

TWO ESSAYS IN DYNAMICS OF STOCK LIQUIDITY AND ASSET RETURNS

by

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(Under the Direction of CHRISTOPHER T. STIVERS)

ABSTRACT

This dissertation consists of two essays. In the first essay, we study how the correlations between stock portfolios and Treasury bonds vary jointly with the stock's volatility and the stock's illiquidity. Our goals are to: (1) better understand time-variation in stock-bond correlations, (2) help distinguish between flight-to-quality and flight-to-liquidity pricing influences, and (3) evaluate the performance of alternate liquidity metrics in this setting. In the time series, we find that aggregate stock market illiquidity is negatively associated with the future stock-bond return correlation, although the illiquidity relation is generally weaker than the negative volatility-correlation relation. However, in the cross-section of stocks during times of market stress, a stock's illiquidity is more informative about the cross-sectional variation in the correlation changes than is a stock's volatility. Thus, stock volatility appears better at identifying the times when stock-bond correlations become more negative, but illiquidity appears better at identifying which stocks have stronger correlation variation. In our setting, the Amihud (2002) price impact measure of illiquidity performs better than Pastor and Stambaugh (2003) return reversal measure of illiquidity.

The second essay characterizes the movements and co-movements in stock market volatility, illiquidity and idiosyncratic volatility. We examine the commonality in the three variables when moving from good times to bad times by studying regime-switching models. We find that the regimes identified by using one or two or all three of the variables have similar characteristics. This suggests that these variables are closely related and may, to some extent, be capturing the same information about the market environment. Our Granger-causality tests suggest that each of these series have some ability in forecasting the other two series. Our findings have important implications on research that examine if these variables affect stock returns. We show that a study that only examines the relation between returns and market volatility may attribute a return pattern to price-volatility effects, when it might be more of price-liquidity effect (or some combination of the two effects).

INDEX WORDS: Flight-to-Quality, Flight-to-Liquidity, Illiquidity, Volatility, Idiosyncratic Volatility, Stock-Bond Correlation, Regime-Switching.

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DEDICATION

To my wife

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CHAPTER 1

INTRODUCTION

Illiquidity of an asset is related to volatility of its return. There are both theoretical models and empirical papers that establish a positive relationship between the two. This dissertation consists of two essays that study stock illiquidity and volatility in two different settings. In first essay, we investigate whether stock's volatility and the stock's illiquidity have information regarding correlation of stock portfolios and Treasury bonds. The second essay characterizes the movements and co-movements in aggregate stock market volatility, illiquidity and idiosyncratic volatility.

1.1. Essay 1

Flight-to-quality (flight to less volatile assets) and flight-to-liquidity (flight to more liquid assets) are two related phenomenon that can materially change asset prices in times of market stress. In this paper, we study how the correlations between stock portfolios and Treasury bonds vary jointly with the stock's volatility and the stock's illiquidity. Our goals are to: (1) better understand time-variation in stock-bond correlations, (2) help distinguish between flight-to-quality and flight-to-liquidity pricing influences, and (3) evaluate the performance of alternate liquidity metrics in this setting. In the time series, we find that aggregate stock market illiquidity is negatively associated with the future stock-bond return correlation, although the illiquidity relation is generally weaker than the negative relation between stock market volatility and subsequent stock-bond

correlation. However, in the cross-section of stocks during times of market stress, a stock's illiquidity is more informative about the cross-sectional variation in the correlation changes than is a stock's volatility. Thus, market volatility appears better at identifying the times when stock-bond correlations become more negative, but illiquidity appears better at identifying which stocks have stronger correlation variation. In our setting, the Amihud (2002) price impact measure of illiquidity performs better than Pastor and Stambaugh (2003) return reversal measure of illiquidity.

1.2. Essay 2

Financial economists have worked in several directions to find the factors that influence stock returns. Three such factors that have gained particular attention recently are market volatility, market illiquidity and idiosyncratic volatility. To date there has been little attempt to connect the three variables, yet there are good theoretical reasons to do so. This paper tries to fill the gap by characterizing the movements and co-movements in stock market volatility, illiquidity and idiosyncratic volatility. To achieve our objectives, we first examine the commonality in the three variables when moving from good times to bad times by studying regime-switching models. We find that the regimes identified by using one or two or all three of the variables have similar characteristics. This suggests that these variables are closely related and may, to some extent, be capturing the same information about the market environment. Next, encouraged by the contemporaneous relationship between the three variables, we take a forward-looking perspective and ask whether these variables help to forecast each other. Our Granger-causality tests suggest that each of these series have some ability in forecasting the other two series. This

further supports the notion that these variables may be responding to the same latent shocks to financial markets.

Our finding has important implications on research that examine if these variables affect stock returns. Our findings would suggest that each of these factors may individually affect stock returns as they all capture information about the state of the economy. However, the incremental effect should become substantially weaker, or disappear altogether, once one controls for other two factors as they may be capturing the same information. To illustrate this point, we examine the explanatory power (R-square) of illiquidity and market volatility in explaining the variations in stock market returns. We find that the joint explanatory power of the two variables is not much different than that of illiquidity alone. This suggests a study that only examines the relation between returns and market volatility may attribute a return pattern to price-volatility effects, when it might be more of price-liquidity effect (or some combination of the two effects).

CHAPTER 2

STOCK MARKET ILLIQUIDITY AND STOCK-BOND RETURN RELATION

2.1. Introduction

It is now well known that the cross-market hedging and cross-market portfolio rebalancing play an important role in linkages between financial markets of different assets classes (Fleming, Kirby, and Ostdiek (1998) and Kodres and Pristker (2002)). A shock in one market may change the market participants' assessment about the risk in that market, and might lead to investors' optimally readjusting their positions in other markets. This action transmits the shocks, so that a shock in one asset market, which may appear to be largely asset specific, may have a material influence on different (non-shocked) markets.

In the stock and the bond market, Connolly, Stivers and Sun (2005, henceforth CSS) find a negative relation between stock uncertainty (as proxied by CBOE implied volatility and stock turnover) and the future correlation between stock and bond returns. They conjecture that dynamic cross-market portfolio rebalancing is likely to have an important role in understanding their results. In a similar vein, one would expect stock illiquidity as another factor that may affect the correlation between stock and bond returns.

In this paper, we study how the correlations between stock portfolios and Treasury bonds vary jointly with the stock's volatility and the stock's illiquidity. Our objectives are to better understand time-variation in stock-bond correlations and to help distinguish

between flight-to-quality and flight-to-liquidity pricing influences¹. Note that the flight-to-quality refers to investors rebalancing their portfolios towards *less volatile assets*, whereas the flight-to-liquidity refers to investors rebalancing their portfolios towards *more liquid assets*. While the two phenomena are related as the two attributes – volatility and illiquidity - are usually positively correlated, the economic motives of these phenomena are clearly distinct from each other (Beber, Brandt, and Kavajecz (2007) and Vayanos (2004)).

While it is natural to associate discussions of flight-to-quality and flight-to-liquidity with “rare events” such as Asian Crisis (1997) and Russian bond default (1998), we are concerned with the question – does stock illiquidity in everyday markets convey information about the stock-bond return relation. The central idea is that when the stock illiquidity increases, *ceteris paribus*, the stocks’ expected returns should go up, which would generate a contemporaneous decline in stock prices and an observed negative return for that day. Further, it may increase investors’ effective risk aversion (for reasons discussed in next paragraph) and they may want to hedge the increase in stock-specific illiquidity risk. This may make bonds (the non-shocked market) more attractive. Thus, the risk premia of the bonds could actually decline with increased risk in the stock-specific factor, which would generate a contemporaneous increase in bond prices and an observed positive bond return for that day. With high illiquidity, there is also more

¹ Another objective of our study is to evaluate the performance of alternate illiquidity measures with respect to their information content about stock-bond correlation. The motivation of this objective stems from the manner in which a popular illiquidity measure is defined. We discuss this point in more detail after we have introduced our illiquidity measures.

volatility in illiquidity². Thus, this behavior could induce a more negative stock-bond correlation.

There can be several reasons why investors' may be less willing to hold illiquid assets during illiquid stock markets. First, the investors can be thought of as fund managers who are subject to withdrawals that depend on the fund's performance (Vayanos (2004)). During illiquid times, the probability that performance falls below an exogenous threshold increases, and withdrawals become more likely. This reduces the managers' willingness to hold illiquid assets. The notion that withdrawals from a fund are based on the fund's performance is also closely related to that of limits of arbitrage (e.g. Shleifer and Vishny (1997)). Second, liquid assets have an option-type feature because they give their owner the option to convert them easily into cash if needed (Scholes (2000)). As higher illiquidity is also associated with higher volatility, liquid assets are more valuable during illiquid times. Substituting a liquid asset for an illiquid asset one saves the manager the transaction cost of selling the illiquid asset when performance falls below the threshold (Vayanos (2004)). A third reason is related to liquidity spirals, as proposed in Brunnermeier and Pedersen (2007). We discuss it briefly in the Section 2.2.2.

Our paper has two parts. The first part has a time series perspective and examines the joint effect of stock market illiquidity and stock market volatility on comovement between bond returns and aggregate stock returns. This part is closely related to CSS (2005). Their focus is on the effect of stock market uncertainty (proxied by implied volatility and turnover); our focus is on the joint effect of stock market illiquidity and stock market volatility (proxied by realized and implied volatility). The second part of

² Our findings in Chapter 3 provide support to this claim. In that chapter, we use a two-state regime-switching approach and show that volatility of illiquidity is more in that regime that has higher illiquidity.

paper examines the effect of stock's illiquidity and stock's volatility on cross-sectional variation in correlation of bonds with stock portfolios. This approach is novel and helps us in better understanding how the illiquidity and volatility affect stock-bond return correlation.

In our empirical study, we employ Amihud's (2002) price impact measure and the negative³ of Pastor and Stambaugh's (2003) return reversal measure as proxy for stock market illiquidity. These two measures have become very popular in the recent empirical papers involving liquidity. We estimate these measures for a rolling 22-trading-day period, instead of a traditional one-month period, as this allows us to capture sizable changes in stock market illiquidity that may occur over a trading day.

In the time series, we find that both aggregate stock market illiquidity and stock market volatility is negatively associated with the future stock-bond return correlation, although the illiquidity relation is generally weaker than the volatility relation. More specifically, the tendency of the bonds and stocks to move together on day t as well as the stock-bond correlation over days $t+1$ to $t+22$ decreases with the realized stock market volatility and the stock market illiquidity estimated over the previous 22-trading-days (from day $t-22$ to day $t-1$). We find both the price impact and return reversal measure of illiquidity are informative at an individual level. However, only Amihud's price impact measure is incrementally informative once we control for stock market volatility. The lagged market volatility remains informative even after controlling either of the lagged market illiquidity measures. We find qualitatively similar results across different sample periods and with alternate empirical frameworks.

³ We flip the sign of original Pastor and Stambaugh measure in order to make it a measure of illiquidity.

In the cross-section of stocks, both a stock's illiquidity⁴ and stock's volatility is informative about the variation in correlation of bonds with stock portfolios. We double-sort the stocks into illiquidity and volatility quintiles and find that the stock portfolios with highest illiquidity (volatility) in the previous 22-trading-days have the lowest comovement with the bonds at day t . The comovement monotonically decreases as the illiquidity (volatility) of the portfolios decrease. The negative relation between illiquidity and stock-bond correlation is visible across all volatility quintiles, and both during uncertain and stable market conditions. Interestingly during times of stress, a stock's illiquidity is more informative about the cross-sectional variation in the correlation changes than is a stock's volatility. This evidence supports the findings of Beber, Brandt, and Kavajecz (2007) that in times of market stress, investors chase liquidity, not quality.

From our time series and cross-sectional analysis, one can conclude that market volatility appears better at identifying the times when stock-bond correlations become more negative, but illiquidity appears better at identifying which stocks have stronger correlation variation.

Our contribution can be summarized as follows. We extend the stock-bond return comovement literature by including the stock market illiquidity as another factor that may affect the return dynamics. Further, we are the first ones to link the cross-market pricing influences to the comovement of bonds with cross-section of stock portfolios. Next, we complement and extend findings in CSS (2005) in several ways – we show their results are valid both using implied volatility and realized volatility as a proxy for market

⁴ All the results related to the effect of stock's illiquidity on cross-sectional variations in correlations hold only for Amihud measure. Pastor and Stambaugh measure seem to have no information about stock-bond correlation in a cross-sectional setting.

uncertainty over much extended period of time, from 1962-2004 (they use only implied volatility and study a sample of 1986-2000). The extended sample period is important as there has been substantial time variation in stock-bond correlation in the first few years of this century.

An additional contribution of this paper stems from the manner in which Pastor and Stambaugh choose specification for their illiquidity measure. They experiment with 24 possible alternatives and they choose a one in which the resulting periods of high illiquidity are associated with negative stock-bond correlation. If that is a correct criterion for choosing an illiquidity measure, then this paper provides a direct test for comparing which of the two measures of illiquidity – Amihud or Pastor and Stambaugh – is better in regards to being informative of stock-bond correlation. We do a detailed analysis how these illiquidity measures are associated with stock-bond correlations.

Apart from CSS (2005), our paper is related to Chordia, Sarkar and Subrahmanyam (2005), Goyenko and Ukhov (2007), Goyenko (2006), and Underwood (2006). All these papers explore the cross-market dynamics in the stock-bond market. The first three papers examine the liquidity linkages between the stock and Treasury bond markets. Underwood (2006) examines the informational content of aggregate order flows in the US equity and Treasury Markets. None of these papers study the cross-markets effects in light of stock-bond correlations, which is the focus of this paper.

Finally, the cross-sectional results in our paper are related to Baker and Wurgler (2005). They find the US government bonds comove more strongly with “bond-like-stocks”. They find large and low-volatility stocks have more strongly with bonds than the small

and more-volatile stocks, respectively. These results are largely consistent with findings in our paper.

The stock-bond correlations are crucial to practitioners and academicians, alike. Stocks and bonds being the two most important financial asset classes, their correlation is extremely important in asset allocation and risk management decisions. Moreover, the observed correlation patterns in these two assets provide information that help disentangle the factors that dominate the valuation mechanism of stocks and bonds.

The rest of the paper is organized as follows. Section 2.2. presents a brief review of the related literature. Section 2.3. presents the data description. This section also includes a detailed discussion on computation of the illiquidity measures on a rolling 22-trading-days. Section 2.4. includes discussion on results for time series analysis and Section 2.5. discusses results for the cross-sectional analysis. Section 2.6. compares the two illiquidity measures in the settings of this paper, and Section 2.7. concludes.

