.2.1. The Objective Dividend Growth

The objective dividend growth is computed based on the decomposition of a return on a given stock, r_t, into news about the cash flows and news about the discount rate. Following Chen and Zhao (2009), this decomposition can be written as,

$$r_t = Ncf_{t+j} - Ndr_{t+j} \tag{4}$$

where Ncf_{t+j} is the Cash Flow News and Ndr_{t+j} is the Discount Rate News. Following Campbell and Vuolteenaho (2004), this return decomposition can be applied to obtain the objective dividend growth by using Campbell and Shiller's (1988) log-linear return on a dividend paying asset,

$$r_{t+1} = log(P_{t+1} + D_{t+1}) - log(P_t) \quad (5)$$

where P denotes price and D is dividend. The first order Taylor approximation of equation 5 around the log dividend-price ratio, $(d_{t-1} - p_{t-1})$, is

$$r_t \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t \quad (6)$$

where $\rho = \frac{1}{1+exp(d_t - p_t)}$ and $k = -\log(\rho) - (1-\rho)\log\left(\frac{1}{\rho-1}\right)$. Lower case d_t and p_t represent log transformations of D denotes price and P respectively. Solving equation 6 iteratively, taking expectation, imposing the condition $\lim_{j\to\infty} \rho^j\left(d_{t+j} - p_{t+j}\right) = 0$, and subtracting $d_t$yields,

$$d_t - \rho_t = \frac{k}{\rho-1} + \sum_{j=0}^{\infty} \rho^j E_t(r_{t+J+1})^e - \sum_{j=0}^{\infty} \rho^j E_{t-1}(\Delta d_{t+J+1})^e \quad (7)$$

where Δd denotes log dividend growth. Substituting equation 7 into equation 6, taking expectation and the difference between $r_{t+1}$and $E_t r_{t+1}$results in,

$$E_{t+1} \sum_{j=0}^{\infty} \rho^j (\Delta d_{t+j+1}^e)^e = \quad (r_{t+1} - E_t r_{t+1}) + (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \left(r_{t+J+1}\right)^e +$$
$$E_t \sum_{j=0}^{\infty} \rho^j (\Delta d_{t+j+1}^e) \quad (8)$$

In equation 8, the objective expectation about future dividend growth is expressed as a function of three elements. The term $(r_{t+1} - E_t r_{t+1})$ represent unexpected return at *t+1*, $(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \left(r_{t+J+1}\right)^e$ represent news about future discount rates, and $E_t \sum_{j=0}^{\infty} \rho^j (\Delta d_{t+j+1}^e)$ measure expectation about future cash flows. The estimation procedure for each of the three components of the objective dividend growth is outlined below.

Following Chen and Zhao (2009), this chapter implements a VAR system to model the discount rate news variable in equation 8. The intuition is that returns are projected onto predictive variables and the discount rate news is expressed as a function of these shocks to expected return. Let z_t be a vector of state variables used to predict returns, the first order VAR is given by;

$$z_t = Az_{t-1} + u_{t+1} \tag{9}$$

News about the discount rate (NDR_{t+1}) is then estimated as,

$$NDR_{t+1} = k'\rho A(I - \rho A)^{-1}u_{t+1} \tag{10}$$

where k is a vector whose first element is equal to one and zero otherwise. It is used to pick out the return variable from the vector z_t. The idea is that any news in the state variables is incorporated into the expected return in the future period because the expected return is predictable through the VAR system. Hence, the difference between the current period and next period expected return represent the surprise or news component for that period. In this chapter, z_t contains return on S&P index, price-earning ratio, inflation, yield difference between 10-year and 3-month U.S. treasury bonds. These variables are selected based on the works of Davis, Aliaga-Díaz, and Thomas (2012) and McMillan (2018). Unexpected stock return and expectation about future cash flows in equation 8 are modeled using a simple AR(1) process. The unexpected stock return series is generated by taking the difference between the actual return and predicted return from the AR(1) model. On the other hand, expectations about future cash flows are given by the prediction from the AR(1) model on the dividend series. Monthly data are obtained from the Center for Research in Security Prices (CRSP) database, Professor Shiller's website, and the St. Louis FED (FRED) website. The sample period covered in the study is from January 1983 to December 2016. All the data are seasonally adjusted.

2.2.2 The Subjective Discount Rate

The subjective discount rate component of the dividend yield ratio in equation 3 is estimated using the Gamma discounting model developed by Weitzman (2001). Using the notations in Cameron and Gerdes (2005), the model starts with the traditional individual discount factor given by,

$$\phi_i(t) = e^{x_i, t} \tag{11}$$

where the x_i is the individual discount rate. Weitzman (2001) argues that x_i is a random variable from a gamma distribution with a probability distribution function given by;

$$f(x) = \frac{b^c}{\Gamma(c)} x^{c-1} e^{-bx} \tag{12}$$

where b is a scale parameter and c is a shape parameter, both strictly positive. The mean of this gamma distribution is $\mu = \frac{c}{b}$ and the variance $\delta^2 = \frac{c}{b^2}$. Weitzman (2001) proposes that the expected value today of an extra dollar is the expected present discounted value of a dollar weighted by the probability of occurrence of the rate at which it is being discounted. This can be expressed as,

$$\varphi(t) = \int_0^\infty e^{xt} f(x) d_x \tag{13}$$

$\varphi(t)$ is known as the effective discount function for time t. Weitzman shows that for the Gamma distribution function, this integration can be solved as,

$$\varphi(t) = (1 + \frac{1}{b} t)^{-c} \tag{14}$$

According to Weitzman (2001), the instantaneous effective discount rate at time t is defined to be,

$$r(t) = \frac{d\varphi(t)/dt}{\varphi(t)} = \frac{\mu}{1 + {t\delta^2}/{\mu}} \tag{15}$$

Equation 15 is then used to generate the subjective discount rate component of the dividend price ratio. For the random variable, *x*, in the gamma distribution function, the number of stocks owned by investors is used from the Survey of Consumer Finances. This variable serves as an indicator of the time preference of investors. When investors value today's income more (less) than future earnings, they buy less (more) stocks today. The survey covers approximately 30,000 households in the U.S. It is conducted every three years by the Board of Governors of the Federal Reserve System. I use surveys from 1983 to 2013 to obtain data on the number of stocks owned. This number of stocks owned series is used to pin down the values of μ and δ^2 in the Gamma distribution for the period in between two surveys. The estimate of μ and δ^2 are updated at the end of the third year when new survey data is available. Table 2.1 presents the average and standard deviation of the subjective discount rate computed using equation 15.

Table 2.1
The Average and Standard Deviation of Stock Yield, Bond Yield, Corporate Bond Market Illiquidity, and Stock Market Illiquidity

	Stock yield	Treasury bond yield	Stock market Mis-pricing measure	Unexpected stock return	Discount rate news	Subjective discount rate
Average	2.431%	5.749%	71.429	-0.0002%	0.133	2.569%
Standard Deviation	0.903%	2.726%	14.557	0.044%	7.452	0.128%

2.2.3. Measuring the Correlation and the Impact of Mis-pricing

The stock market mis-pricing measure computed using equation 3 is plotted in Figure 2.2. This measure tends to be high in periods preceding major crashes where mis-pricing is expected to be high such as the pre-October 1987 black Monday crash, the pre-May 2000 dot-com crash period, and the pre 2007/08 financial crisis. The average and standard deviation of this measure are presented in Table 2.1. After the mis-pricing component is calculated, the next step in the analysis is to examine its impact on the correlation between stock yield and bond yield. Following Katzke (2013), I measure the correlation using the Asymmetric Generalized Dynamic Conditional Correlation (AG-DCC) model proposed by Cappiello, Engle, and Sheppard (2006). The AG-DCC model extends the Dynamic Conditional Correlation (DCC) model proposed by Engle (2002) to allow for leverage effects in the underlying correlation structure. The authors argue that the model is specifically useful to examine interdependence between different asset