2.2. Related Literature

In this section, we briefly discuss the related literature that provides important perspective to our empirical investigation.

2.2.1. *Return Comovement of stocks and bonds*

Given that the stocks and bonds represent two most important assets for asset allocation decisions, there is considerable literature in this area⁵. Initial papers, Shiller and Beltratti (1992) and Campbell and Ammer (1993), assumed that the stock-bond correlations are

⁵ Some of the recent work that has examined the comovement of stock and bond returns include Fleming, Kirby, and Ostidiek (1998), (2001), and (2003), Hartmann, Straetmans, and Devries (2001), Li (2002), Gulko (2002), Scruggs and Glabadanis (2003) and Connolly, Stivers, and Sun (2005) and (2007).

constant over time. However, this assumption has been challenged and rejected. It is now well known that while stock and bond returns exhibit a modest positive correlation over the long term, there is a substantial time variation over the short term including sustained periods of negative correlation.

Surprisingly, little is known about the forces that can drive a negative correlation in stock and bond returns. One variable that, in theory, may affect this correlation is inflation since increases in inflation are bad news for bonds and ambiguous news for stocks. However, the empirical evidence is inconclusive. Li (2002) finds that while the uncertainty about the expected inflation increases the comovement between stock and bond returns, the effect of unexpected inflation is ambiguous and depends on how dividends and the real interest rate respond to unexpected inflation shocks. Further, during the 1986 to 2000 sample period, inflation was both relatively low and stable and there were sizeable periods of negative correlations (CSS(2005)). This suggests other influences may be important for understanding stock-bond price comovements. While heteroskedasticity can induce time variation in observed correlations (Forbes and Rigobon (2002)), heteroskedasticity cannot explain why two return series that normally have a positive correlation occasionally have periods of negative correlation.

Another variable that may induce negative stock and bond return correlation is market uncertainty (market risk). From a theoretical perspective, Barsky (1989) argues that the stock and bond comovement is state dependent. His contention is that the low productivity growth and high market risk are likely to lower both corporate profits and the real interest rate, which propels stock and bond prices in opposite directions. A few recent papers, motivated by literature on dynamic cross-market hedging, link the time-

variation in stock-bond returns correlation to stock-market uncertainty. Gulko (2002) focuses on the stock-bond correlations around stock market crashes, and shows that the periods of negative stock-bond correlation tend to coincide with stock market crashes. CSS investigate the “flight to quality” issue by examining the effect of stock market volatility on bond returns. They use implied volatility from equity index options and detrended share turnover as a proxy for stock market uncertainty and find a negative relation between stock market uncertainty and future correlation between stock and bond returns. In their follow on paper, CSS (2007) find that this negative relation holds not only for US but also for other European countries like UK and Germany.

In this paper, we provide evidence that the stock market illiquidity is another factor that may affect the correlation between stock and bond returns.

2.2.2. Flight-to-liquidity and Flight-to-quality

Our work is also related to the vast literature on the importance of liquidity. Goldreich, Hanke and Nath (2005) and Longstaff (2004) provide evidence of preference for liquidity through the comparison of carefully chosen samples of on and off-the run paired Treasury securities and Treasury and RefCorp securities, respectively. Longstaff also finds that the liquidity premium is directly related to consumer confidence which is consistent with the view that the investors are willing to pay a premium for liquidity when markets are unsettled. This provides a clear evidence of flight-to-liquidity.

Flight-to-liquidity, as discussed earlier in the Introduction, is related to flight-to-quality, but it has a distinct economic rationale. Empirically disentangling these effects is difficult because volatility and illiquidity are usually positively related. Beber, Brandt, and

Kavajecz (2007) , however, are able to accomplish this by studying yield spreads and order-flow in Euro-area government bond market, which exhibits a strong and unique negative relation between (credit) quality and liquidity. They find that the while quality matters, in times of market stress, investors chase liquidity, not quality. This result is consistent with the theoretical work by Vayanos (2004) who finds that the liquidity premium increases with volatility. His intuition is that , during volatile times, managers are concerned with the withdrawals from the fund as the probability that the performance falls below threshold increases, and withdrawals become more likely.

In another theoretical work, Brunnermeier and Pedersen (2007) argue that funding conditions of the speculators (who are responsible for providing liquidity in the markets) plays an important role at times when markets are illiquid. According to them, a “*loss spiral*” arises if speculators hold a large initial position that is negatively correlated with customers’ demand shock. In such a case, a funding shock increases market illiquidity, leading to speculator losses on their initial position, forcing speculators to sell more, causing a further price drop, and so on.

2.3. Data Description

We use CRSP to get the daily stock returns. The aggregate daily stock returns is the CRSP value-weighted returns on NYSE/AMEX/NASDAQ portfolio. For daily bond returns, we analyze ten-year US Treasury notes. The daily bond returns are calculated as the implied returns from the constant maturity yield from the Federal Reserve (for details, see Jones, Lamont and Lumsdaine (1998)). We report the results using raw returns, rather than excess returns above the risk-free rate. Since we are interested in daily return comovements, this choice should not affect our results.

2.3.1. Measures of Stock Illiquidity

For our empirical examination, we require illiquidity series that extend over sufficiently long periods. For this reason, the microstructure data based measures of illiquidity- such as bid-ask spread (quoted or effective), transaction-by-transaction market impact or the probability of information based trading, etc - are not suitable for our study. In recent years, however, researchers have introduced liquidity series that can be constructed using only the daily return and volume data obtainable from CRSP.

In our study, we use Amihud's (2002) price impact measure, henceforth PIM, and Pastor and Stambaugh's (2003) return reversal measure, henceforth RRV. These two measures have become very popular in the recent empirical papers involving liquidity. While PIM is closely correlated with price-impact measures based on high-frequency data (Hasbrouck (2006)), RRV adequately captures many of the known historical properties of the stock market liquidity (Pastor and Stambaugh (2003)). We construct both PIM and RRV such that they measure illiquidity; in other words, higher values indicates markets are more illiquid.

Though illiquidity is normally measured on a monthly basis, we use a novel approach to estimate illiquidity. We estimate illiquidity over rolling 22-consecutive-trading-day period. We do so to mitigate concerns associated with monthly measures. The concerns are: first, as compared to a rolling daily measure, a monthly measure is not as responsive to short-term changes in market conditions; second, using monthly estimates we don't get enough observations to study daily return dynamics. Using rolling estimates allow us to construct a daily time-series for illiquidity. In our time series, the illiquidity on day t

refers to illiquidity measured over a backward-looking 22-trading-day period ending on day t . That is, $ILLIQ_t$ refers to the illiquidity estimated over the period $t - 21$ to t .

From computational perspective, the two measures are similar in some ways. In both, we first estimate the illiquidity measures for individual stocks, and then take a cross-sectional average to get the market-wide illiquidity measure, and finally scale-up the series to make it relatively stationary. In the cross-sectional average, we include only those stocks that meet the following conditions: [a] there should be more than 15 observations to estimate illiquidity measure of individual stocks [b] it should be a ordinary share (CRSP share code 10 or 11) [c] it should be listed on NYSE/AMEX⁶ (CRSP exchange code 1 or 2) [d] share price should be between \$5 and \$1000 [e] the first (or the last day) that stock appears (or disappears) on CRSP should not fall between the 22-trading-day period. The values for share code, exchange code and share price for purpose of sample stock selection is the values as of the beginning of the 22-trading-day period. To scale up the resulting series, we multiply by m_t/m_1 , where m_t is the total dollar value of the stocks (included in the cross-sectional average) as of the beginning of that period and m_1 is the corresponding value for the first 22-trading-day period⁷. The two measures differ in the first step, i.e. the estimation of illiquidity measure of individual stocks.

The return reversal measure of Pastor and Stambaugh is based on the idea that the price changes accompanying large volumes tend to be reversed when market-wide liquidity is

⁶ NASDAQ stocks are excluded because their data are available only from 1982 and their reported volumes are overstated due to the inclusion of inter-dealer trades.

⁷ We begin our first 22-trading period from August 1st 1962. Choosing this date allows the scaling factor in monthly and rolling illiquidity estimates to be comparable. Most papers that use these liquidity measures construct time series starting from August 1962. By choosing August 1st 1962 as starting date for our first 22-trading-day period, the m_1 in both the monthly and rolling series is the dollar value of stocks at the beginning of August 1st 1962.

low. Specifically, the liquidity value for stock i in a 22-consecutive-trading-day period ending on day t is given by

$$r_{i,d+1,t}^e = \theta_{i,t} + \phi_{i,t} \cdot r_{i,d,t} + \gamma_{i,t} \cdot \text{sign}(r_{i,d,t}^e) \cdot \text{vol}_{i,d,t} + \varepsilon_{i,d+1,t} \quad (2-1)$$

$$ILLIQ_{i,t}^{RRV} = -\gamma_{i,t} \quad (2-2)$$

where $r_{i,d,t}$ and $\text{vol}_{i,d,t}$ are the return and the dollar volume (measured in millions), respectively, of stock i on day d in the 22-trading-day period, and $r_{i,d+1,t}^e$ is the excess return given by $r_{i,d,t} - r_{m,d,t}$ where $r_{m,d,t}$ is the CRSP value-weighted market return on day d . If we regard $\text{sign}(r_{i,d,t}^e)$ as a proxy for order-flow, $\gamma_{i,t}$ represents an order-flow return reversal. Note that we flip the sign of return reversal measure in order to make it a measure of illiquidity.

The price impact measure of Amihud (2002) measure is based on the idea that there is a positive relationship between the price change and the net order flow which results from the information asymmetry between market makers and traders. Following Amihud (2002), we use the illiquidity ratio as a price impact proxy. We remove the stock-days with zero volume and measure the illiquidity value for stock i in a 22-consecutive-trading-day period ending on day t as

$$ILLIQ_{i,t}^{PIM} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|r_{i,d,t}|}{\text{vol}_{i,d,t}} \quad (2-3)$$

where $r_{i,d,t}$ and $\text{vol}_{i,d,t}$ are the return and the dollar volume (measured in millions), respectively, of stock i on day d in the 22-trading-day period, and $D_{i,t}$ is the number of days the stock i traded (non-zero volume) in the 22-trading-day period.

2.3.2. *Stock Volatility*

For stock market volatility, we use both the realized and implied volatility measures. To measure the implied volatility of the U.S. stock market, we use the original VIX measure produced by from Chicago Board Options Exchange (CBOE)⁸, now denoted as VXO by the CBOE. VXO series starts in 1986. The use of realized volatility allows us to construct a time series from 1962. We define the realized volatility on day t as the annualized standard deviation of daily returns in backward-looking 22-trading-day period ending on day t . Therefore, $RVOLT_t$ refers to the realized volatility estimated over the period $t - 21$ to t . Our realized volatility series is available from August 1962. We find that the correlation between $RVOLT_t$ and VXO_t for the overlapping period is 0.82.

2.3.3. *Stock-Bond Return Correlation*

Following from Fleming, Kirby, and Ostdiek (1998) and CSS (2005), we calculate the correlation between daily stock and bond returns assuming that the daily mean stock and bond returns are zero (rather than the sample mean for the trading days in the estimation period). We make this choice because expected daily returns are essentially zero and this method prevents extreme return realizations from implying large positive or negative expected returns over the estimation period.

To obtain a daily time series, we measure 22-trading-day stock-bond return correlation. We define correlation such that the value on day t refers to correlation in daily asset

⁸ Starting from 2003, CBOE report two implied volatility series. The new series (denoted as VIX) is available from 1990 and the old series (now renamed as VXO) is available from 1986. We use VXO to be consistent with CSS. We tested that our results are not sensitive to this choice. In any case, the correlation between the two series for the overlapping period is 0.98.

returns over a forward-looking 22-trading-day period starting on day t . That is, $CORR_t$ refers to the correlation estimated over the period t to $t + 21$. Specifically,

$$CORR_t = \frac{\sum_{i=0}^{21} r_{b,t+i} \cdot r_{s,t+i}}{\sqrt{\sum_{i=0}^{21} r_{b,t+i}^2} \cdot \sqrt{\sum_{i=0}^{21} r_{s,t+i}^2}} \quad (2-4)$$

2.3.4. Summary Statistics

Table 2-1 presents the descriptive statistics. Panel A (Panel B) reports univariate statistics for the data series over the 1962 to 2004 period (the 1986 to 2004 period). Panel C reports the simple correlation between the variables. Note that the average 22-trading-day stock-bond correlation is modest at around 0.21 to 0.22, which is quite close to the monthly return correlation reported in Campbell and Ammer (1993).

Figure 2-1 exhibits the time-series of the different variables. Plot A illustrates the substantial time-series variation in the stock-bond return relation. The casual inspection of the various figures suggest that the periods of high market illiquidity and high market volatility are associated with the periods of negative correlation in Plot A.

2.4. Aggregate Stock Illiquidity and Stock-Bond Return Relation

In this section, we are interested in examining whether the aggregate stock market illiquidity has any information regarding the future return comovement in stocks and bonds. In this regard, we focus on two empirical questions. To understand these question, consider a 22-trading-day period from day $t - 22$ to day $t - 1$. Our first question asks whether the stock market volatility and stock market illiquidity estimated over this period is informative about the tendency of stocks and bonds to move together on the next day,

that is at day t . However, one-day ahead comovement variation may have little implication for portfolio risk management, as compared to longer term shifts. Accordingly, we further examine if the information in these lagged variables is limited to the next day or do they have information about stock-bond return correlation in the subsequent 22-trading-day period. More specifically, in our second question, we “skip-a-day” and investigate if the lagged market illiquidity and lagged market volatility (both estimated over days $t - 22$ to day $t - 1$) can be linked to the stock-bond return correlation from day $t + 1$ to day $t + 22$. Section 2.4.1. and Section 2.4.2. presents the results for the first question and Section 2.4.3. reports the results for the second question.

2.4.1. Stock-Bond Comovement as a function of lagged liquidity and volatility

In this subsection, we investigate return comovements from the perspective of the conditional bond return distributions, given the stock returns. We assume that the stock market liquidity has a first-order effect on the stock market and a second-order effect on the bond market, and thus we are interested in $E(B_t | S_t)$ rather than the $E(S_t | B_t)$.

Specifically, our primary interest in this subsection is whether the $E(B_t | S_t)$ varies with the stock market liquidity and volatility as depicted by the following regression,

$$B_t = a_0 + (a_1 + a_2 \cdot ILLIQ_{t-1}^X + a_3 \cdot \ln(VOLT)_{t-1} + a_4 \cdot CORR_{t-1}) \times S_t + v_t \quad (2-5)$$

where B_t and S_t are the daily 10-year T-bond and stock returns, respectively; $ILLIQ_{t-1}^X$ is the lagged value of stock market illiquidity; an upper case X denotes a generic illiquidity measure (X=PIM or X=RRV); $\ln(VOLT)_{t-1}$ is the natural log of lagged stock market volatility; $CORR_{t-1}$ is the lagged correlation between bond-stock returns. Note that the

lagged values are computed from the backward-looking 22-trading-day period ending on day $t-1$, i.e. from day $t-22$ to day $t-1$. We take the natural log of volatility as both the measures of volatility (realized volatility and implied volatility) have very high kurtosis. The primary coefficients of interest are a_2 and a_3 , which indicate, how the stock-to-bond return relation varies with market illiquidity and market volatility, respectively. We hypothesize both a_2 and a_3 to be negative and significant. CSS use implied volatility from CBOE as measure of market volatility and find a_3 to be significant and negative for the time period 1986-2000. Note that the above formulation represents only statistical relationship and does not imply economic causality. Stock and bond returns are both endogenous variables and are jointly determined. The estimated coefficients simply represent the statistical association in return comovement.

We estimate the different variants of the regression using both the return reversal measure and the price impact measure of illiquidity. Results for the price impact measure are reported in Table 2-2 and for the return reversal measure in Table 2-3. In both the tables, Panel A corresponds to the overall sample period 1962-2004, and Panel B corresponds to the sub-period 1986-2004. Panel C is also for the sub-period 1986-2004⁹, but uses implied stock market volatility instead of realized stock volatility. Further note that for easy reference, each specification in a Panel is given a number between [1] to [6]; the numbering is such that the same specifications in different Panels are given the same numbers; for example, the specification [2] in all the Panels refer to the same variant of

⁹ We don't report results separately for 1962-1985 sub-period to save space (the tables Table 2-2 and Table 2-3 are already very crowded). Furthermore, for reasons mentioned earlier, the sub-period 1986-2004 is of prime interest to us. Nevertheless, we do test our findings for 1962-1985 sub-period, and find qualitatively similar results.

the above regression but estimated for different sample periods and /or different volatility measure.

First, results for specification [1] in Panel A, a base line variant that restricts all coefficients other than a_1 to be equal to zero, indicate an unconditional positive relation between the B_t and S_t . Next, specifications [2] study the individual effect of lagged stock-market illiquidity on stock-to-bond relation. We find that the coefficient on lagged illiquidity, a_2 , is always negative and statistical significant for both measures of illiquidity. Further, this holds for the overall sample period as well as for the sub-period. This indicates the stock-to-bond relation varies negatively and very reliably with the lagged stock market illiquidity. For example, over the 1962 to 2004 period, the total implied coefficient on S_t , $a_1 + a_2$, is 0.189 (0.106) at the 5th percentile of $ILLIQ_{t-1}^{PIM}$ ($ILLIQ_{t-1}^{RRV}$). In contrast, at 95th percentile of $ILLIQ_{t-1}^{PIM}$ ($ILLIQ_{t-1}^{RRV}$), the total implied coefficient on S_t is -0.031 (0.051). Results for the sub-period are qualitatively similar.

In specification [3], we study the individual effect of lagged volatility. Panel A and Panel B use realized volatility and Panel C uses implied volatility. A negative and statistically significant value of coefficient a_3 indicates that the stock-to-bond relation varies negatively with both the measures of lagged stock market volatility. Over the 1986-2004 period, the total implied coefficient on S_t , $a_1 + a_3$, is 0.255 (0.209) at the 5th percentile of $RVOLT_{t-1}(VXO_{t-1})$ and is only -0.067 (-0.025) at 95th percentile of the $RVOLT_{t-1}(VXO_{t-1})$. Results for the over-all period are qualitatively similar. Our findings provide further support to CSS's findings. Further, CSS were limited in their choice of

sample period, from 1986 to 2000, due to the availability of implied volatility. Using realized volatility, allows us to extend their results over a much longer time period, from 1962-2004.

Next, in specification [4], we study the combined effect of lagged illiquidity and lagged volatility. We find that the lagged volatility is informative about the bond-stock return relation even after controlling for either measure of illiquidity. However, the results for illiquidity measures are mixed. Once we control for volatility, only the price impact measure provides incremental information. The coefficient on return reversal measure is no more significant.

Further, in specification [5], we study whether the lagged illiquidity and lagged volatility have information beyond that in the recent historical stock-bond correlation. We find that the negative relation on volatility remains very reliably evident. The coefficient on price impact measure is negative in all three Panels of Table 2 but is statistically significant only during the entire sample period. As expected from results in specification [4], the return reversal illiquidity measure has no additional information. The estimated a_4 coefficient is positive and significant for all the Panels in both Table 2 and Table 3, so there do tend to be information from the lagged rolling correlation estimates.

Finally, flight-to-quality and flight-to-liquidity is normally associated with “rare events” such as Asian Crisis (1997) and Russian bond default (1998). It is plausible that these events may drive our results. To control for the Asian and Russian crisis, we study another specification in which we interact S_t with a dummy variable which is set equal to one for October 1, 1997 through December 31, 1997 (Asian Crisis) and for July 6, 1998

through December 31, 1998 (Russian Crisis), and zero otherwise¹⁰. We find (results not reported) that the estimated coefficient on the dummy variable is negative and statistically significant. At the same time, the estimated coefficient on the lagged price measure of illiquidity and on the lagged volatility also remains negative and highly statistically significant. Thus, both the lagged illiquidity and the lagged volatility have information even when directly controlling for these crisis periods.

Overall, our results in Table 2 and Table 3 suggest lagged volatility on day $t-1$ (measured either as the realized volatility over days $t-22$ to $t-1$ or as the implied volatility on day $t-1$) has information about the bond-stock return relation on day t . These results hold not only at individual level but even also after controlling for the lagged illiquidity measures, for the recent stock-bond correlation, and for crisis periods. For illiquidity measures, we find support that both the price impact and return reversal measure of illiquidity are informative at an individual level. However, only the price impact measure of Amihud (2002) is incrementally informative once we control for stock volatility.

2.4.2. Comovement in GARCH (1,1) residuals

One criticism of our equation (5) is the endogeneity of stock and bond returns. This concern is best addressed if the specification is based on an asset pricing theory that takes into account that stock and bond returns are jointly determined as a function of underlying state variables, see for example Bekaert and Grenadier (2001) and Mamaysky (2002). However, there is no obvious specification from which we can empirically

¹⁰ We use the crises dates from CSS (2005).

examine time variation in daily stock-bond return dynamics. In this section, we estimate an alternate specification to support our results in Section 2.4.1.

Specifically, following from CSS (2005), we estimate a standard GARCH (1,1) model on each return series and then divide the residual by the conditional standard deviation to form a standard normal variable (approximately). We use the product of the standardized residuals for stock and bond returns as a measure of stock-bond comovement. In our specification, we take this measure as dependent variable and lagged illiquidity and lagged volatility as the explanatory variables.

$$B_t^{std} S_t^{std} = a_0 + a_1 \cdot ILLIQ_{t-1}^x + a_2 \cdot \ln(VOLT)_{t-1} + v_t \quad (2-6)$$

The dependent variable measures the tendency for the standardized residuals to move together and is in spirit of a daily correlation measure.

Table 2-4 reports the results for the regression. As earlier, we study the overall sample period (1962-2004) and the sub period (1986-2004) for which implied volatility information is available. The results in Table 2-4 strongly support our findings in Section 2.4.1. Both the estimated coefficients on lagged volatility and lagged price impact illiquidity measure are negative and highly statistically significant, both individually and jointly. Coefficient on return reversal illiquidity measure is negative and statistically significant at individual level but loses statistical significance when we add lagged volatility.

2.4.3. *Forward-looking 22-trading-day stock-bond correlation*

The previous two specifications provide strong evidence that the volatility and illiquidity measured over days $t - 22$ to $t - 1$ is negatively related to the tendency of the bond and

stock returns to move together on day t . So far, we haven't analyzed if these explanatory variables have any information about the stock-bond correlation in the subsequent 22-trading-day period. In this section, we ask if the lagged volatility and lagged illiquidity is informative about the stock-bond return correlation measured over subsequent 22-trading-days, i.e. from day $t+1$ to $t+22$ ¹¹. Specifically, we estimate the following regression.

$$CORR_{t+1} = a_0 + a_1 \cdot ILLIQ_{t-1}^x + a_2 \cdot \ln(VOLT)_{t-1} + a_3 \cdot CORR_{t-1} + v_t \quad (2-7)$$

where $CORR_{t+1}$ is stock-bond correlation measured over days $t+1$ to $t+22$ and all the lagged variables – illiquidity, volatility, and stock-bond correlation – are measured over the 22-trading-days from day $t-22$ to day $t-1$.

We stress that we are interested in temporary negative or low stock-bond correlations that may occur due to sizeable changes in stock market illiquidity and volatility over a trading day. The macroeconomic factors are unlikely to vary over a day. Controlling for lagged correlation mitigates some of the concern that we are not controlling for macroeconomic factors in above regression. Further, we also study the 1986-2004 sub period over which inflation has been fairly constant. Lastly, this regression framework allows us to make some direct comments regarding the economic significance of the explanatory variables.

Table 2-5 reports the results. We find that the stock-bond correlation in the forward-looking 22-trading-day period starting at time t is negatively and reliably related to the lagged volatility and the lagged price-impact illiquidity measure. Note that the coefficients on both the explanatory variables are highly significant even after controlling

¹¹ We skip a day to avoid any microstructure related problems that might have affected our results for day t .

for information in the recent stock-bond correlation. Once again, the coefficient on return-reversal measure is significant on individual basis but losses significance once we control for other two variables in the regression.

As the dependent variable in the equation (7) is limited between $[-1,1]$, it is better to estimate the above regression by replacing stock-bond correlation by its Fisher transformation . It transforms the correlation coefficient from the range $[-1, 1]$ to $(-\infty, \infty)$ with continuous and monotonic function. We prefer to report results using correlation, instead of its Fisher transformation, because it is more intuitive to interpret the coefficients. Nevertheless, we do estimate the regression using Fisher transformation and find qualitatively similar results.

Using *CORR* as the dependent variable in equation (7) allows us to study the economic significance of our explanatory variables. Consider the specification [4] in Panel B of the Table 5. This specification represents the effect of realized volatility on stock-bond correlation after controlling for the previous stock-bond correlation. The coefficient of -0.115 implies that if a period's realized volatility were to double, the stock-bond correlation in the subsequent 22-trading-day period is lowered by 0.08. Further, it also implies that the stock-bond correlation following a period in which the realized volatility is at its 95th percentile ($RVOLT = 23.90$, annualized) is 0.18 less than the stock-bond correlation following a period in which realized volatility is at 5th percentile ($RVOLT = 5.05$). This change is substantial considering that the long-term unconditional correlation is around 0.2. We study the similar specification for *VXO*. The coefficient on *VXO* in specification [4] in Panel C of Table 5 is -0.154. This implies that if the implied volatility doubles, the subsequent stock-bond correlation approximately

changes by -0.11 and if a period's implied volatility changes from its 5th percentile ($VXO = 12.01$) to its 95th percentile ($VXO = 35.88$), the correlation changes by -0.17. Hence, our findings suggest that if a period's stock market volatility increases from its 5th percentile value to its 95th percentile value, the unconditional correlation in subsequent 22-trading-days reduces by 0.17 to 0.18. Note this is incremental information beyond that in the recent stock-bond correlation.

To study the significance of price-impact illiquidity measure, we take the coefficient on illiquidity in the specification [2] of Panel A in Table 5. We find that during the entire sample period a change in a period's illiquidity value from its 5th percentile ($ILLIQ^{PIM} = 1.46$) to its 95th percentile ($ILLIQ^{PIM} = 4.56$) leads to a reduction of 0.11 in the stock-bond correlation in the 22-trading-day period. Again, this is incremental information beyond that in the recent stock-bond correlation.

2.5. Comovement of Bonds with Cross-Section of Stocks

In this section, stocks are assigned into different portfolios based on their volatility and illiquidity. We examine the correlations of each these portfolios with the bonds to better understand how volatility and illiquidity affect stock-bond return correlation.

In the following sub-sections, we first discuss the results for the portfolios formed on the Amihud measure, and we then discuss the results for the portfolios formed on the Pastor and Stambaugh measure.

2.5.1. *Stock Portfolios based on Amihud Measure of illiquidity*

We begin our analysis by looking at twenty-five portfolios created by sorting stocks first on their volatility and then on their illiquidity. Each day, we assign stocks into five quintiles based on their realized volatility in the daily returns in the previous 22-trading-days. Then, within each volatility group, we further assign stocks into five quintiles based on their illiquidity estimated over the previous 22-trading-days¹². The portfolios are rebalanced on a daily basis. We calculate the value-weighted average return of all the stocks in the portfolio and then estimate the stock-bond correlations for each of these twenty-five portfolios. We restrict our sample to 1986-2004 because we also study stock-bond correlations for these twenty-five portfolios for different sub-samples based on the VXO criterion¹³. The reason for sub-sampling based on the VXO criteria is explained later. As noted earlier, 1986-2004 is also the period that is of interest to us.

The results are reported in Panel A of Table 2-6. A note about reading Table 2-6: Correlation of bonds with different stock portfolios (Amihud measure of illiquidity) the leftmost column (topmost row) lists the first (second) sorting criterion and portfolios are arranged in ascending order from top to bottom (left to right). For instance, VOL-1 (ILLIQ-1) represents the quintile with least volatile (illiquid) stocks and VOL-5 represents the quintile with most volatile (illiquid) stocks. For purpose of comparing correlations across 25 portfolios, one must keep in mind that one can either compare numbers across Columns 2 to 6 for each row or compare numbers across Rows 2 to 6 for the first column. One must be careful that, with a exception of first column, one can't

¹² The presumption is that volatility and illiquidity are persistent. Thus, lagged measures are informative about current conditions.

¹³ Recall that the VXO series is available only from 1986 onwards.

compare numbers across rows. To understand why, consider two portfolios – let first portfolio be the least-illiquid stocks from the second volatility quintile and second portfolio be the least-illiquid stocks from the first volatility quintile. We don't know which of the two has higher illiquidity. So, it doesn't make sense to compare the stock-bond correlations for these portfolios.

In the first column of Table 2-6, Panel A, we observe that the correlations monotonically decrease along the volatility quintiles. That is, the stock portfolios with higher volatility have lower correlations with the bonds. In the columns 2 (least illiquid) to 6 (most illiquid), we observe a very strong (almost monotonic) trend that the correlations decrease as the illiquidity of the portfolio increases. In other words, within each volatility quintile, the portfolios with higher illiquidity have lower stock-bond correlations. We use bootstrap methods¹⁴ to test the statistical significance of our results. We find that within each volatility quintile, the differences in correlations of most illiquid stock portfolios (ILLIQ-5) with that of least illiquid stock portfolios (ILLIQ-1) is statistically significant at 1%. Overall, the results in Panel A provide strong evidence that the Amihud measure of illiquidity has information regarding stock-bond correlation even after controlling for volatility.