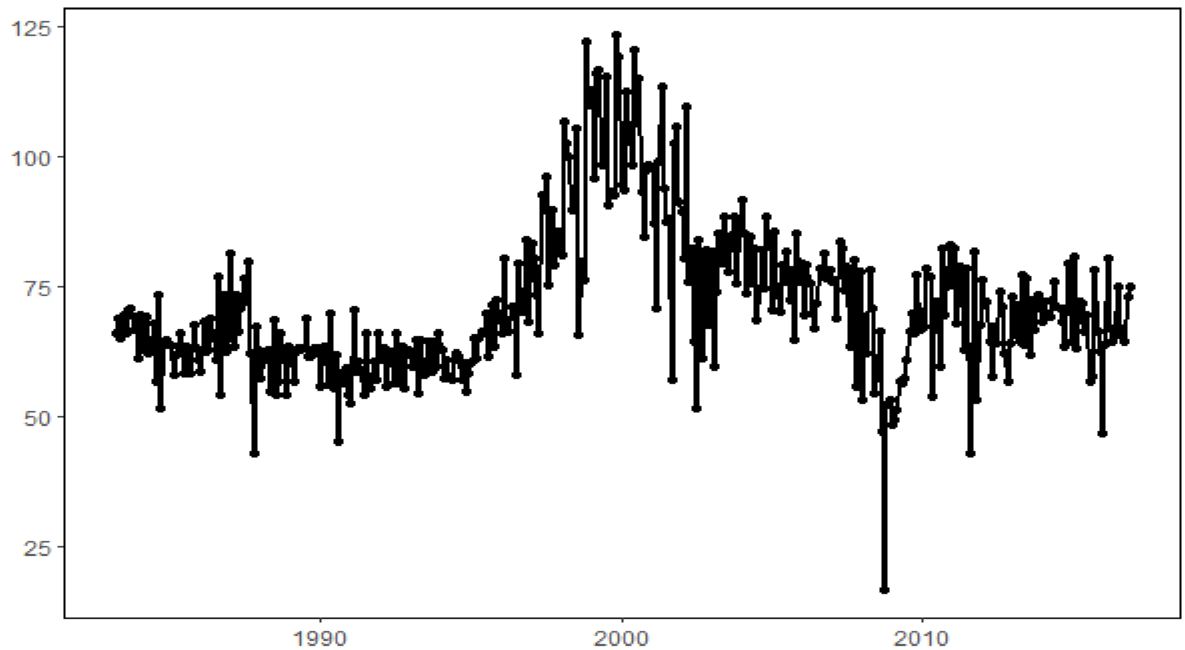

Figure 2.2. The time series plot of the mispricing measure in the U.S. stock market.

markets. In addition, it is also suited to investigate the asymmetric responses in conditional variances and correlations to negative and positive news shocks.

The AG-DCC model assumes that the two variables, stock yield and bond yield, follow a conditionally heteroskedastic normal distribution with variance-covariance processH_t, and mean zero. The conditional variances in H_t are modeled using GARCH (1,1) process. These conditional variances are used to standardize the residuals from the mean equations. In the second step, the covariance matrix, H_t is expressed as $H_t = D_t R_t D_t'$ where D_t is a diagonal matrix consisting of the squared root of the conditional variances and R_t is the correlation matrix estimated using the standardized residuals from the first stage. R_t has ones on the diagonal and the off-diagonal elements are less than or equal to one in absolute value. R_t is constructed by using the quasi covariance $q_{i,j,t}$ as $\frac{q_{i,j,t}}{\sqrt{q_{i,it} q_{j,j,t}}}$. According to Cappiello et al. (2006), the GARCH (1,1) model for $q_{i,j,t}$ is given by,

$$q_{i,j,t} = (1-\theta_1-\theta_2)\rho_{i,j} - \kappa\Sigma_t + \theta_1\left(\epsilon_{i,t-1}\epsilon_{j,t-1}\right) + \theta_2 q_{i,j,t-1} + \kappa\left(\eta_{i,t-1}\eta_{j,t-1}\right) \tag{16}$$

where $\Sigma_t = E[\eta_{i,t}, \eta'_{j,t}]$ and $\eta_t = (I[\epsilon_t < 0]\ o\ \epsilon_t)$. The latter represent element by element Hadamard product of the residuals if the yield shocks are negative and zero otherwise. Hence, κ captures the asymmetric effect where both markets experience negative shocks. $\rho_{i,j}$ is the unconditional correlation of the standardized residuals $\epsilon_{i,t}$ and $\epsilon_{i,t}$. The parameters of the AG-DCC model are estimated by the maximum likelihood technique. I use data on stock yield and government bond yield from Professor Shiller's website. The sample period for both data is from January 1983 to December 2016.

To examine the impact that mis-pricing has on the correlation between bond and stock yield, I follow Andersson, Krylova and Vähämaa (2008) and regress the correlation coefficient on mis-pricing with GDP and inflation as control variables reflecting the overall economic condition. A difficulty in this regression is that the correlation coefficient is bounded in the range [-1,1]. In order to make the dependent variable unrestricted, a logit transformation is applied in the spirit of Andersson et al. (2008). The following model is then estimated,

$$log\frac{(1+\rho_t)}{(1-\rho_t)} = \theta_1 + \sum_{j=1}^{\infty}\theta_2^j GDP_{t-j} + \sum_{j=1}^{\infty}\theta_3^j INF_{t-j} + \sum_{j=1}^{\infty}\theta_4^j MISP_{t-j} + \epsilon_t \tag{17}$$

where ρ_t is the correlation coefficient at time t, $MISP_t$ is the mis-pricing component, $INF_t$is the inflation rate, and GDP_t is GDP measured by the industrial production. Inflation and GDP are used as a control for the overall economic condition. Monthly data on industrial production and Consumer Price Index (CPI) is obtained from St. Louis FED (FRED) website for the period January 1983 to December 2016. The optimal lag length in equation 17 is chosen using the Shwartz Information Criterion (SIC) method.

2.3. Findings of the Study

The conditional correlation estimate from the asymmetric DCC model is presented in Figure 2.3. In order to control for estimation uncertainty 95% confidence bands are reported and it indicates a low degree of estimation uncertainty. The correlation plot in Figure 2.3 shows that there is a significant positive relationship between stock yield and bond yield. On average the correlation between the two is 0.997 over the period 1983 to 2016. The correlation shows little variation over the sample period with the value being higher than 0.985 for the majority of the sample period. This finding is consistent with the prediction of the Fed model.

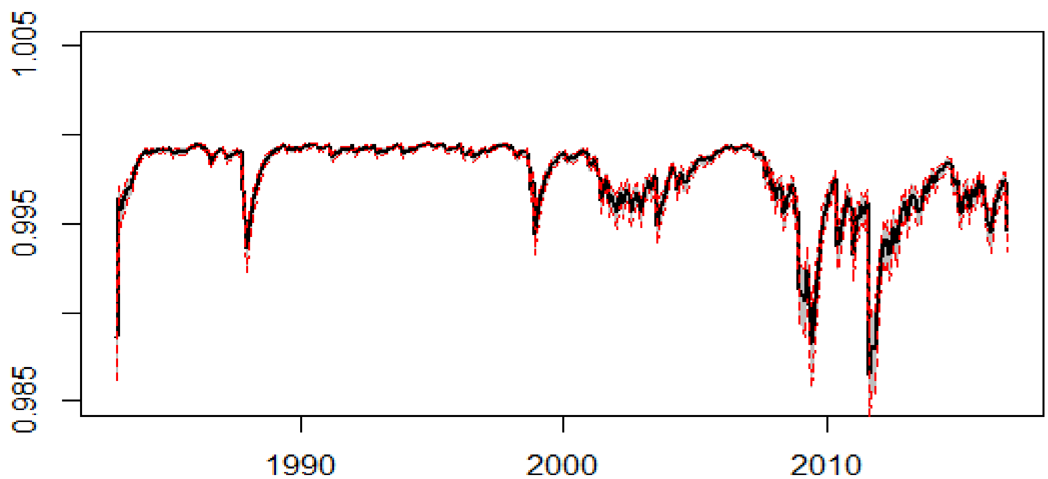

Figure 2.3. The correlation between bond yield and stock yield. The grey shaded region with red boundaries represents the 95% confidence interval.

Forbes and Rigobon (2002) argue that cross market correlation coefficients can be biased due to heteroskedasticity in market returns. According to these authors, the bias is from the tendency of financial markets to be more volatile after a crisis. As a consequence of the higher volatility, one tends to find increased conditional correlation even if the underlying cross market relationship is the same as more stable periods. Without adjustment for this bias, it is hard to differentiate if there is an increase in the correlation between the markets under consideration or just increase in the volatilities of the two markets. Given that the sample period considered in this paper covers a few recession periods including the Great Recession era, the high correlation result in Figure 2.3 could potentially be due to a higher volatility. As a robustness check, I follow Forbes and Rigobon (2002) and use the following transformation that takes into account the relative increase in the volatility:

$$\rho_t^* = \frac{\rho_t}{\sqrt{1+\delta[1-(\rho_t^2)]}} \tag{18}$$

In this transformation, ρ_t is the time variant correlation from the AG-DCC model and δ is the relative increase in the variance of stock yield (which I picked given the stock market is more volatile than the bond market) from period of high volatility to period of low volatility. This is given by the ratio of variance of stock yield during high volatility period to variance of stock yield during low volatility period. The transformed correlation is presented in Figure 2.4 and it can be seen that the correlation between bond yield and stock yield remains high. Consistent with the baseline results, this correlation is above 0.7 for the entire sample period, implying a significant positive relationship as predicted by the Fed model.

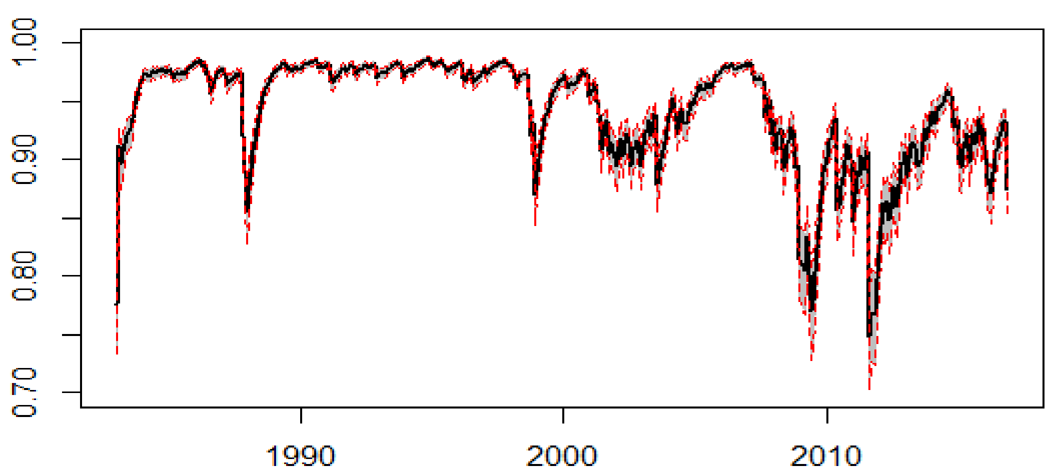

Figure 2.4. The adjusted correlation between bond yield and stock yield. The grey shaded region with red boundaries represents the 95% confidence interval.

The next step in the analysis is to examine if the correlation between bond yield and stock yield is significantly driven by mis-pricing in the stock market using equation 17. In estimating this equation, I used a lag order of 2 as suggested by SIC. The result of this estimation is presented in Table 2.2. It can be seen from the p-values that the coefficients on both the first and the second lags of mis-pricing are insignificant at the 5% level of significance, leading to rejection of the inflation illusion hypothesis. In contrast, GDP has a significant positive impact on the correlation between bond yield and stock yield. A 1 percentage point increase in GDP increases the correlation between bond yield and stock yield next month by 0.173 percentage points. The effect gets bigger after two months when the correlation increases by 0.213 percentage points. This result can be associated with increased trading activities as the overall economic condition improves, driving up the price of stocks and bonds at the same time. Similarly, overall inflation has a significant positive impact. A 1 percentage point increase in the inflation rate increases the correlation between stock yield and bond yield by 0.31 percentage points.

In order to provide further evidence on the significance of the model variables, I undertake a joint significance test using the Wald test. Table 2.3 reports the null hypothesis as well as

Table 2.2
Regression Result of the Correlation Equation

	Coefficient Estimate	P-value
Constant	5.806	2.16×10^{-16}*
Mis_{t-1}	-0.0005	0.886
Mis_{t-2}	0.001	0.729
GDP_{t-1}	0.173	0.007 *
GDP_{t-2}	0.213	0.001 *
$Inflation_{t-1}$	0.069	0.612
$Inflation_{t-2}$	0.311	0.024 *
Adjusted R-squared: 0.09171 F-statistic: 7.782**		

* indicates significance at 5%

the p-values. The result for mis-pricing is presented in the second column. The p-value indicates that the null hypothesis of coefficients of the lags of mis-pricing are jointly zero is not rejected at the 5% significance level, implying that mis-pricing in the stock market has insignificant impact on the correlation between bond yield and stock yield. In contrast, it can be seen from column 3 of Table 2.3 that the test for joint significance of GDP has a very small p-value, suggesting economic growth has a significant effect on the correlation. Similarly, the joint significance test for inflation has very small p-value, leading to rejection of the null hypothesis of previous rates of inflation has insignificant impact on the correlation between bond yield and stock yield.

Table 2.3
Joint Significance Test Results

Ho:	$\theta_4^1 = \theta_4^2 = 0$	$\theta_2^1 = \theta_2^2 = 0$	$\theta_3^1 = \theta_3^2 = 0$
P-values	0.936	$7.69\text{x}10^{-6}$*	0.027*

* indicates significance at 5%

As a further robustness check, the above regression analysis is also conducted for the transformed correlation from equation 18. The result and the associated test from this regression are presented in Tables 2.4 and 2.5. It can be seen from Table 2.4 that the coefficients on the first and second lag of the mis-pricing term are insignificant in affecting the correlation between bond yield and stock yield. The p-values of the joint significance test of the coefficients of the two lags of mis-pricing is also presented in the second column of Table 2.5. The result indicates that both the first and second lag of mis-pricing are jointly insignificant. In contrast, GDP significantly affects the correlation between bond yield and stock yield. A 1 percentage point increase in GDP increases the correlation by 0.99 percentage points after a month and by 1.26 percentage points after two months.

Table 2.4
Regression Result Using Transformed Correlations as the Dependent Variable

	Coefficient Estimate	P-value
Constant	0.842	2.16×10^{-16}*
Mis_{t-1}	0.0001	0.517
Mis_{t-2}	0.0003	0.199
GDP_{t-1}	0.004	0.006 *
GDP_{t-2}	0.013	0.0005*
$Inflation_{t-1}$	0.004	0.566
$Inflation_{t-2}$	0.018	0.021*
Adjusted R-squared: 0.1005 F-statistic: 8.505*		

* indicates significance at 5% level

Table 2.5
Significance Test Results from Transformed Correlations

Ho:	$\theta_4^1 = \theta_4^2 = 0$	$\theta_2^1 = \theta_2^2 = 0$	$\theta_3^1 = \theta_3^2 = 0$
P-values	0.064*	2.89×10^{-6}*	4.17×10^{-6}*

* indicates significance at 5% level.

The p-value for the joint significance test of the coefficients of GDP is presented in the second column of Table 2.5 and it reveals that both coefficients are jointly significant at 5% level of significance. On the other hand, consistent with the baseline results, inflation only affects the correlation between bond yield and stock yield only after two months. A 1 percentage point increase in the inflation increases the correlation by 1.79 percentage points after two months. The joint significance test for the effects of the lags of inflation is presented in the 4th column of Table 2.5. The p-value is found to be very small implying a significant joint effect.