In Section 2.4.1. , we have shown that at an aggregate level, the tendency of stocks and bonds to move together at day t is negatively related to the aggregate stock market illiquidity in the previous 22-trading-days. Table 2-6, Panel A extends these findings in a

¹⁴ In our bootstrap methods, we make random draws, with replacement, of the actual return pairs in the sample. The number of drawn return-pairs is equal to the number of observations in the sample. We calculate the correlation for the set of drawn return pairs. We repeat this process for 5000 cycles to generate a distribution of the “differences in correlations”.

cross-sectional setting - the comovement is more negative for stock portfolios with higher illiquidity in the previous 22-trading-days.

The cross-market pricing influences are more likely to be observed during the periods of high stock market uncertainty. To study the roles of illiquidity during such times, in Panel B, we sub-sample the days on which level of VXO is greater than its 95th percentile¹⁵. As expected, correlations for all the twenty-five portfolios in Panel B are not only substantially lower than the corresponding values in Panel A but are also negative. The negative relation between stock-bond correlation and the implied volatility has been documented by CSS (2005). Comparing across Columns 2 to 6, we find that the correlations are more negative as the illiquidity of the stock portfolio increases. However, in our bootstrapping methods, we find that the differences in correlations of ILLIQ-5 and ILLIQ-1 portfolios are not statistically significant. Nevertheless, for volatility quintile 1-3 (which should include stocks that make up the substantial majority of market capitalization), there appears to be a strong trend that as the illiquidity increases, the correlation decreases. If the negative correlations during highly uncertain times are due to cross-market rebalancing with investors moving their assets from stocks to bonds, then the stronger pricing influences on illiquid stocks represent that the investors rebalance portfolios also due to illiquidity related reasons.

In Panel C, we examine the role of illiquidity when markets are relatively stable. We sub-sample days on which level of VXO is less than its 50th percentile. The correlations for all twenty-five portfolios are much higher than corresponding values in the either of three earlier panels. Within each volatility quintile, the correlations for most illiquid stocks

¹⁵ We sub sample based on the level of implied volatility on the previous day, i.e. day $t-1$.

(column 6) are consistently lower than those for least illiquid stocks (column 2). Further, the bootstrap methods tell us that for each volatility quintile, the differences in correlations of ILLIQ-5 with that of ILLIQ-1 is statistically significant at 1%. This confirms our result that the illiquidity affects stock-bond correlation, both during uncertain or stable periods.

In Panel D to F, we reverse the sorting order – stocks are first assigned into illiquidity quintiles and then into volatility quintiles. In Panel D, which reports results for the entire sample period, the correlations in the first column monotonically decreases as the illiquidity of the portfolio increases. Panel E (Panel F) report the correlations of these portfolios with the bonds when markets are highly uncertain (stable). As earlier, this is achieved by sub-sampling the days on which level of VXO is greater (lesser) than its 95th (50th) percentile. The results confirm our previous findings that the correlations decrease as the illiquidity of the portfolio increases.

It is interesting to note the information content of a stock's volatility at times markets are highly uncertain. Both in Panel B and in Panel E (the panels that study uncertain market times), we find that there is little variation in correlations across volatility quintiles. This is in contrast to negative relationship we find for illiquidity. These findings suggest that during times of market stress, a stock's illiquidity is more informative about the cross-sectional variation in the correlation changes than is a stock's volatility.

The illiquidity is also known to be related to the size of the stocks. Small stocks are expected to be most illiquid and most volatile. If investors trade between stocks and bonds for “flight-to-quality” or “flight-to-liquidity” related reasons, one would expect that the stock-bond correlation to be highest for large stocks and lowest for small stocks.

We are interested in examining the role of illiquidity within each size quintile. In Panel A of Table 2-7, we first sort the stocks on market capitalization, and then on illiquidity. In the first column of this panel, we observe that the correlations increase with the size of stock portfolios. Within each size quintile, the correlations decrease with the increase in illiquidity.

The Panel B in Table 2-7 is a little different than all the panels so far. Each day, we first assign stocks into five-quintiles based on their illiquidity in previous 22-trading-days. We then study the correlations of bonds with these five different portfolios under five different sub samples based on contemporaneous aggregate stock returns. The second (sixth) column, with label RET-1 (RET-5), represents the days on which aggregate stock returns was least (most). We observe that for each of the sub samples, RET-1 to RET-5, the correlation decrease as the illiquidity of the portfolio increases. These results completely rule out the concern that days with negative return shocks to the stock markets are driving our results in the paper.

2.5.2. Stock Portfolios based on Pastor and Stambaugh Measure of illiquidity

We now repeat the entire exercise in Section 2.5.1. for the Pastor and Stambaugh measure of illiquidity. That is, whenever we assign stocks into illiquidity quintiles, we do it on basis of return reversal measure of Pastor and Stambaugh. The results are reported in Table 2-8. Note that in Panels A, B, and C, the column labeled ALL is same as that in Table 2-6, because there is no sorting on illiquidity.

Unlike as in case of Amihud Measure, we don't see any decreasing trend when moving from the columns 2 (least illiquid) to 6 (most illiquid) across any volatility quintiles in

Table 2-8, Panel A. This suggests that the Pastor and Stambaugh illiquidity measure doesn't offer any information regarding stock-bond correlations beyond that in volatility. This result is further confirmed by looking at findings in sub-samples when markets are highly uncertain (Panel B), and in sub-samples when markets are relatively stable (Panel C).

Recall that earlier in Section 2.4.1. and Section 2.4.2. , we have seen that the correlations in stocks and bonds are negatively related to Pastor and Stambaugh aggregate stock market illiquidity estimated over previous 22-trading-days. We also found that statistical significance of this relationship is lost once we control for stock market volatility. Table 2-8 confirms the later result in a cross-section framework; that is, within the same volatility quintiles, the more illiquid stocks don't necessarily have lower correlations than that for less illiquid stocks.

However, it is still interesting to ask if Pastor and Stambaugh illiquidity measure has any information about stock-bond comovement in a cross-sectional setting. The findings in first column of Panel D suggests that the answer is NO. We fail to observe any decreasing trend in stock-bond correlations across illiquidity quintiles. The Panel E and Panel F further confirm these results.

2.6. Comment on illiquidity measures

Of the illiquidity measures which rely on returns and volume only (and thus can be used over long periods), the Amihud and Pastor and Stambaugh measures are the two best known and widely used. In this paper, we find that with respect to the information these measures contain regarding future stock-bond comovements, the results for Pastor and

Stambaugh measure are in sharp contrast to the results for Amihud measure. Amihud measure is informative even after controlling for volatility both at aggregate and cross-sectional level, whereas Pastor and Stambaugh measure has no information at cross-section level and is uninformative at aggregate level once one controls for volatility.

The results seem particularly interesting because the Pastor and Stambaugh state one of the criteria for picking the specification for their illiquidity measure was the negative association with stock-bond correlation. Recall that they use the following specification for their illiquidity measure (repeat of equation (2-1))

$$r_{i,d+1,t}^e = \theta_{i,t} + \phi_{i,t} \cdot r_{i,d,t} + \gamma_{i,t} \cdot \text{sign}(r_{i,d,t}^e) \cdot \text{vol}_{i,d,t} + \varepsilon_{i,d+1,t} \quad (2-8)$$

They experiment with different specifications for their illiquidity measure. The variable on the left-hand side can be either the excess or total stock return. On the right-hand side, the first regressor can be either total return or excess return, or it can be absent. Next, one can use not only excess return but also total return to sign volume for the purpose of obtaining a proxy for order flow. Finally, the return sign can be replaced by the return itself, for both excess and total return. Among these 24 possible alternatives, they choose a one in which the resulting periods of high illiquidity are associated with negative stock-bond correlation.

The findings in this paper suggest that the Amihud illiquidity measure is more strongly associated with negative stock-bond correlation than is the Pastor and Stambaugh

illiquidity measure. Therefore, in this regard, one can say that Amihud illiquidity measure is better than the Pastor and Stambaugh illiquidity measure¹⁶.

2.7. Conclusion

In this paper, we study how the correlations between stock portfolios and Treasury bonds vary jointly with the stock's volatility and the stock's illiquidity. In a time series, we find that the tendency of the bonds and stocks to move together on day t as well as the stock-bond correlation over days $t+1$ to $t+22$ decreases with the realized market volatility and the market illiquidity estimated over the previous 22-trading-days ($t-22$ to $t-1$). Both the price impact and return reversal measure of illiquidity are informative at an individual level. However, only Amihud's price impact measure is incrementally informative once we control for stock volatility. We also find the lagged market volatility remains informative even after controlling either of the lagged illiquidity measures. Our results are qualitatively similar across alternate empirical frameworks and across different sample periods (including the 1986-2004 subperiod over which inflation has been fairly constant). Further, our findings results are not only statistically significant but also appear to be economically significant.

In the cross-section of stocks, both a stock's illiquidity and stock's volatility is informative about the variation in correlation of bonds with stock portfolios. We find that the negative relation between illiquidity and stock-bond correlation is visible across all volatility quintiles, and both during uncertain and stable market conditions. Our results

¹⁶ Note that we look at subsequent stock-bond correlations, as compared to Pastor and Stambaugh who look at contemporaneous correlations in these two assets. Our findings suggest that Amihud measure is better in identifying times in which stock-bond correlation is more negative.

also indicate that during times of stress, a stock's illiquidity is more informative about the cross-sectional variation in the correlation changes than is a stock's volatility.

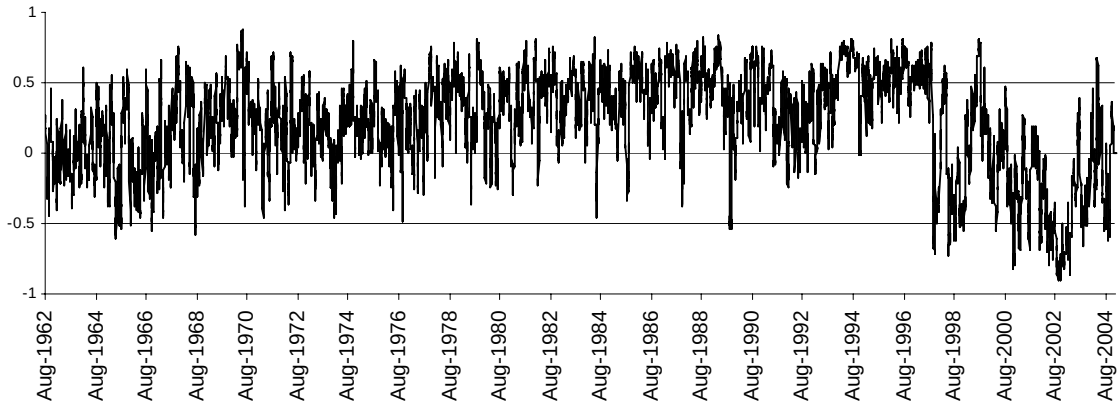
Our results indicate that the illiquidity has information regarding stock-bond return comovement. However, there may be a concern that market illiquidity is not a state variable per se; it is an outcome of (driven by) some other economic factors. Theoretically, it is plausible that the time variation in stock market volatility and in stock market illiquidity is caused by inflation shocks. However, we stress that we are interested in temporary negative or low stock-bond correlations that may occur due to sizeable changes in stock market illiquidity and volatility over a trading day. The macroeconomic factors are unlikely to vary over such short durations. Controlling for lagged correlation in our regressions also mitigates some of this concern. Also, we study the 1986-2004 subperiod over which inflation has been fairly constant. Further, using the same two illiquidity measure that we use in our study, Fujimoto (2004) finds that under the more stable economic environment of the recent two decades, the macro-level innovations play substantially smaller role in explaining the movements of the market illiquidity and of the market uncertainty measures like volatility.

Our findings suggest that times of high stock illiquidity are also times of frequent revisions in investors' assessments of the relative attractiveness of stocks versus bonds. If that is the case, then time-varying stock market illiquidity may have an important role in understanding periods of negative stock-bond correlation, especially during stable inflationary times. Our results suggest that stock-bond diversification benefits increase with stock market illiquidity.

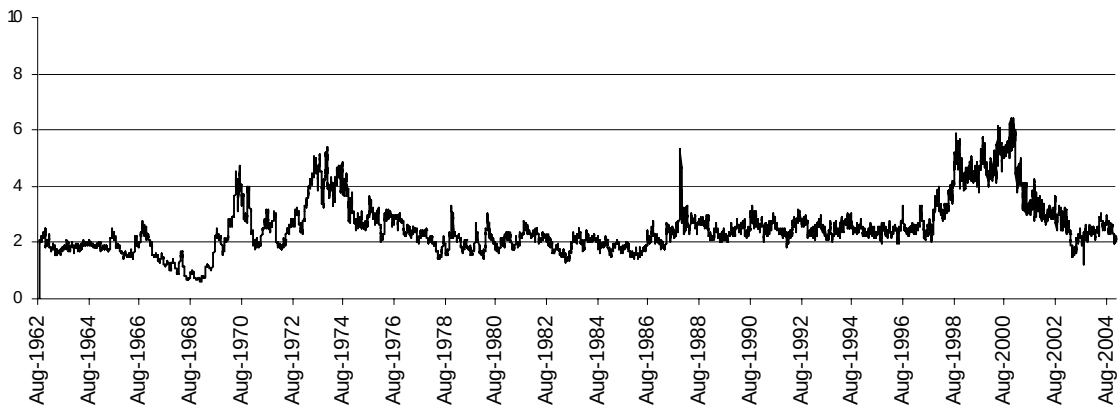
Figures

Figure 2-1: Stock-Bond Correlation, Return Reversal and Price Impact Measure of Illiquidity, Realized Volatility and the Implied Volatility