CHAPTER 3

THE FED MODEL: A RE-EXAMINATION THROUGH ILLIQUIDITY CONTAGION

3.1. Introduction

This chapter examines the Fed model by using illiquidity contagion between the stock market and the corporate bond market as the driving force behind the high correlation between stock yield and government bond yield. The Fed model has been the leading practitioners' model used for valuation of equities. It postulates that there tends to be a strong correlation between the two and in the long run the yield on stocks equals the yield on government bonds. This equality between the yield on stocks and the yield on bonds determines the normal yield in the stock market. The Fed model postulates that if the measured stock yield exceeds the normal yield, the stock under consideration is attractively priced. This is because the price of the stock is expected to rise in the future to attain the equality. On the other hand, if the measured yield falls below the normal yield, then stocks are overpriced because their price is expected to fall to attain the equality.

Previous studies—such as Campbell and Vuolteenaho (2004) and Bekaert and Engstrom (2010)—resort to the inflation illusion hypothesis to explain the treasury bond yield-stock yield relationship. The argument is that stock market investors are subject to inflation related mis-pricing, but not bond market investors. Stock market investors, it is hypothesized, fail to under-stand the effect of inflation on dividends. Thus, when inflation rises, bond market participants increase nominal interest rates, which are used by stock market participants to discount unchanged expectations of future dividends and the real value of firms' debt. The dividend-price ratio in the stock market (stock yield), then, co-moves with the nominal bond yield simply because stock market investors irrationally fail to adjust the dividend growth to inflation. A study by Campbell and Vuolteenaho (2004) argues that inflation illusion is a major phenomenon driving the relationship between stock yield and inflation. The authors argue that about 80 percent of the mis-pricing in the stock market is due to inflation. However, this author shows in Chapter 2 that the inflation illusion explanation overlooks two important variables that determine the value of any stock: news about cash flows and news about the discount rate, and the hypothesis is rejected once these two variables are incorporated in to the determination of mis-pricing in the stock market.

This chapter attempts to provide an alternative explanation for the high correlation between government bond yield and stock yield on the basis of illiquidity contagion. The idea is that when liquidity drops in the stock market, firms' credit risk rises as the deterioration in the liquidity in the stock market increases firms' probability of default (Huang, Huang, & Oxman, 2015). As a consequence, the liquidity of corporate bonds deteriorates and investors' preference shifts away from corporate bonds to government bonds. Higher demand for government bonds keeps their yield to be low. In the stock market, stock yield is already low because of the liquidity drop, leading to a co-movement.

This chapter contributes to the ongoing literature in two ways. First, it presents evidence of a significant impact of illiquidity shocks from the stock market on the liquidity of the corporate bond market using the Markov regime switching model. Secondly, in order to support the claim that illiquidity contagion is the source of high correlation between bond yield and stock yield, it shows how the two variables react to liquidity shocks in the stock market.

The rest of the chapter is organized as follows. I first discuss in section 3.2 the empirical models used in the paper including the Markov switching model, Convergent Cross Mapping, and

Auto Regressive Distributed Lag (ARDL) model. Section 3.3 presents the illiquidity measures of the stock market and the corporate bond market. I then discuss the empirical results in section 3.4, and section 3.5 is the conclusion.

3.2. Model Specification

The study implements two forms of analysis to show that the spillover of liquidity shocks from the stock market to the corporate bond market can explain the high correlation between treasury bond yield and stock yield. For this explanation to work, there are two conditions that need to be satisfied. First, there must be liquidity shocks spillover from the stock market to the corporate bond market. In order to show this, I use a Markov switching model in the mean and variance. The model allows examining the interaction between the liquidity of the stock market and the liquidity of the corporate bond market at times of low liquidity as well as high liquidity. Following Kim, Piger, and Startz (2008), let Y_t be the liquidity in the corporate bond market, X_t be a set of explanatory variables consist of liquidity in the stock market, economic growth as measured by GDP change, and inflation, consider the following regression model,

$$Y_t = X_t^{'}\beta_{S_t} + u_t \tag{1}$$

where $u_t \sim N\left(0, \delta_{st}^2\right)$, and $S_t = 0 \; or \; 1$, representing the two possible regimes that the liquidity condition of the corporate bond market can have: high illiquidity and low illiquidity. The parameter vector β varies based on the state of the liquidity condition. This permit testing for the impact of the stock market liquidity shocks at low and high states of market liquidity. The model in equation 1 also allows the variance of the error term to vary based on the state of the liquidity condition. In the Markov regime switching model, the state of the prevailing regime is not directly observable. Rather, the current state depends on the state before. As a result, there are transition probabilities from one state to another denoted by,

$$P(S_t = j \mid S_{t-1} = i) = p_{ij} \; for \; (i, j = 0,1) \tag{2}$$

where $p_{i0} + p_{i1} = 1$, for $i = 0,1$. The model parameters and the transition probabilities are estimated by maximum likelihood procedure as follows. Using the condition that $u_t \sim N\left(0, \delta_{st}^2\right)$, the conditional probability density for the observations Y_t given the previous observations, $§_{t-1} = \{Y_{t-1}, Y_{t-2}, \ldots.\}$ and the state variable S_t, S_{t-1} is given by,

$$f(Y_t \mid S_t, S_{t-1}, \; §_{t-1}) = \frac{1}{\sqrt{2\Pi\delta_{st}^2}} \exp\{-\frac{[Y_t - X_t^{'}\beta_{S_t}]^2}{2\delta_{st}^2} \tag{3}$$

The joint probability density function, $f(Y_t \; S_t, S_{t-1} | §_{t-1})$, can be expressed as

$$f(Y_t \; S_t, S_{t-1} \mid \; §_{t-1}) = \; f(Y_t \mid S_t, S_{t-1}, \; §_{t-1}) \; P(S_t, S_{t-1} \mid §_{t-1}) \tag{4}$$

Using this relationship, the log-likelihood function to be maximized with respect to the model parameters becomes,

$$L(\theta) = \; \sum_{t=1}^{T} l_t(\theta) \tag{5}$$

where,

$$l_t(\theta) = Log \; \sum_{S_i=0}^{1} \sum_{S_i=0}^{1} f(Y_t \mid S_t, S_{t-1}, §_{t-1}) \quad P(S_t, S_{t-1} \mid §_{t-1}) \tag{6}$$

where $= (\beta_0, \beta_{1,} \; \delta_0^2, \delta_1^2, p, q)$. p represents the transition probability, $p = P \; (S_t = 0 \mid S_{t-1} = 0)$ and q represent the transition probability, $q = P \; (S_t = 1 \mid S_{t-1} = 1)$. The conditional joint probabilities, $P(S_t, S_{t-1} \mid §_{t-1})$, are computed based on the Chain rule for conditional probabilities,

$$P(S_t, S_{t-1} \mid §_{t-1}) = \; P(S_t | S_{t-1}) \; P\big(S_{t-1} \mid §_{t-1}\big) \tag{7}$$

where $P(S_{t-1} \mid §_{t-1})$ is the time dependent state probabilities. The probabilities $P(S_{t-1} \mid §_{t-1})$ and $P(S_t, S_{t-1} \mid §_{t-1})$ are obtained using the following recursive filter as in Kim et al (2004).

Given, $P(S_{t-1} = i \mid §_{t-1})$ at the beginning of time t, equation 7 is used to obtain,

$$P(S_t = j, S_{t-1} = i \mid §_{t-1}) = \; P(S_t = j | S_{t-1} = i) \; P\big(S_{t-1} = i \mid §_{t-1}\big) \tag{8}$$

Once Y_t is realized, the information set is updated to, $\S_{t=}\{\S_{t-1}, Y_t\}$. The probability estimates are then updated by,

$$P(S_t = j, S_{t-1} = i | \S_{t-1}, Y_t) = \frac{f(Y_t | S_t = j, S_{t-1} = i, \S_{t-1}) \; P(S_t = j, S_{t-1} = i | \S_{t-1})}{\sum_{S_t, S_{t-1}=0}^{1} f(Y_t | S_t, S_{t-1}, \S_{t-1}) \; P(S_t = s_t, S_{t-1} = s_{t-1} | \S_{t-1})} \tag{9}$$

Finally, $P(S_{t-1} = i | \S_{t-1})$ is estimated using the Law of Total Probability as,

$$P(S_t = i | \S_t) = \sum_{j=0}^{1} P(S_t = i, S_{t-1} = j \mid \S_t) \tag{10}$$

Once the joint probability for the time point *t* is obtained, the maximum likelihood estimates are obtained iteratively by maximizing the likelihood function. The filtered probabilities of each state are also defined by,

$$P(S_t = j, | \S_t), \; j = 0.1 \tag{11}$$

In order to get further insight into how the liquidity condition in the stock market and the corporate bond market are related, I use the filtered probabilities in a newly developed non-parametric framework called Convergent Cross Mapping (CCM). This is for testing if the illiquidity in the stock market causes the probability of being in a low or high illiquidity state in the corporate bond market to change. This approach overcomes the difficulty of applying a regression analysis on a restricted dependent variable such as probabilities that are bounded between 0 and 1.

According to Sugihara et al. (2012), the CCM model is an extension of the Empirical Dynamic Modeling (ECM) and Takens' Theorem. In the ECM approach, a time series can be described as a point in a high-dimensional space. The axes of this space can be thought of as fundamental state variables. The EDM uses Takens' Theorem to reconstruct the system dynamics from time series data. The idea is that a high-dimensional state space can be represented by lags of a time series for a given set of variables. By Takens' Theorem, if sufficient lags are used, the reconstructed states will map one-to-one to actual system states, and nearby points in the reconstruction will correspond to similar system states.

The CCM approach applies the idea of ECM and Takens' Theorem to test for a cause and effect relationship between two time series variables. To illustrate the idea, suppose we want to examine if variable X causes variable Y. The first step in CCM is to construct attractor manifold (often denoted as Mx). The next step is to predict Y from Mx using the K-nearest neighbors algorithm. This estimate of Y is called Y | Mx. Convergence is identified by computing the Pearson's correlation between observed and predicted values over many random subsamples. High positive correlation between predicted values and actual observations provides evidence of X causing Y. In this paper, X is the illiquidity measure of the stock market and Y is probability of regime 1 (low corporate bond market illiquidity) and regime 2 (high corporate bond market illiquidity).

The second part in the liquidity shocks spillover explanation provided in this paper is both treasury bond yield and stock yield increase following a deterioration in the liquidity condition of the stock market. This is because, investors prefer bonds issued by the government rather than corporate bonds during times of low liquidity as the probability of default by corporations rise. The higher demand for treasury bonds lower its yield. In the stock market, yield on equities is also low triggered by a decrease in liquidity. This can be shown by using an Auto Regressive Distributed Lag (ARDL) model. In this model, the dependent variables are stock yield and treasury bond yield while the stock market illiquidity is the main explanatory variable. Let Y_t be a vector consisting of the yield on stocks and the yield on treasury bond, the ARDL model is given by,

$$Y_t = \alpha_o + \sum_{i=1}^{j} \beta_{1i} \; Mktil_{t-i} + \sum_{i=1}^{j} \beta_{2i} \; X_{t-i} + u_t \tag{12}$$

where $Mktil_t$ is illiquidity shocks in the stock market, and X_t is a vector of GDP, inflation, and lags of the dependent variable. GDP and Inflation are used as control variables for the overall economic condition. u_t is a vector residual terms for the respective equations. α_o, β_1, and β_2 are a vector of parameters. The lag order is selected based on Shwartz Information Criterion (SIC). Monthly data on stock yield and bond yield are obtained from Professor Shiller's website for the period January 1997 to December 2016.

3.3. Illiquidity Measure

Following Acharya and Pedersen (2005) and Goyenko and Ukhov (2009), this study measures illiquidity in the stock market based on Amihud's (2002) illiquidity measure, which defines the illiquidity of stock *i* in month *t* as

$$ILLIQ_t^i = \frac{1}{\mathrm{Days}_t^i} \sum_{d=1}^{\mathrm{Days}_t^i} \frac{\mathrm{abs}(R_{td}^i)}{\mathrm{V}_{td}^i} \tag{13}$$

where R_{td}^i is the return on day *d* in month *t*, and V_{td}^i is the dollar volume on day *d* in month *t*. Amihud's illiquidity index is measured in percent per dollars. A high value of $ILLIQ_t^i$ indicates that the stock price moves a lot in response to little volume change. When a stock is illiquid, the spread between the price the seller is willing to accept (the ask price) and the price the buyer is willing to accept (the bid price) is wide, so that sellers who want to offload their properties quickly have to reduce the price by a large amount. This implies that the ratio of return to volume traded will be higher. Acharya and Pedersen (2005) suggest the following transformation to normalize the illiquidity measure:

$$c_t^i = \min(0.25 + 0.3 \cdot ILLIQ_t^i \cdot P_{t-1}^m, 30.00), \tag{14}$$

where P_t^m is the ratio of the total market capitalization at the end of month *t* to that at the end of a base month, for which we pick July 1998. This normalized measure is capped at a maximum value of 30% to ensure that the results are not driven by outliers. The market illiquidity is then measured by taking the average of the illiquidity of each stock, c_t^i,

Contrary to the stock market, liquidity in the corporate bond market is highly difficult to measure. Indices such as bid-ask spreads require data on each of the corporate bonds traded in the market, which is not easy to get. To overcome this problem, I use the idea of spread in the yield from Frank et al (2008). Accordingly, I use the spread between the yield on corporate bond and the yield on treasury bond as a measure of the corporate bond market illiquidity. The idea behind this measure is when investors' preference shifts away from corporate bonds to government bonds, the spread in the yield between the two widens. Daily stock return and volume traded data are used from the CRSP database to compute the stock market illiquidity measure. The St. Louis Federal Reserve (FRED) website is used to obtain data on corporate bond yield. Monthly data on 10-year government bond yield is obtained from Professor Shiller's website. The sample period covered in the study is from January 1997 to December 2016. The average and standard deviation of these variables is provided in Table 3.1.

Table 3.1
The Average and Standard Deviation of Stock Yield, Bond Yield, Corporate Bond Market Illiquidity, and Stock Market Illiquidity

	Stock yield	Bond yield	Corporate bond market illiquidity	Stock market illiquidity
Average	1.8264	3.9351	2.5857	5.4611×10^{-19}
Standard Deviation	0.4065	1.4134	0.7846	0.0633

3.4. Result

The estimation result of the Markov switching model is presented in Table 3.2. The model has corporate bond market illiquidity as the dependent variable with the stock market liquidity condition as one of the explanatory variables. The model also has inflation and GDP as measured by the industrial production as a control for the overall economic condition. Regime 1 represents low illiquidity states whereas regime 2 covers high illiquidity states in the corporate bond market. It can be seen that the stock market liquidity condition has a significant impact on the liquidity condition of the corporate bond market. This impact is strong at states of low liquidity as well as high liquidity. Specifically, a 1 percentage point increase in the illiquidity of the stock market increases the illiquidity of the corporate bond market by 0.453 percentage points

Table 3.2
Estimation Results from the Markov-Regime Switching Model

Regime 1		
Variable	Estimate	t-value
Constant	3.063	11.633*
Stock market liquidity	0.453	3.116*
GDP	-0.262	4.298*
Inflation	-0.403	5.361*
Regime 2		
Constant	3.593	7.881*
Stock market liquidity	0.953	1.918*
GDP	-0.517	-7.450*
Inflation	-0.271	-2.634*
Transition Probabilities		
	Regime 1 (low illiquidity)	Regime 2 (high illiquidity)
Regime 1 (low illiquidity)	0.978	0.029
Regime 2 (high illiquidity)	0.022	0.971

* indicates significance at 5% level.

during low illiquidity regimes and by 0.953 percentage points during high illiquidity periods. These findings provide strong evidence of liquidity shocks in the stock market having a significant impact on the liquidity condition of the corporate bond market.