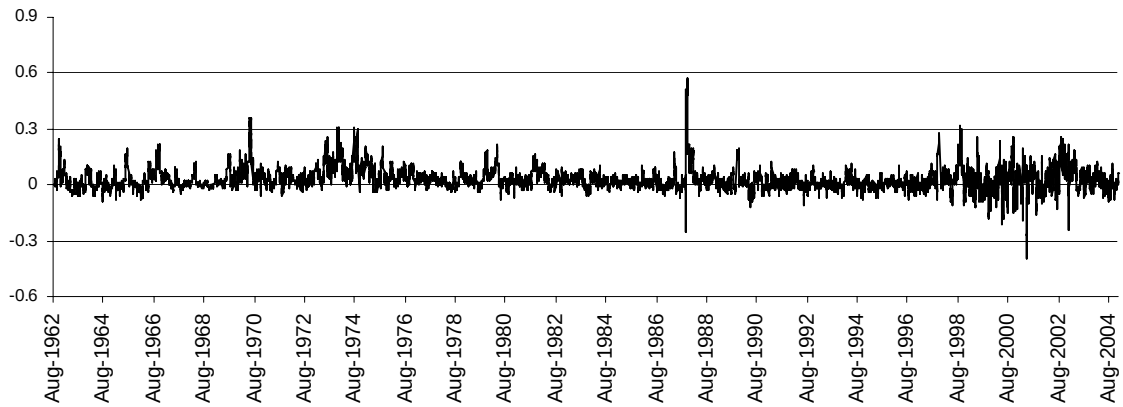
Plot A: 22-Trading-Day Stock-Bond Correlation (from Day t to $t + 21$)



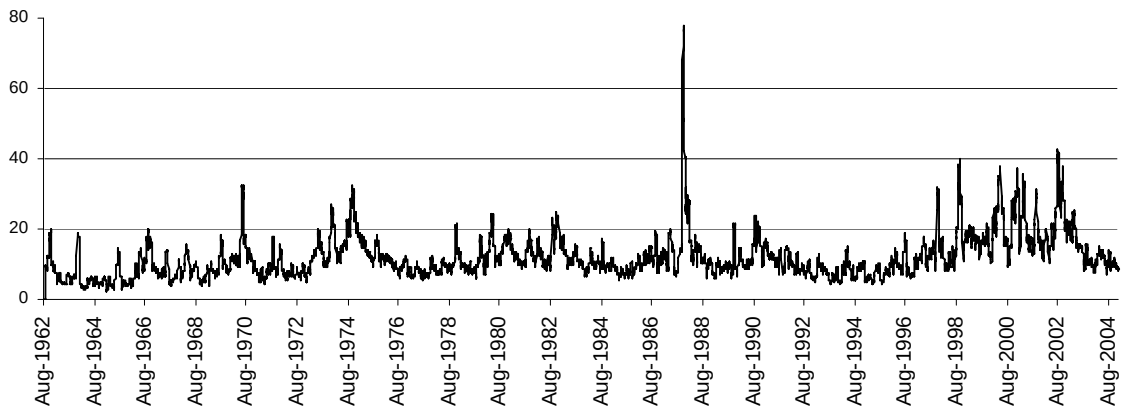
Plot B: Amihud's Price Impact Measure of Illiquidity (from Day $t - 21$ to t)



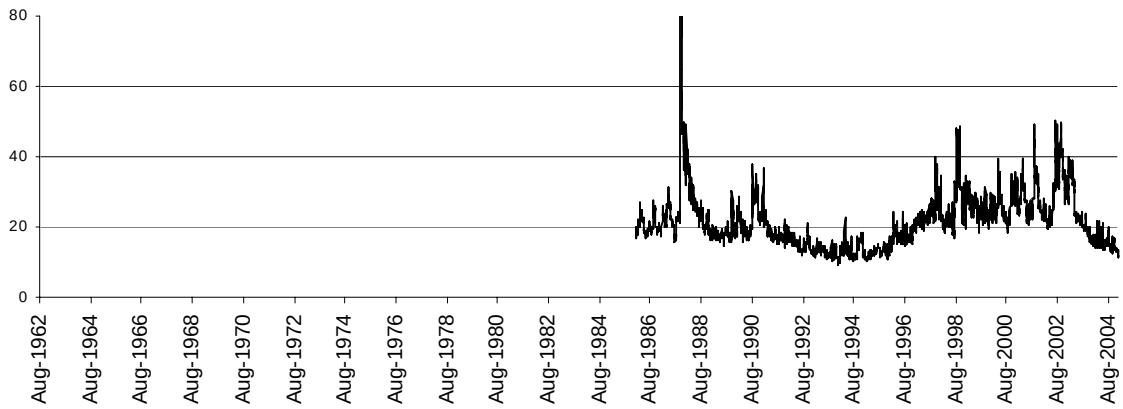
Plot C: Pastor and Stambaugh's Measure of Illiquidity (from Day $t - 21$ to t)



Plot D: Realized Volatility in Daily Stock Returns (from Day $t - 21$ to t)



Plot E: Implied Volatility from CBOE on day t



Tables

Table 2-1: Descriptive Statistics

Table 2-1 reports the descriptive statistics for the data used in this paper. S_t and B_t refer to the stock and 10-year Treasury bond return series, respectively. $CORR_t$ is forward-looking 22-trading-day correlation between daily stock and bond returns, formed from day t to day $t+21$. $ILLIQ_t^{PIM}$ is the price impact illiquidity measure of Amihud (2002) and $ILLIQ_t^{RRV}$ is the negative of the return reversal liquidity measure of Pastor and Stambaugh (2003). $RVOLT_t$ is the realized volatility in the daily stock returns. The illiquidity and realized volatility are measured over a backward-looking rolling 22-trading-days from day $t-21$ to day t . Finally, VXO_t is the implied volatility series from CBOE. Panel A reports the sample moments of the data from 1962:08 to 2004:12. Panel B reports the sample moments of the data for the sub period 1986:01 to 2004:12. In Panel C, the correlation coefficients for the overall period 1962:08-2004:12 are on the lower triangle. The correlation coefficients for sub period 1986:01-2004:12 are shown in brackets and are on the upper triangle.

	S_t	B_t	$CORR_t$	$ILLIQ_t^{PIM}$	$ILLIQ_t^{RRV}$	$RVOLT_t$	VXO_t
<i>Panel A: Sample Moments 1962-2004</i>							
N	10678	10553	10657	10657	10657	10657	
Mean	0.05	0.03	0.22	2.53	0.03	12.07	
Median	0.07	0.02	0.26	2.36	0.02	10.46	
Max	8.66	4.82	0.88	6.43	0.58	77.87	
Min	-17.14	-3.57	-0.90	0.62	-0.39	2.23	
Std Dev	0.89	0.45	0.35	0.91	0.06	6.48	
Skewness	-0.75	0.27	-0.66	1.26	1.85	2.94	
Kurtosis	21.23	9.78	2.96	4.95	14.11	21.71	
<i>Panel B: Sample Moments 1986-2004</i>							
N	4795	4748	4774	4795	4795	4795	4787
Mean	0.05	0.03	0.21	2.88	0.02	13.84	21.38
Median	0.08	0.02	0.32	2.57	0.01	11.81	20.20
Max	8.66	4.82	0.84	6.43	0.58	77.87	150.19
Min	-17.14	-2.73	-0.90	1.19	-0.39	4.20	9.04
Std Dev	1.02	0.46	0.42	0.92	0.07	7.76	8.10
Skewness	-1.18	-0.02	-0.70	1.53	2.20	3.03	3.31
Kurtosis	24.75	7.26	2.45	4.71	18.25	19.70	36.09
<i>Panel C: Correlation Matrix</i>							
	S_t	B_t	$ILLIQ_t^{PIM}$	$ILLIQ_t^{RRV}$	$RVOLT_t$	VXO_t	
S_t	1	{ 0.06 }	{ -0.01 }	{ 0.02 }	{ -0.02 }	{ -0.17 }	
B_t	0.15	1	{ 0.00 }	{ 0.00 }	{ 0.02 }	{ 0.04 }	
$ILLIQ_t^{PIM}$	-0.02	0.02	1	{ 0.12 }	{ 0.54 }	{ 0.41 }	
$ILLIQ_t^{RRV}$	0.01	0.01	0.25	1	{ 0.52 }	{ 0.45 }	
$RVOLT_t$	0.00	0.03	0.56	0.50	1	{ 0.82 }	
VXO_t	-	-	-	-	-	1	

Table 2-2: Stock-Bond Comovement as a function of lagged PRICE IMPACT measure of Illiquidity and lagged volatility

Table 2-2 reports results from estimating various variants of the regression $B_t = a_0 + (a_1 + a_2 \cdot ILLIQ_{t-1}^{PIM} + a_3 \cdot \ln(VOLT)_{t-1} + a_4 \cdot CORR_{t-1}) \times S_t + v_t$. B_t and S_t are the daily 10-year T-bond and stock returns, respectively. $ILLIQ_{t-1}^{PIM}$ is the price impact illiquidity measure of Amihud (2002) estimated over the period from day $t-21$ to day t . $\ln(VOLT)_{t-1}$ is the natural log of the stock market volatility. We use two different measures of volatility. In Panel A and B, we use the realized volatility over day $t-21$ to day t and in Panel C we use the implied volatility at day $t-21$. $CORR_{t-1}$ is the correlation between daily bond-stock returns in the period from day $t-22$ to day $t-1$. The regression is estimated by OLS and p-values are in parenthesis, calculated with autocorrelation and Heteroskedastic consistent standard errors per Newey and West (1987) method with twenty-one lags. Panel A reports results for overall sample period 1962:08-2004:12 and uses realized volatility. Panel B reports results for sub-period 1986:01-2004:12 and uses realized volatility. Panel C also reports results for sub-period 1986:01-2004:12 but uses implied volatility.

	Panel A: 1962-2004					Panel B: 1986-2004				Panel C: 1986-2004			
	[1]	[2]	[3]	[4]	[5]	[2]	[3]	[4]	[5]		[3]	[4]	[5]
$a_1 : S_t$	0.076 [0.000]	0.293 [0.000]	0.565 [0.000]	0.562 [0.000]	0.148 [0.000]	0.243 [0.000]	0.645 [0.000]	0.664 [0.000]	0.198 [0.000]	S_t	0.745 [0.001]	0.806 [0.000]	0.198 [0.001]
$a_2 : ILLIQ_{t-1}^{PIM} \times S_t$		-0.071 [0.000]		-0.039 [0.000]	-0.014 [0.055]	-0.065 [0.000]		-0.027 [0.049]	-0.002 [0.779]	$ILLIQ_{t-1}^{PIM} \times S_t$		-0.048 [0.000]	-0.008 [0.307]
$a_3 : \ln(RVOLT)_{t-1} \times S_t$			-0.177 [0.000]	-0.133 [0.000]	-0.025 [0.059]		-0.213 [0.000]	-0.189 [0.000]	-0.052 [0.001]	$\ln(VXO)_{t-1} \times S_t$	-0.216 [0.003]	-0.186 [0.002]	-0.039 [0.028]
$a_4 : CORR_{t-1} \times S_t$					0.412 [0.000]				0.405 [0.000]	$CORR_{t-1} \times S_t$			0.413 [0.000]
$a_1 + a_2 \times ILLIQ$													
at ILLIQ's 5 th pctl.		0.189				0.118							
at median ILLIQ		0.126				0.077							
at ILLIQ's 95th pctl.		-0.031				-0.084							
$a_1 + a_3 \times \ln(RVOLT)$													
at VOLT's 5 th pctl.			0.278				0.255				0.209		
at median VOLT			0.149				0.119				0.097		
at VOLT's 95 th pctl.			0.003				-0.067				-0.025		

Table 2-3: Stock-Bond Comovement as a function of lagged RETURN REVERSAL measure of Illiquidity and lagged volatility

Table 2-3 reports results from estimating various variants of the regression $B_t = a_0 + (a_1 + a_2 \cdot ILLIQ_{t-1}^{RRV} + a_3 \cdot \ln(VOLT)_{t-1} + a_4 \cdot CORR_{t-1}) \times S_t + v_t$. B_t and S_t are the daily 10-year T-bond and stock returns, respectively. $ILLIQ_{t-1}^{RRV}$ is the return reversal illiquidity measure of Pastor and Stambaugh (2003) estimated over period from day $t-21$ to day t . $\ln(VOLT)_{t-1}$ is the natural log of the stock market volatility. We use two different measures of volatility. In Panel A and B, we use the realized volatility over day $t-21$ to day t and in Panel C we use the implied volatility at day $t-21$. $CORR_{t-1}$ is the correlation between daily bond-stock returns in the period from day $t-22$ to day $t-1$. The regression is estimated by OLS and p-values are in parenthesis, calculated with autocorrelation and Heteroskedastic consistent standard errors per Newey and West (1987) method with twenty-one lags. Panel A reports results for overall sample period 1962:08-2004:12 and uses realized volatility. Panel B reports results for sub-period 1986:01-2004:12 and uses realized volatility. Panel C also reports results for sub-period 1986:01-2004:12 but uses implied volatility.

	Panel A: 1962-2004					Panel B: 1986-2004				Panel C: 1986-2004			
	[1]	[2]	[3]	[4]	[5]	[2]	[3]	[4]	[5]		[3]	[4]	[5]
$a_1 : S_t$	0.076 [0.000]	0.094 [0.000]	0.565 [0.000]	0.604 [0.000]	0.124 [0.002]	0.043 [0.024]	0.645 [0.000]	0.737 [0.000]	0.209 [0.000]	S_t	0.745 [0.001]	0.868 [0.000]	0.174 [0.057]
$a_2 : ILLIQ_{t-1}^{RRV} \times S_t$		-0.306 [0.002]		0.164 [0.108]	-0.073 [0.238]	-0.310 [0.010]		0.269 [0.038]	0.034 [0.556]	$ILLIQ_{t-1}^{RRV} \times S_t$		0.218 [0.035]	-0.013 [0.859]
$a_3 : \ln(RVOLT)_{t-1} \times S_t$			-0.177 [0.000]	-0.195 [0.000]	-0.030 [0.046]		-0.213 [0.000]	-0.249 [0.000]	-0.059 [0.001]	$\ln(VXO)_{t-1} \times S_t$	-0.216 [0.003]	-0.256 [0.000]	-0.040 [0.163]
$a_4 : CORR_{t-1} \times S_t$					0.419 [0.000]				0.404 [0.000]	$CORR_{t-1} \times S_t$			0.418 [0.000]
$a_1 + a_2 \times ILLIQ$													
at ILLIQ's 5 th pctl.		0.106				0.060							
at median ILLIQ		0.087				0.039							
at ILLIQ's 95th pctl.		0.051				0.001							

Table 2-4: Comovement in GARCH-standardized return residuals

Table 2-4 reports results from the regression $B_t^{std} S_t^{std} = a_0 + a_1 \cdot ILLIQ_{t-1}^X + a_2 \cdot \ln(VOLT)_{t-1} + \nu_t$ where $B_t^{std} S_t^{std}$ is the product of the GARCH-standardized residuals of the daily 10-year T-bond and stock returns (see text of the paper for complete discussion). $ILLIQ^X$ is either the price impact measure of Amihud (2002) or the negative of return reversal measure of Pastor and Stambaugh (2003), both estimated over period from day $t-22$ to day $t-1$. $\ln(VOLT)_{t-1}$ is the natural log of the stock market volatility. We use two different measures of volatility. In Panel A and B, we use the realized volatility over day $t-22$ to day $t-1$ and in Panel C we use the implied volatility at day $t-1$. The regression is estimated by OLS and p-values are in parenthesis, calculated with autocorrelation and Heteroskedastic consistent standard errors per Newey and West (1987) method with twenty-one lags. Panel A reports results for overall sample period 1962:08-2004:12 and uses realized volatility. Panel B reports results for sub-period 1986:01-2004:12 and use realized volatility. Panel C also reports results for sub-period 1986:01-2004:12 but uses implied volatility.