As hypothesized in this chapter, the above result can be explained as follows. When liquidity drops in the stock market, firms' credit risk rises as the deterioration in liquidity in the stock market increases firms' probability of default. Huang et al. (2015) have provided evidence that deterioration in liquidity in the stock market increases the firms' default boundary and their credit risk. As a consequence, the liquidity of corporate bonds deteriorates and investors' preference shifts away from corporate bonds to government bonds. This leads to decrease in the volume traded and consequently deterioration in the liquidity of the corporate bond market.

The filtered and smoothed probabilities for both regimes are presented in Figure 3.1. Observations of the corporate bond market illiquidity measure corresponding to regime 1 (low illiquidity) are plotted in Figure 3.2. Both figures indicate that the model perfectly detects the periods of each state. In order to provide further evidence regarding the interaction between the liquidity condition in the stock market and in the corporate bond market, I examined the causality between the filtered probabilities of the two liquidity regimes in the corporate bond market and the liquidity of the stock market using the Convergent Cross Mapping (CCM) technique. Following Sugihara et al. (2012) and Ye, Deyle, Gilarranz, and Sugihara (2015), the first step in implementing CCM is to determine the optimum size of embedding dimension—i.e., the number of lags to use in constructing the space of predictor variables. The embedding dimension can be conceptualized as the number of dimensions of the state-space used to produce the forecast. If enough lags are used, the reconstruction will map one-to-one to the true attractor. However, if the number of lags is insufficient (the embedding dimension is too small), then the reconstruction

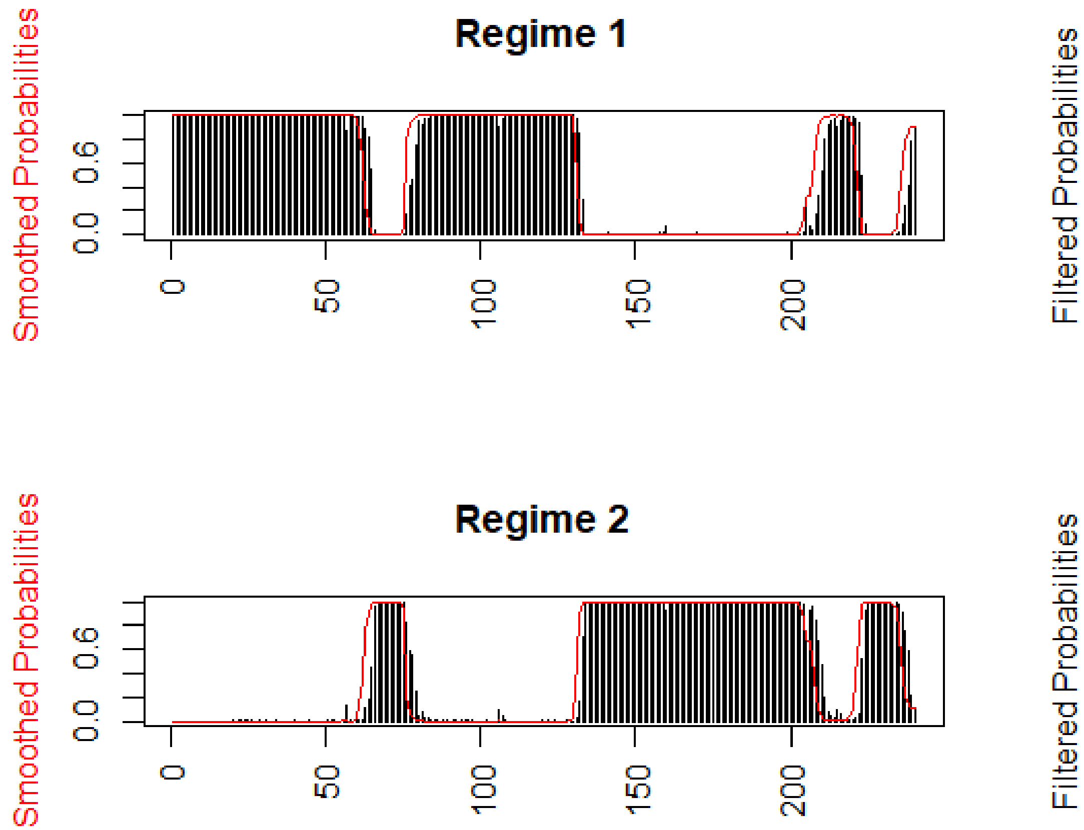

Figure 3.1. Filtered and smoothed probabilities for regime 1 (low corporate bond market illiquidity) and regime 2 (high corporate bond market illiquidity).

will have points that correspond to different system states. When this occurs, the reconstruction will fail to distinguish between different trajectories and forecast performance will suffer.

In line with this, the optimal embedding dimension is chosen by using a nearest neighbor simplex forecasting and evaluating the prediction accuracy using the correlation between observed and predicted values at different embedding dimension levels. I considered up to 10 embedding dimension in doing the prediction. I found that the forecast skill peaks at the embedding dimension of 3. This implies that the attractor construction using the liquidity condition in the stock market is best done using up to 3 lags.

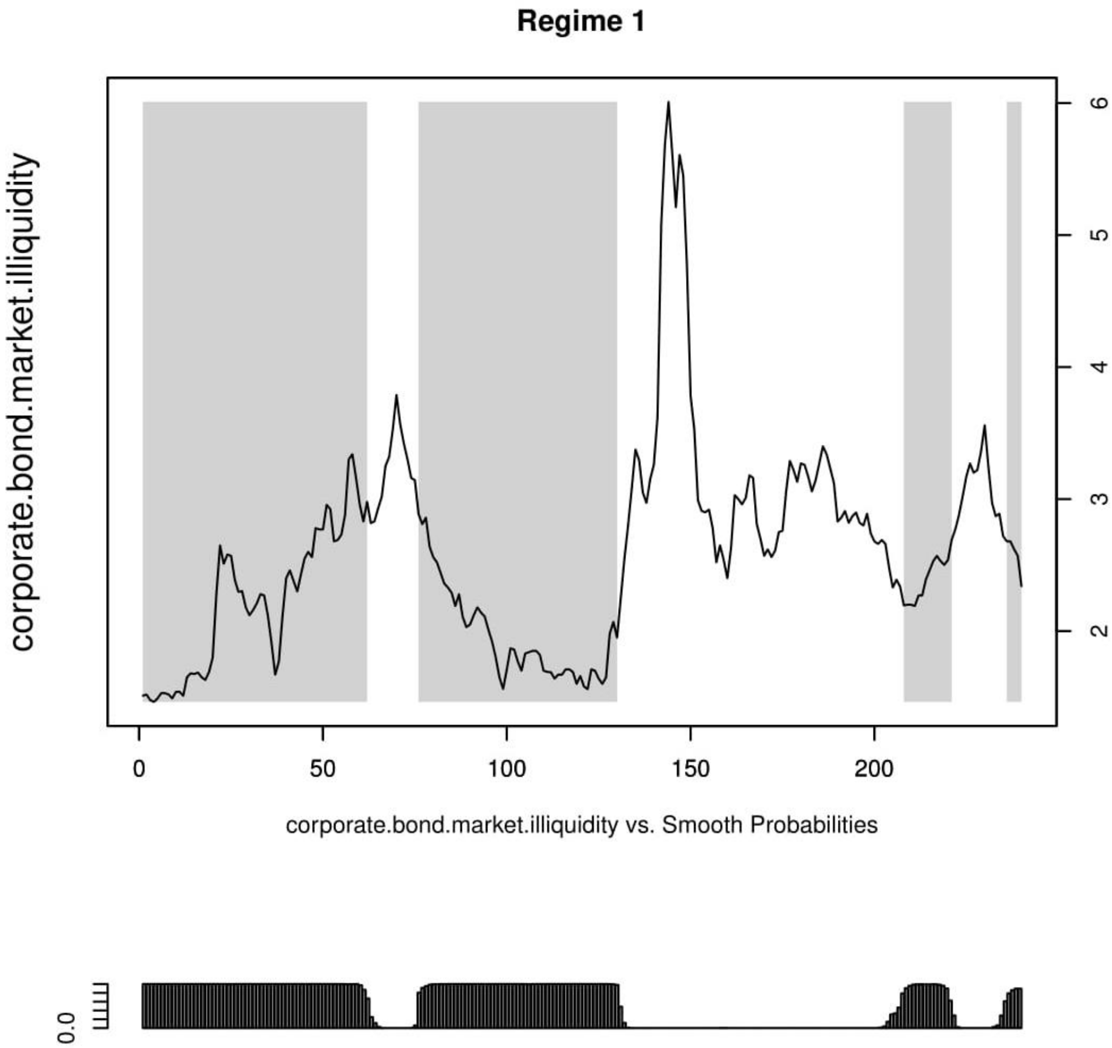

Figure 3.2. Observations of the corporate bond market illiquidity measure that belongs to regime 1.

The next step in CCM is to test for causality by using the lags of liquidity in the stock market to predict the filtered probabilities of being in regime 1 as well as regime 2. Convergence is identified using Pearson's correlation between observed and predicted probabilities over random subsamples of the illiquidity measure of the stock market. The plot of cross map skill for the probability of low corporate bond market illiquidity is presented in Figure 3.3. It can be seen that there is a positive correlation between the actual and predicted probabilities of the corporate bond market being in the state of low illiqudiity. This correlation remains well above 0.25 across different

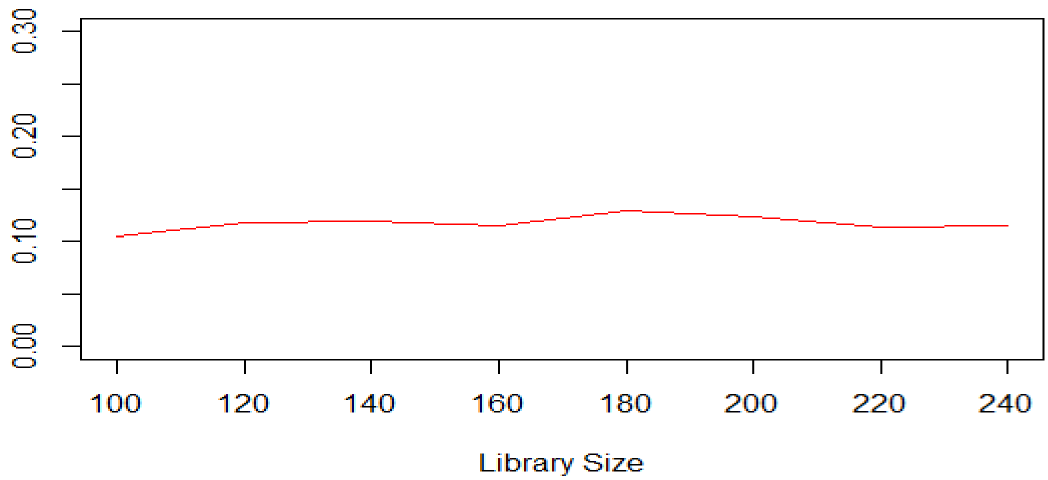

Figure 3.3. Cross map skill from illiquidity in the stock market to probability of being in regime 1 (low illiquidity state in the corporate bond market). The red line is the average correlation between actual and predicted values of probability of regime 1 at different sample sizes.

sample sizes used to do the prediction. Similar results are found for the high illiquidity corporate bond market state (regime 2) in Figure 3.4. These results provide evidence that the liquidity condition of the stock market is a major driver of the liquidity state of the corporate bond market. The second part in testing the contagion liquidity shocks explanation provided in this chapter is

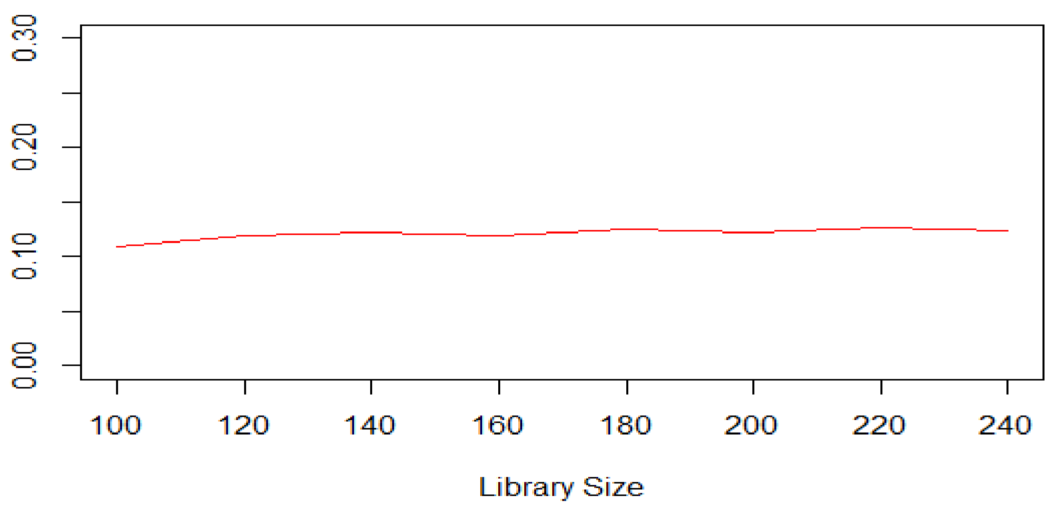

Figure 3.4. Cross map skill from illiquidity in the stock market to probability of being in regime 2 (high illiquidity state in the corporate bond market). The red line is the average correlation between actual and predicted values of probability of regime 2 at different sample sizes.

to examine if stock yield and the treasury bond yield respond to liquidity shocks in the stock market using the ARDL model outlined in equation 12. Based on the Shwartz Information Criterion, I use a lag order of two. Inflation and GDP are used as a control for the overall economic condition. The ARDL model estimation results for government bond yield and stock yield are presented in the second and third columns of Table 3.3, respectively. The results reveal that the liquidity condition in the stock market in both the previous month and the previous two months have insignificant impact on the government bond yield. In contrast, the impact on stock yield is found to be significant. A 1 percentage point decrease in the liquidity condition in the stock market in the previous month decreases stock yield by 0.001 percentage points in the current month. This effect, however, dies out after two months. Based on this finding, I undertake a joint significance test for the coefficients on the stock market illiquidity using Wald test. The test finds a very small p-value of 9.31×10^{-8}, leading to rejection of the null hypothesis that the coefficients are jointly zero. This further strengthens the evidence of a significant impact of the liquidity condition of the stock market on stock yield. Overall these results support the illiquidity contagion explanation provided in this paper.

3.5. Conclusions and Policy Implications

The 2007/08 financial crisis has emphasized the importance of highly integrated financial markets amid fast growth in trading technology and increasing interdependence in their liquidity. In light of this, the three essays of this dissertation focus on incorporating the commonality in the liquidity condition between assets and markets into asset pricing and valuation models. The first chapter examines the importance of commonality risk as a priced factor in the Liquidity-adjusted Capital Asset Pricing Model (LCAPM). Commonality risk is the risk of holding an asset that becomes illiquid when the overall market is illiquid. Previous studies label commonality risk as

Table 3.3
ARDL Estimation Results for Government Bond Yield and Stock Yield Equation

Coefficient	Government bond yield equation estimation result	Stock yield equation estimation result
$Constant$	0.295 (2.883*)	0.002 (3.624*)
$Mktil_{t-1}$	-0.136 (0.619)	-0.001 (2.340*)
$Mktil_{t-2}$	0.093 (0.421)	0.0005 (0.689)
Y_{t-1}	1.151 (17.727*)	1.192 (19.609*)
Y_{t-2}	-0.165 (2.527*)	-0.031 (5.095*)
GDP_{t-1}	-0.0231 (1.059)	-0.0003 (4.017*)
GDP_{t-2}	-.0.022 (1.031)	-0.0004 (5.362)
$Inflation_{t-1}$	0.071 (1.477)	0.0001 (0.790)
$Inflation_{t-2}$	0.148 (3.081*)	0.0004 (2.225*)
	Joint significance test for the coefficients on the stock market illiquidity: P-value = 0.779	Joint significance test for the coefficients on the stock market illiquidity: P-value = 9.31×10^{-8}*

The numbers in parentheses are t-values * indicates significance at 5%.

the least important one based on its nearly zero premium. This finding motivates another look at its pricing using a different measure of market illiquidity. Previous studies measure the illiquidity of the market portfolio by taking the average of the illiquidity of each stock. This approach, however, overlooks the possibility of a diversified market portfolio. Harrington and Korajczyk (1993) and Damodaran (1999) argue that since investors diversify, only a risk added to a diversified portfolio should be measured and priced in the market. This paper attempts to use a market illiquidity measure that can reflect the liquidity condition of different asset classes. Using the results of the study by Frank et al. (2008), this is attained by focusing on liquidity shocks measured using the spread between the yield of commercial papers and that of U.S. treasury bill.