<i>I. Price Impact measure of Amihud (2002)</i>									
	Panel A: 1962-2004			Panel B: 1986-2004			Panel C: 1986-2004		
	[1]	[2]	[3]	[1]	[2]	[3]	[2]	[3]	
$ILLIQ_{t-1}^{PIM}$	-0.091 [0.000]		-0.059 [0.009]	-0.188 [0.000]		-0.074 [0.042]	$ILLIQ_{t-1}^{RRV}$	-0.131 [0.000]	
$\ln(RVOLT)_{t-1}$		-0.179 [0.000]	-0.112 [0.014]		-0.498 [0.000]	-0.413 [0.000]	$\ln(VXO)_{t-1}$	-0.528 [0.000]	-0.363 [0.001]
Constant	0.437 [0.000]	0.632 [0.000]	0.621 [0.000]	0.730 [0.000]	1.440 [0.000]	1.439 [0.000]	Constant	1.774 [0.000]	1.656 [0.000]
N	10531	10531	10531	4748	4748	4748	N	4739	4739

<i>II. Return Reversal Measure of Pastor and Stambaugh (2003)</i>									
	Panel A: 1962-2004			Panel B: 1986-2004			Panel C: 1986-2004		
	[1]	[2]	[3]	[1]	[2]	[3]	[2]	[3]	
$ILLIQ_{t-1}^{RRV}$	-0.625 [0.031]		-0.058 [0.850]	-1.480 [0.000]		-0.133 [0.752]	$ILLIQ_{t-1}^{RRV}$	-0.576 [0.149]	
$\ln(RVOLT)_{t-1}$		-0.179 [0.000]	-0.175 [0.000]		-0.498 [0.000]	-0.490 [0.000]	$\ln(VXO)_{t-1}$	-0.528 [0.000]	-0.482 [0.000]
Constant	0.227 [0.000]	0.632 [0.000]	0.625 [0.000]	0.220 [0.000]	1.440 [0.000]	1.423 [0.000]	Constant	1.774 [0.000]	1.649 [0.000]
N	10531	10531	10531	4748	4748	4748	N	4739	4739

Table 2-5: Forward Looking 22-trading-day stock-bond return correlation

Table 2-5 reports results from the regression $CORR_{t+1} = a_0 + a_1 \cdot ILLIQ_{t-1}^X + a_2 \cdot \ln(VOLT)_{t-1} + a_3 \cdot CORR_{t-1} + v_t$ where $CORR_{t+1}$ is the correlation between daily bond-stock returns in the 22-trading-day period from day $t+1$ to day $t+22$; $CORR_{t-1}$ is the lagged value computed from period from day $t-22$ to day $t-1$; $ILLIQ^X$ is either the price impact measure of Amihud (2002) or negative of the return reversal measure of Pastor and Stambaugh (2003), both estimated over period from day $t-22$ to day $t-1$. $\ln(VOLT)_{t-1}$ is the natural log of the stock market volatility. We use two different measures of volatility. In Panel A and B, we use the realized volatility over day $t-22$ to day $t-1$ and in Panel C we use the implied volatility at day $t-1$. The regression is estimated by OLS and p-values are in parenthesis, calculated with autocorrelation and Heteroskedastic consistent standard errors per Newey and West (1987) method with twenty-one lags. Panel A reports results for overall sample period 1962:08-2004:12 and uses realized volatility. Panel B reports results for sub-period 1986:01-2004:12 and uses realized volatility. Panel C also reports results for sub-period 1986:01-2004:12 but uses implied volatility.

I. Price Impact measure of Amihud (2002)

I. Price Impact Measure of Annuity (2002)																		
	Panel A (1962-2004)						Panel B: 1986-2004						Panel C: 1986-2004					
	[1]	[2]	[3]	[4]	[5]	[6]	[1]	[2]	[3]	[4]	[5]	[6]		[3]	[4]	[5]	[6]	
$ILLIQ_{t-1}^{PIM}$	-0.074 [0.000]	-0.034 [0.004]			-0.052 [0.004]	-0.024 [0.091]	-0.160 [0.000]	-0.051 [0.006]			-0.063 [0.033]	-0.035 [0.105]	$ILLIQ_{t-1}^{PIM}$			-0.096 [0.000]	-0.037 [0.064]	
$\ln(RVOLT)_{t-1}$					-0.133 [0.000]	-0.064 [0.006]				-0.422 [0.000]	-0.114 [0.001]	-0.349 [0.000]	-0.078 [0.049]	$\ln(VXO)_{t-1}$	-0.520 [0.000]	-0.154 [0.002]	-0.400 [0.000]	-0.117 [0.032]
$CORR_{t-1}$		0.516 [0.000]		0.519 [0.000]		0.528 [0.000]		0.652 [0.000]		0.628 [0.000]		0.621 [0.000]	$CORR_{t-1}$		0.639 [0.000]		0.622 [0.000]	

II. Return Reversal Measure of Pastor and Stambaugh (2003)

II. Return Reversal Measure of Pastor and Staibach (2003)																		
	Panel A (1962-2004)						Panel B: 1986-2004						Panel C: 1986-2004					
	[1]	[2]	[3]	[4]	[5]	[6]	[1]	[2]	[3]	[4]	[5]	[6]		[3]	[4]	[5]	[6]	
$ILLIQ_{t-1}^{RRV}$	-0.648 [0.002]	-0.198 [0.209]			-0.267 [0.205]	0.001 [0.998]	-1.209 [0.000]	0.019 [0.917]			-0.059 [0.853]	0.264 [0.163]	$ILLIQ_{t-1}^{RRV}$			-0.271 [0.372]	0.256 [0.169]	
$\ln(RVOLT)_{t-1}$				-0.133 [0.000]	-0.064 [0.006]	-0.118 [0.001]	-0.064 [0.012]			-0.422 [0.000]	-0.115 [0.001]	-0.418 [0.000]	-0.128 [0.000]	$\ln(VXO)_{t-1}$	-0.520 [0.000]	-0.154 [0.002]	-0.498 [0.000]	-0.172 [0.001]
$CORR_{t-1}$		0.528 [0.000]		0.519 [0.000]		0.519 [0.000]		0.693 [0.000]		0.628 [0.000]		0.632 [0.000]	$CORR_{t-1}$		0.639 [0.000]		0.644 [0.000]	

Table 2-6: Correlation of bonds with different stock portfolios (Amihud measure of illiquidity)

Table 2-6 reports correlations of bonds with the 25 stock portfolios formed by double-sorting stocks on various criteria. The stock portfolios are formed as follows. Each day, we begin by assigning stocks into five quintiles based on the first sorting criterion. Then, within each of the five groups, we further assign stocks into five quintiles based on the second sorting criterion. In each panel, the leftmost column (topmost row) lists the first (second) sorting criterion and are arranged in ascending order from top to bottom (left to right). To compute correlations, Panels A and D use observations in the full sample period and while all other panels use observations in sub-samples based on the VXO criterion. VXO refers to the level of implied volatility from CBOE on day $t-1$. The stock-bond correlations are computed assuming that the daily expected returns for both the stock and bond returns are zero, rather than the sub-sample mean. The sample period is 1986 to 2004. In this table, illiquidity refers to price impact measure of Amihud (2002).

First sort : Volatility / Second Sort: Illiquidity							First sort : Illiquidity / Second Sort: Volatility						
<i>Panel A: Entire Sample (1986-2004)</i>							<i>Panel D: Entire Sample (1986-2004)</i>						
	ALL	ILLIQ-1	ILLIQ-2	ILLIQ-3	ILLIQ-4	ILLIQ-5		ALL	VOL-1	VOL-2	VOL-3	VOL-4	VOL-5
VOL-1	0.156	0.163	0.134	0.082	0.046	0.010	ILLIQ-1	0.112	0.160	0.144	0.121	0.092	0.031
VOL-2	0.129	0.139	0.099	0.055	0.006	-0.026	ILLIQ-2	0.053	0.110	0.086	0.062	0.050	-0.010
VOL-3	0.093	0.103	0.067	0.038	-0.005	-0.022	ILLIQ-3	0.016	0.041	0.023	0.025	0.023	-0.014
VOL-4	0.057	0.063	0.045	0.009	-0.013	-0.036	ILLIQ-4	-0.017	0.004	-0.004	-0.006	-0.010	-0.036
VOL-5	-0.008	-0.004	-0.011	-0.019	-0.035	-0.035	ILLIQ-5	-0.028	0.013	0.002	-0.013	-0.027	-0.024
<i>Panel B: VXO > 95th percentile</i>							<i>Panel E: VXO > 95th percentile</i>						
	ALL	ILLIQ-1	ILLIQ-2	ILLIQ-3	ILLIQ-4	ILLIQ-5		ALL	VOL-1	VOL-2	VOL-3	VOL-4	VOL-5
VOL-1	-0.254	-0.223	-0.320	-0.337	-0.362	-0.336	ILLIQ-1	-0.204	-0.209	-0.211	-0.200	-0.193	-0.210
VOL-2	-0.266	-0.239	-0.333	-0.360	-0.339	-0.376	ILLIQ-2	-0.331	-0.306	-0.333	-0.348	-0.302	-0.302
VOL-3	-0.243	-0.210	-0.344	-0.321	-0.325	-0.361	ILLIQ-3	-0.337	-0.353	-0.365	-0.315	-0.303	-0.313
VOL-4	-0.252	-0.237	-0.293	-0.307	-0.322	-0.297	ILLIQ-4	-0.340	-0.356	-0.350	-0.303	-0.322	-0.306
VOL-5	-0.236	-0.222	-0.252	-0.273	-0.287	-0.246	ILLIQ-5	-0.336	-0.318	-0.331	-0.350	-0.290	-0.264
<i>Panel C: VXO < 50th percentile</i>							<i>Panel F: VXO < 50th percentile</i>						
	ALL	ILLIQ-1	ILLIQ-2	ILLIQ-3	ILLIQ-4	ILLIQ-5		ALL	VOL-1	VOL-2	VOL-3	VOL-4	VOL-5
VOL-1	0.364	0.354	0.383	0.317	0.231	0.152	ILLIQ-1	0.335	0.355	0.352	0.324	0.294	0.221
VOL-2	0.332	0.331	0.309	0.266	0.197	0.143	ILLIQ-2	0.291	0.351	0.306	0.278	0.251	0.202
VOL-3	0.296	0.296	0.267	0.223	0.167	0.162	ILLIQ-3	0.233	0.267	0.230	0.203	0.211	0.167
VOL-4	0.250	0.248	0.233	0.183	0.149	0.105	ILLIQ-4	0.172	0.170	0.160	0.153	0.153	0.129
VOL-5	0.157	0.146	0.170	0.148	0.116	0.093	ILLIQ-5	0.148	0.136	0.141	0.139	0.096	0.109

Table 2-7: Correlation of bonds with stock portfolios formed on size and market returns

Table 2-7 Panel A reports correlations of bonds with 25 stock portfolios formed by double-sorting stocks based on their size and their Amihud measure of illiquidity. In Panel B, we first assign stocks into five-portfolios based on their illiquidity (Amihud measure), and we then study the correlations of bonds with these five different portfolios under five different sub samples based on contemporaneous aggregate stock returns. In this panel, the second (sixth) column, with label RET-1 (RET-5), represents the days on which aggregate stock returns was least (most). The stock-bond correlations are computed assuming that the daily expected returns for both the stock and bond returns are zero, rather than the sub- sample mean. The sample period is 1986 to 2004.

Panel A (Sample Period 1986-2004)

First sort : Size / Second sort: Amihud Measure of Illiquidity

	ALL	ILLIQ-1	ILLIQ-2	ILLIQ-3	ILLIQ-4	ILLIQ-5
SIZE-1	-0.004	0.007	-0.002	-0.010	-0.005	-0.011
SIZE-2	-0.005	0.016	0.014	-0.010	-0.022	-0.034
SIZE-3	0.005	0.036	0.023	0.005	-0.003	-0.034
SIZE-4	0.074	0.093	0.075	0.053	0.047	0.015
SIZE-5	0.132	0.144	0.115	0.109	0.092	0.074

Panel B (Sample Period 1986-2004)

First sort : Amihud Measure of Illiquidity / Sub-sample on Stock Market Returns

	ALL	RET-1	RET-2	RET-3	RET-4	RET-5
ILLIQ-1	0.112	0.015	0.141	0.127	0.419	0.176
ILLIQ-2	0.053	-0.008	0.050	0.037	0.100	0.121
ILLIQ-3	0.016	-0.035	0.014	-0.003	-0.023	0.089
ILLIQ-4	-0.017	-0.056	0.011	-0.006	-0.120	0.051
ILLIQ-5	-0.028	-0.064	0.000	-0.020	-0.191	0.068

Table 2-8: Correlation of bonds with different stock portfolios (Pastor and Stambaugh measure of illiquidity)

See description for Table 2-6. The only difference in this table is that the illiquidity refers to negative of return reversal measure of Pastor and Stambaugh (2003).

First sort : Volatility / Second Sort: Illiquidity							First sort : Illiquidity / Second Sort: Volatility						
<i>Panel A: Entire Sample (1986-2004)</i>							<i>Panel D: Entire Sample (1986-2004)</i>						
	ALL	ILLIQ-1	ILLIQ-2	ILLIQ-3	ILLIQ-4	ILLIQ-5		ALL	VOL-1	VOL-2	VOL-3	VOL-4	VOL-5
VOL-1	0.156	0.055	0.148	0.152	0.128	0.080	ILLIQ-1	-0.010	0.041	0.018	0.013	-0.012	-0.036
VOL-2	0.129	0.020	0.115	0.125	0.105	0.022	ILLIQ-2	0.070	0.136	0.108	0.074	0.048	0.000
VOL-3	0.093	0.019	0.074	0.101	0.070	0.009	ILLIQ-3	0.109	0.144	0.137	0.116	0.086	0.028
VOL-4	0.057	-0.007	0.060	0.052	0.038	-0.009	ILLIQ-4	0.061	0.088	0.093	0.075	0.066	-0.007
VOL-5	-0.008	-0.025	0.006	-0.012	-0.021	-0.020	ILLIQ-5	0.006	0.036	0.040	0.010	-0.007	-0.001
<i>Panel B: VXO > 95th percentile</i>							<i>Panel E: VXO > 95th percentile</i>						
	ALL	ILLIQ-1	ILLIQ-2	ILLIQ-3	ILLIQ-4	ILLIQ-5		ALL	VOL-1	VOL-2	VOL-3	VOL-4	VOL-5
VOL-1	-0.254	-0.371	-0.290	-0.278	-0.284	-0.238	ILLIQ-1	-0.369	-0.324	-0.358	-0.360	-0.366	-0.364
VOL-2	-0.266	-0.408	-0.313	-0.288	-0.251	-0.363	ILLIQ-2	-0.359	-0.302	-0.315	-0.358	-0.379	-0.325
VOL-3	-0.243	-0.310	-0.345	-0.205	-0.293	-0.295	ILLIQ-3	-0.207	-0.220	-0.235	-0.203	-0.208	-0.209
VOL-4	-0.252	-0.335	-0.183	-0.296	-0.326	-0.287	ILLIQ-4	-0.237	-0.345	-0.244	-0.259	-0.207	-0.194
VOL-5	-0.236	-0.254	-0.195	-0.249	-0.241	-0.232	ILLIQ-5	-0.272	-0.318	-0.285	-0.276	-0.274	-0.183
<i>Panel C: VXO < 50th percentile</i>							<i>Panel F: VXO < 50th percentile</i>						
	ALL	ILLIQ-1	ILLIQ-2	ILLIQ-3	ILLIQ-4	ILLIQ-5		ALL	VOL-1	VOL-2	VOL-3	VOL-4	VOL-5
VOL-1	0.364	0.248	0.358	0.350	0.357	0.256	ILLIQ-1	0.184	0.198	0.177	0.170	0.151	0.109
VOL-2	0.332	0.239	0.321	0.323	0.292	0.204	ILLIQ-2	0.309	0.355	0.322	0.274	0.255	0.170
VOL-3	0.296	0.188	0.274	0.291	0.261	0.174	ILLIQ-3	0.334	0.345	0.348	0.319	0.289	0.212
VOL-4	0.250	0.146	0.221	0.244	0.228	0.155	ILLIQ-4	0.283	0.327	0.284	0.265	0.245	0.185
VOL-5	0.157	0.098	0.160	0.146	0.152	0.131	ILLIQ-5	0.194	0.196	0.196	0.168	0.141	0.144

CHAPTER 3

COMMONALITY IN MARKET VOLATILITY, ILLIQUIDITY AND IDIOSYNCRATIC VOLATILITY

3.1. Introduction

Financial economists have worked in several directions to find the factors that influence stock returns. Three such factors that have gained particular attention recently are market volatility, market illiquidity and idiosyncratic volatility. For example numerous studies examine the relationship between stock market return and volatility (French, Schwert and Stambaugh (1987), Glosten, Jagannathan and Runkle (1993), Scruggs (1998), Ghysels, Santa-Clara and Valkanov (2005), and Lundblad (2007)) and find mixed results. Amihud (2002) examines only illiquidity and finds that the ex ante stock excess return is increasing in the expected illiquidity of the stock market. Goyal and Santa-Clara (2003) examines idiosyncratic volatility and finds a significant positive relation between average stock variance, which is largely idiosyncratic variance, and the stock returns. However, their results disappear once one controls for stocks' illiquidity (Bali, Cakici, Yan, and Zhang (2005)).

To date there has been little attempt to connect the three variables, yet there are good theoretical reasons to do so. This paper tries to fill the gap by characterizing the movements and co-movements in stock market volatility, illiquidity and idiosyncratic

volatility¹. To achieve our objectives, we first examine the commonality in the three variables when moving from good times to bad times by studying regime-switching models. We find that the regimes identified by using one or two or all three of the variables have similar characteristics. This suggests that these variables are closely related and may, to some extent, be capturing the same information about the market environment. Next, encouraged by the contemporaneous relationship between the three variables, we take a forward-looking perspective and ask whether these variables help to forecast each other. Our Granger-causality tests suggest that each of these series have some ability in forecasting the other two series. This further supports the notion that these variables may be responding to the same latent shocks to financial markets.

Our finding has important implications on research that examine if these variables affect stock returns. Our findings would suggest that each of these factors may individually affect stock returns as they all capture information about the state of the economy. However, the incremental effect should become substantially weaker, or disappear altogether, once one controls for other two factors as they may be capturing the same information. To illustrate this point, we examine the explanatory power (R-square) of illiquidity and market volatility in explaining the variations in stock market returns. We find that the joint explanatory power of the two variables is not much different than that of illiquidity alone. This suggests a study that only examines the relation between returns and market volatility may attribute a return pattern to price-volatility effects, when it might be more of price-liquidity effect (or some combination of the two effects).

¹ In the sense that our paper provides a simple summary of historical movements in these parameters without a formal model to predict these movements, our paper is in the spirit of the Campbell, Lettau, Malkiel, and Xu (2001) study on market, industry, and firm volatility.

This article proceeds as follows. Section 3.2 provides the related literature on the three measures. Next, Section 3.3 presents the data and variable construction. Section 3.4 presents the regime-switching models and discusses the associated empirical results. Section 3.5 discusses the Granger-causality tests and Section 3.6 presents a simple illustration of implications from our findings. Finally, Section 3.7 concludes.

3.2. Related Literature

To date there has been little attempt to study jointly all three variables. However, there are separate studies that look at two of them at a time. In the next subsections, we provide summary of the literature related to each pair of two measures.

3.2.1. *Market Volatility and Illiquidity*

The market microstructure theories predict a positive relation between illiquidity of an asset and its volatility. Both the inventory explanation and information asymmetry explanation of bid-ask spreads predict a positive relationship between spreads and volatility (Stoll (1978 a,b), Amihud and Mendelson (1980), Ho and Stoll (1981), Admati and Pfleiderer (1988), and Foster and Viswanathan (1990)). The empirical evidence is also positive [Tinic (1972), Stoll (1978b, 2000 and 2003)].

The relation between illiquidity and volatility at an aggregate level has received little attention in the past. But, there are a few recent papers that provide theoretical models for the joint behavior of market volatility and market illiquidity (see, Brunnermeier and Pedersen (2007), Carlin, Lobo and Viswanathan (2007), and Deuskar (2007). All these papers predict a positive relationship. However, the empirical evidence is inconclusive. While Pastor and Stambaugh (2003) show that correlation between aggregate illiquidity

and volatility is sizable positive at 0.57, Chordia, Roll and Subrahmanyam (2001) document a negative relation between the two².

3.2.2. Market Volatility and Idiosyncratic Volatility

Campbell, Lettau, Malkiel and Xu (2001, hereafter CLMX) was the first paper to use a disaggregated approach to study the volatility of common stocks at a market, industry and firm level. They show that, in their 1962 to 1997 sample period, there is a strong evidence of positive deterministic trend in idiosyncratic volatility. They find no such trend in market volatility. A trend increase in idiosyncratic volatility relative to market volatility implies that the R^2 of a typical market model have declined. However, later studies cast doubt on whether there has been a long-term upward time trend in the idiosyncratic volatility (Brandt, Brav and Graham (2005)).

On studying the variations of these volatility measures around their long-term trends, CLMX find that both the market volatility and idiosyncratic volatility are positively correlated with each other as well as are auto-correlated. Their Granger-causality tests suggest that market volatility tends to lead the other volatility series.

3.2.3. Illiquidity and Idiosyncratic Volatility

Inventory control models such as Merton (1987), and Brunnermeier and Pedersen (2007) predict that there should be a negative relationship between idiosyncratic risk and liquidity. Spiegel and Wang (2006) present a derivation of this result from Merton's (1987) model. Empirically, Benston and Hagerman (1974) find that bid-ask spreads in the

² The two papers use different measures of liquidity. Pastor and Stambaugh (2003) introduce a return reversal measure of liquidity based on daily returns and volume; Chordia, Roll and Subrahmanyam (2001) use micro-structure based quoted and effective spreads.

OTC market are positively correlated with the residual variance from the one factor market model. Also, Stoll (1978) documents a relationship between a firm's return variance and the bid-ask spread on the NASDAQ. Thus, there is good reason to believe that liquidity may be more generally correlated with idiosyncratic risk.

3.3. Data Description

We use CRSP daily stock returns dataset to measure market volatility, idiosyncratic volatility and market illiquidity. The FF-3 factors, needed to estimate idiosyncratic volatility, are from Kenneth French's website. As the daily FF-3 factors are available starting from July 1963, our sample period is July 1963 to December 2006 (522 months).

3.3.1. Market Volatility

The market volatility at time t is estimated as follows³:

$$MKT_t = \sum_{d=1}^{D_t} r_{m,d}^2 + 2 \sum_{d=2}^{D_t} r_{m,d} \cdot r_{m,d-1} \quad (3-1)$$

where D_t is the number of trading days in month t and $r_{m,d}$ is the excess returns on CRSP value-weighted NYSE, AMEX and NASDAQ portfolio d in month t . The second term on the right hand side adjusts for the autocorrelation in daily returns using the approach proposed by French, Schwert and Stambaugh (1987).

3.3.2. Idiosyncratic Volatility

Idiosyncratic volatility is computed as the value-weighted average of the individual stock's variance of daily residual from an asset pricing model.

³ This is not strictly speaking a variance measure since we do not subtract mean returns before taking expectation. However, for short holding periods, the impact of subtracting the means is minimal.

$$IV_t = \sum_{i=1}^{N_t} w_{i,t-1} \left[\sum_{d=1}^{D_{i,t}} \varepsilon_{i,d}^2 + 2 \sum_{d=2}^{D_{i,t}} \varepsilon_{i,d} \varepsilon_{i,d-1} \right] \quad (3-2)$$

where N_t is the number of stocks in the month t , $D_{i,t}$ is the number of trading days for stock i in the month t , $w_{i,t-1} = v_{i,t-1} / \sum_{i=1}^{N_{t-1}} v_{i,t-1}$ with $v_{i,t-1}$ defined as the market capitalization of stock i in the month $t-1$, and $\varepsilon_{i,d}$ is the idiosyncratic shock to the excess return on stock i in day d of month t . These idiosyncratic shocks are model dependent. Given the ubiquity of FF-3 in empirical finance applications, we report our findings using idiosyncratic shock estimated with respect to FF-3 model. That is, $\varepsilon_{i,d}$ is estimated from the regression:

$$r_{i,d} = \beta_{i,1} \cdot r_{m,d} + \beta_{i,2} \cdot SMB_d + \beta_{i,3} \cdot HML_d + \varepsilon_{i,d} \quad (3-3)$$

In Appendix A, we compare the different estimates of idiosyncratic volatility obtained from several different asset pricing models – market model, market-adjusted model, FF-3 model, the four factor model. In the comparison, we also include the CLMX measure of idiosyncratic volatility. We find that the different measures have very high correlations ($\rho = 0.96$ or higher). Therefore, our choice of using FF-3 model over other models should not affect our findings.

Note that second term in equation (3-1) and (3-2) adjusts for autocorrelation in daily returns or residuals, respectively. If the autocorrelation is negative, then the second term may dominate and may make the variance estimates negative. Following the literature,

we avoid this issue by dropping the second term whenever the sum of the first and second term is negative⁴.

3.3.3. *Illiquidity*

For the empirical examination, we require illiquidity series that extend over sufficiently long periods. For this reason, the microstructure data based measures of illiquidity- such as bid-ask spread (quoted or effective), transaction-by-transaction market impact or the probability of information based trading, etc - are not suitable for the study. In recent years, however, researchers have introduced liquidity series that can be constructed using only the daily return and volume data obtainable from CRSP.

We use Amihud's (2002) price impact measure. It is a measure based on the idea that there is a positive relationship between the price change and the net order flow which results from the information asymmetry between market makers and traders. Amihud reports a significant positive relationship between his measure and two microstructure based measures of illiquidity, Kyle's λ and a fixed-cost component of the bid-ask spread used by Brennan and Subramanyam (1996). Hasbrouck (2006) also finds Amihud's measure is closely correlated with price-impact measures based on high-frequency data. Furthermore, in our first essay, we show that the Amihud measure is better among the two popular measures that are based on return and volume data only⁵.

⁴ Goyal and Santa-Clara (2003), Bali et. al. (2005), and Guo and Savickas (2007) also follow similar approach to correct for autocorrelation. Further, we also estimate market volatility and idiosyncratic volatility with no adjustments for autocorrelation (that is, dropping the second term altogether), and find that the resulting series have very high correlations, $\rho = 0.96$ or higher, with the respective series used in this paper.

⁵ The other popular measure is the Pastor and Stambaugh (2003) return reversal measure. It is based on the idea that the price changes accompanying large volumes tend to be reversed when market-wide liquidity is low. In our first essay, we find that the Amihud illiquidity measure is more strongly associated with negative stock-bond correlation than is the Pastor and Stambaugh illiquidity measure, and hence Amihud illiquidity measure is better in this regard.

We construct the illiquidity series in following manner. We first estimate the illiquidity measures for individual stocks. We remove the stock-days with zero volume and measure the value for stock i in the month t as

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|r_{i,d}|}{vol_{i,d}} \quad (3-4)$$

where $|r_{i,d}|$ and $vol_{i,d}$ are the absolute return, the dollar volume (measured in millions), respectively, on day d of month t . We then take a cross-sectional average to get the market-wide illiquidity measure. In the cross-sectional average for a month, we include only those stocks that meet the following conditions: [a] there should be more than 15 observations to estimate illiquidity measure of individual stocks [b] it should be a ordinary share (CRSP share code 10 or 11) [c] it should be listed on NYSE/AMEX⁶ (CRSP exchange code 1 or 2) [d] share price should be between \$5 and \$1000 [e] the first day (or the last day) that stock appears (or disappears) on CRSP should not fall in that month. The values for share code, exchange code and share price for purpose of sample stock selection is the values as of the beginning of the month.