Moreover, in examining the economic significance of the commonality risk, previous studies form portfolios based on the illiquidity level of the stocks in their sample, which contradicts the definition of commonality risk. The source of commonality risk is the co-movement of the illiquidity of a given stock and the overall market illiquidity. The paper addresses this issue by forming portfolios based on the sensitivity of each stock's illiquidity to the market illiquidity. The pricing of the commonality risk is then examined by estimating the LCAPM using the Dynamic Conditional Correlation (DCC) technique. The sample period considered in the study is from January 1997 to December 2016.

Overall, the paper finds that the commonality risk premium is 0.022% per year when portfolios are readjusted every 12 months. This estimate is significantly higher than the annual premiums found when LCAPM is estimated by following the procedures from Acharya and Pedersen (2005) and Hagströmer et al. (2013), respectively. In addition, the results also indicate that the commonality risk premium markedly increases during periods of economic crisis than periods of tranquility, 0.043% during the 2000 Dot-com crash period, and peaks at 0.149% in the 2007/08 Great Recession era. In order to check for the robustness of the baseline results, the paper extends the 12-month portfolio rebalancing period to 24 months. In this approach, the excess return difference between the highest and the lowest commonality risk portfolios that can be attributed to the difference in their level of commonality risk slightly decreases to 0.0134%. Under the 24 months holding period, the commonality risk premium is also significantly different from zero at 5% level of significance. Furthermore, the commonality risk premium estimate in both the 12-month and 24-month holding period is also higher than the premium for the risk due to the correlation between stock return and market illiquidity. These findings emphasize the importance of easiness of tradability of assets at times of low liquidity.

In order to check if the baseline results are driven by having the Great Recession period in the sample, I dropped observations from that period and re-estimated the LCAPM. The commonality risk premium remains nearly zero when the market illiquidity is measured as the average of the illiquidity of each stock. However, it increases to 0.039% when the market illiquidity is measured as the yield difference between commercial paper and treasury bill. The increase in the premium associated with the commonality risk can be partly attributed to using a broader market illiquidity measure and capturing the true extent of assets' liquidity condition sensitivity including to shocks from other financial markets. Cespa and Foucault (2014) propose a theoretical framework explaining the contagion nature of liquidity shocks across financial markets. However, it deserves more attention in future empirical researches. The major challenge in this literature is the identification issue as the liquidity condition of most markets are highly inter-twined. Lastly, the paper compares the empirical fit of the time varying beta LCAPM when the illiquidity of the market portfolio is measured as the average of the illiquidity of each stock versus the yield difference between commercial paper and treasury bond. The LCAPM with the broader market illiquidity measure performs better in predicting excess return for the low commonality risk portfolios while the LCAPM with the market illiquidity measured as the average of the illiquidity of each stock performs better in predicting the excess return for the high commonality risk portfolios.

The second chapter tests whether the inflation illusion hypothesis can explain the high correlation between stock yield and treasury bond yield as implied by the Fed model. The Fed model compares the yield on stocks to the yield on bonds and proposes that the former tends to be equal to the latter in the long run. Previous studies rationalize this implication by using Modigliani and Cohn's inflation illusion hypothesis. According to this hypothesis, investors adjust interest rate in the bond market in response to overall price change, which is used to discount future stream of cash flows in the stock market. However, this expected cash flow is not adjusted for inflation, leading to mis-pricing. Consequently, there is a co-movement in stock yield and government bond yield. This inflation illusion hypothesis is supported by previous studies such as Campbell and Vuolteenaho (2004) and Bekaert and Engstrom (2010). However, in testing the validity of the hypothesis, these previous studies fail to take into account two important variables which investors can learn about from a change in the general price level and also determine the value of any stock: news about cash flows and news about the discount rate.

The major contribution of the second chapter is it incorporates these new variables in testing for the validity of the inflation illusion hypothesis. This testing is undertaken in two stages. First, I use the Gordon growth model to determine mis-pricing in the stock market. In this process, the mis-pricing component is given by the sum of the dividend price ratio and the objective expectation about dividend growth, less the subjective discount rate. The objective expectation about dividend growth is estimated by the sum of unexpected stock return, news about the discount rate, and time t component of news about cash flows. The subjective discount rate series is generated by applying Weitzman's (2001) Gamma discount function. After obtaining the mis-pricing series in the first stage, the next step involves a regression model in the spirit of Andersson, Krylova, and Vähämaa (2008) to examine the impact of mis-pricing on the correlation between stock yield and government bond yield. This correlation is estimated using the Asymmetric Generalized Dynamic Conditional Correlation (AG-DCC) model. Consistent with the Fed model, this chapter found a very high correlation between stock yield and bond yield over the period January 1983 to December 2016, averaging between 0.942 - 0.997. Moreover, the result from the second stage regression indicates that mis-pricing has insignificant impact on the correlation between bond yield and stock yield, leading to rejection of the inflation illusion hypothesis. This is in contrast to the study by Campbell and Vuolteenaho (2004).

Based on the rejection of the inflation illusion hypothesis in the second chapter, the third chapter of this dissertation provides an alternative explanation for the high correlation between stock yield and government bond yield as implied by the Fed model. The explanation is based on liquidity shocks contagion between the stock market and the corporate bond market. The idea is that when liquidity drops in the stock market, firms' credit risk rises as the deterioration in liquidity in the stock market increases firms' probability of default. As a consequence, the liquidity of corporate bonds deteriorates and investors' preference shifts away from corporate bonds to government bonds. Higher demand for government bonds keeps the interest rate and price of these bonds low. This will also make the yield on these bonds low as well. In the stock market, stock yield is also low due to market illiquidity, leading to a co-movement of stock yield and government bond yield. This explanation contradicts the mis-pricing explanation provided by previous studies. The argument offered by previous studies was that stock market investors are subject to inflation related mis-pricing, but not bond market investors.

In testing the liquidity shocks contagion explanation, I followed two steps. First, I use the Markov switching model and the Convergent Cross Mapping (CCM) to test for the inter-dependence between liquidity shocks in the stock market and the corporate bond market. In the second stage, an Auto Regressive Distributed Lag (ARDL) model is estimated to examine the response of stock yield and government bond yield to liquidity shocks in the stock market. The testing is done using monthly data from January 1997 to December 2016. To sum up, the study provides strong evidence of a significant interaction in the liquidity condition between the corporate bond market and the stock market. The Markov regime model results reveal evidence of liquidity shocks in the stock market affecting liquidity condition of the corporate bond market at times of both high illiquidity and low illiquidity. The results from the CCM model also imply a similar conclusion in that the liquidity condition of the stock market has relevant information useful for predicting the probability of the corporate bond market being in the state of low illiquidity and high illiquidity. In the second step of the testing procedure, stock yield is also found to be strongly affected by the liquidity shocks from the stock market. These findings render support for the illiquidity shocks contagion explanation provided in this paper. These results also shed light on why increasing integration amongst financial markets increase the fragility of overall liquidity condition as a small rise in the illiquidity of one financial market highly likely causes an increase in the illiquidity of other financial markets too.

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