Finally, to make the series stationary, we scale up the resulting series by multiplying by m_t / m_1 , where m_t is the total dollar value of the stocks total dollar value of the stocks (included in the cross-sectional average) as of the beginning of that month and m_1 is the corresponding value for the first month (July 1963). Therefore, the market illiquidity in month t is defined as

⁶ NASDAQ stocks are excluded because their data are available only from 1982 and their reported volumes are overstated due to the inclusion of inter-dealer trades.

$$ILLIQ_t = \frac{m_t}{m_1} \left(\frac{1}{N_t} \sum_{i=1}^{N_t} ILLIQ_{i,t} \right) \quad (3-5)$$

3.3.4. Graphical Analysis and Summary Statistics

Figure 3-1 plots the time series for the three series – market volatility, illiquidity, and the idiosyncratic volatility. Plot A and Plot B shows the MKT and lnMKT, respectively; Plot C shows the illiquidity; and Plot D and Plot E shows the IV and lnIV, respectively. Note that lnMKT and lnIV is the natural log of volatility and idiosyncratic volatility, respectively. We use the natural log transformation to reduce the skewness and kurtosis of the volatility measures. Casual inspection of the series indicates that the three measures tend to move together. There are clusters of months in which all three – MKT, ILLIQ, and IV – are high. These periods coincide with well-known episodes of crisis, such as oil crisis of 1973, Penn Central commercial paper crisis of May-June 1970, the stock market crash of 1987, the Gulf war in 1991, the East Asian financial crisis in the fall of 1997, the Russian default crisis in the fall of 1998, the Brazilian currency crisis in early 1999, and the terrorism crisis in September 2001. This adds to confidence that the three series are related to each other and also to the uncertainty in the market. The relation of these measures to the well known crises supports our regime-switching approach in the next sub-section.

Table 3-1 provides the summary statistics. The table also reports the statistics for the standard deviation of market volatility (denoted by sdMKT) and idiosyncratic volatility (denoted by sdIV). Note that the MKT and IV measure variance, whereas sdMKT and sdIV measure standard deviation. The average realized standard deviation of the market is 13.89%. The average idiosyncratic risk, measured in terms of standard deviation, is

nearly twice (23.64%). Observe that the three parameters – volatility, illiquidity and idiosyncratic volatility - have sizeable positive correlations. Depending on how the volatilities are measured (variance, standard deviations, or the log of variance), the correlation between market volatility and illiquidity is in the range of 0.36 to 0.52; the correlation between market volatility and idiosyncratic volatility is in the range of 0.46 to 0.63; and that between illiquidity and idiosyncratic volatility is in the range of 0.64 to 0.67.

3.4. Regime Switching Models and Empirical Results

In this section, we use two-state regime-switching models to study the inter-linkages between these variables. The motivation behind using regime-switching models is as follows. Economic and political crises can temporarily shock financial markets, which can cause extreme market volatility. Following the episodic nature of such crises, the regime-switching approach has become increasingly popular to model market volatility [see, for example Turner, Startz and Nelson (1989), Whitelaw (2000), Ang and Chen (2002), Kim, Morey and Nelson (2004), Mayfield (2004), Lundblad (2007)].

Further, it is easy to build a case for regime-switching illiquidity. Several papers document theoretical models that imply liquidity is fragile: financial markets are liquid in some equilibrium and illiquid in others (Grossman and Miller (1988), Brunnermeier and Pedersen (2007), and Carlin, Lobo and Viswanathan (2007))⁷. The evidence of the episodic nature of idiosyncratic volatility comes from Brandt, Brav and Graham (2005). They find that idiosyncratic volatility fell to pre-1990s lows over the last few years

⁷ See Henry and Scruggs (2007) for a more detailed discussion on using regime-switching models for market illiquidity.

(2002-2005) and that the period of 1926-1933 exhibited an increase in idiosyncratic volatility closely resembling that the levels observed in the late 1990s. Their results suggest that the high and rising idiosyncratic volatility appears to be an episodic phenomenon. The episodic nature of the variables and the high realized correlation among them supports our regime-switching approach.

In our regime-switching models, one would expect all of the three variables to be higher in one regime (bad regime) than in the other regime (good regime). Also, if all three variables are responding to similar shocks in the market, one should be able to use information in any one or two or all three of the variables to characterize the regimes and still find that all three variables have higher mean values in the same regime. Further, the shock or uncertainty in the markets should also lead to higher uncertainty about these variables. For instance, one would expect the volatility of volatility to be higher during periods of crisis. Therefore, one would expect both the mean and the standard deviation of all of them to be higher in one (bad) regime. Again, this result should hold irrespective of which and how many of these variables are used to characterize the regimes. Finally, it would be interesting to study if there is any change in pair-wise correlations across the two regimes. That is, are the pair-wise correlations regime-specific?

3.4.1. The Model

In our model, the market is assumed to switch between two states. Let denote S_t^0 the good state at time t and S_t^1 denote the bad state at time t . The regimes are assumed to be generated by a first-order Markov-switching process with the constant transition

probabilities, $q = P(S_t^0 | S_t^0)$ and $p = P(S_t^1 | S_t^1)$. The unconditional probability (or steady state) probabilities are given by

$$P(S_t^0) = \frac{1-p}{(1-p)+(1-q)}; \quad P(S_t^1) = \frac{1-q}{(1-p)+(1-q)} \quad (3-6)$$

The episodic nature of the volatility, illiquidity, and idiosyncratic volatility suggests that these are likely candidates for defining the latent regime, S_t . The state in which these variables have higher mean is the good state and the other state is the bad state.

We first assume each of these variables independently characterizes the latent regime. That is, we estimate univariate regime-switching model separately on market volatility, on illiquidity and on idiosyncratic volatility. For each of these estimations, we classify the months into one of the two states based on the filtered probability from the estimation. We then study the regime-specific means of the three variables, the regime-specific uncertainty about the variables, and the regime-specific pair-wise correlations between them. To better understand the differences across regimes, we also report the regime-specific market returns. Furthermore, we also estimate univariate models for each of these parameters with time-varying transition probabilities to examine if the probability of switching regimes varies significantly with the other two variables. For example, for the univariate regime-switching estimation of illiquidity, we allow the transition probability to vary with either market volatility or idiosyncratic volatility.

To foreshadow our results discussed later, we find that the univariate regime-switching models on the three variables result in regime classifications with similar characteristics. This suggests the latent regime could be better characterized, as compared to the

univariate characterization, by using information from more than one series. We next estimate bivariate regime-switching models taking two of these variables at a time. The advantage of using bivariate Markov-switching model is that it is very intuitive and makes it easy to study co-moments without the entire conditional distribution. In our bivariate model, we simultaneously estimate the correlations, means and variance of the two variables. We estimate the models by maximizing the log-likelihood function for the univariate / bivariate normal density while allowing for regime-switching between two states⁸.

The next logical extension would be to estimate a trivariate regime-switching model that allows for regime-specific correlations, means, and variances. But, the number of parameters to be estimated in a trivariate model becomes large, so there are concerns about the stability of the coefficients estimated from the maximization of log-likelihood function. Accordingly, we focus on the univariate and bivariate estimates. The results from the trivariate model are available in Appendix B.

3.4.2. Univariate Regime-Switching Model

The univariate-regime switching model estimated on market volatility is given by:

$$\ln MKT_t = \mu_{\ln MKT}^{S_t} + \sigma_{\ln MKT}^{S_t} \cdot \varepsilon_t \quad (3-7)$$

The illiquidity is modeled as:

$$ILLIQ_t = \mu_{ILLIQ}^{S_t} + \sigma_{ILLIQ}^{S_t} \cdot \eta_t \quad (3-8)$$

Finally, the model estimated on idiosyncratic volatility is:

⁸ To the extent that the resulting residuals are not bivariate normally distributed, our estimation is quasi-maximum likelihood estimation. Bollerslev and Wooldridge (1992) show that the estimated coefficients in a quasi-likelihood estimation are consistent under straight-forward regularity conditions.

$$\ln IV_t = \mu_{\ln IV}^{S_t} + \sigma_{\ln IV}^{S_t} \cdot \xi_t \quad (3-9)$$

To model volatility and idiosyncratic volatility, we use log of variance, instead of variance or standard deviation, to address kurtosis and skewness related concerns. In the models, the $\mu_{\ln MKT}^{S_t}$, $\mu_{\ln ILLIQ}^{S_t}$, and $\mu_{\ln IV}^{S_t}$ are regime specific means, and the $\sigma_{\ln MKT}^{S_t}$, $\sigma_{\ln ILLIQ}^{S_t}$, and $\sigma_{\ln IV}^{S_t}$ are regime-specific standard deviations of the log transformation of volatility, the level of illiquidity and the log transformation of idiosyncratic volatility, respectively. Note that the models allow not only for means to vary across states but also for uncertainty (standard deviations) about the three series to vary across states. We also separately estimate models where the standard deviation is constant across states ($\sigma^0 = \sigma^1 = \sigma$). But given the strong evidence we find for standard deviations to vary across states for each of three estimations, we omit the results for constant standard-deviation models from the paper.

Table 3-2 presents the estimation results. The Group 1, Group 2, and Group 3 in the Panel A of the table reports the coefficients estimated from the equations (3-7), (3-8), and (3-9), respectively. Panel B of the table reports regime-specific characteristics obtained from classifying the months into either one of the two regimes based on the filtered probability from the estimation. In this section, we refer to the regime with the higher mean value of the characterizing variable as the bad regime. That is, the bad regime in Group 1 is the one with higher estimated $\mu_{\ln MKT}$; in Group 2, it is the one with higher estimated $\mu_{\ln ILLIQ}$; and finally in Group 3, it is the one with higher estimated $\mu_{\ln IV}$. A month is classified to be in a good state (bad state) if the filtered probability of being in good state (bad state) is more than 0.8. Note that our classification leaves a few months

unclassified. The filtered probabilities of being in a bad regime based on the estimations from Group 1, 2, and 3 are drawn in Figure 2a, 2b, and 2c, respectively.

The estimated coefficients in all three cases in Panel A indicate that the higher mean is associated with higher standard deviations. That is, the bad regimes are associated with higher uncertainty of the characterizing variables. For instance, in Group 1, the regime with higher estimated mean market volatility ($\mu_{lnMKT}^1 = 5.70$ as compared to $\mu_{lnMKT}^0 = 4.54$) is also associated with higher standard deviation ($\sigma_{lnMKT}^1 = 0.72$ as compared to $\sigma_{lnMKT}^0 = 0.65$). Similarly, in Group 2, the regime with higher estimated mean illiquidity ($\mu_{ILLIQ}^1 = 2.67$ as compared to $\mu_{ILLIQ}^0 = 1.77$) is also associated with higher standard deviation ($\sigma_{ILLIQ}^1 = 1.07$ as compared to $\sigma_{ILLIQ}^0 = 0.33$).

The findings related to regime-specific characteristics obtained from classifying months into regimes (Panel B of the table) include the following. First, in all three groups, the bad regime, which by definition has higher mean value for the characterizing variable, is also associated with higher mean values for the other two variables. For instance, in Group 2, the bad regime is the one with higher illiquidity. This regime also has higher average standard deviation of the market portfolio (Mean[sdMKT] is 20.21% as compared to 11.82% in the other regime) and higher mean idiosyncratic volatility (Mean[sdIV] is 30.10% as compared to 21.67% in other regime). The cross-regime differences in mean values for all the three variables in all three cases are statistically significant with p-value of 0.1%.

Second, in all three groups, the bad regime not only has higher uncertainty (standard deviation) about the characterizing variable but also has higher uncertainty about the

other two variables. Referring to the same instance, the bad regime in Group 2 has higher standard deviation of market volatility (Std.Dev.[sdMKT] is 10.68 as compared to 4.59 in other regime) and higher standard deviation of idiosyncratic volatility (Std.Dev.[sdIV] is 8.79 as compared to 3.59 in other regime). The cross-regime differences in the variances (or the standard deviation) of these variables are statistically significant with p-value of 0.1%.

The two results strongly indicate that the three variables move together. It suggests that there is some underlying latent shock to the economy which causes not only higher market volatility, higher illiquidity, and higher idiosyncratic volatility but also higher uncertainty about these variables.

Next findings relate to the variations in pair-wise correlations across regimes. First, we find evidence that for all the three estimations, the correlation between the illiquidity and idiosyncratic volatility is higher during the bad regime. For instance, in Group 1, the correlation of ILLIQ with lnIV (or with sdIV or with IV) in bad regime is 0.64 (0.65 or 0.64) as compared 0.27 (0.26 or 0.25) in the other regime. Second, there is also some evidence that correlation between volatility and illiquidity is also higher during the bad regime. Note that the pair-wise correlations in the variables will depend on whether the volatility and idiosyncratic volatility is measured as variance or as standard deviation or as log of variance. The extreme values or outliers (bad regime is likely to have more outliers) should have larger effect on correlations in variance series than on correlations in standard deviation or log series. Lastly, we find no clear evidence of any regime-specific variation in correlation between the volatility and idiosyncratic volatility.

We now discuss the extent to which the regimes identified by the three variables overlap. The first row in Panel B of the Table 3-2 gives the number of months in the good and the bad regime under each estimation. The numbers of months in the good (bad) regime are 255 (195) for the estimation on market volatility, 374 (114) for the estimation on illiquidity, and 227 (269) for the estimation on idiosyncratic volatility. Further, we find (not reported in the table) that the number of months that are in good (bad) regime both under estimation of market volatility and of illiquidity are 229 (91). The number of months that are in good (bad) regime both under estimation of market volatility and of idiosyncratic volatility are 179 (167). Lastly, the number of months that are in good (bad) regime both under estimation of illiquidity and of idiosyncratic volatility are 196 (87). The numbers suggest that there is substantial overlapping of regimes.

The final row of Panel B reports the regime-specific mean market returns (returns on CRSP value weighted NYSE, AMEX and NASDAQ portfolio). Consistent with the prior literature, the bad volatility regime in Group 1 is associated with lower mean returns. Lower mean market returns is even more severe for bad illiquidity regimes in Group 2. For instance, the mean market returns in high illiquidity regime is -0.33% as compared to 1.34% during the good regime.

It is interesting to note that in the estimation based on idiosyncratic volatility (Group 3), there is not much difference in the mean market returns across the two regimes. This can partly be explained by the two confounding phenomenon. On one hand, the periods of high idiosyncratic volatility are also the periods of high market uncertainty. In such periods, the stocks' expected returns should go up, which would generate a contemporaneous decline in stock prices and an observed negative return. On the other

hand, Guo and Savickas (2007) argue that the changes in idiosyncratic volatility provide a proxy for changes in the investment opportunity set, and hence may proxy for systematic risk. They find that the average idiosyncratic volatility is negatively related to future stock returns (possibly because of its negative correlation with the aggregate book-to-market ratio). A negative relation with future stock returns implies a positive relation with the contemporaneous stock returns. The two explanations work in opposite directions. As a result, we observe two regimes with distinguishable difference in mean stock returns.

Overall, the findings from univariate regime-switching models on volatility, illiquidity and idiosyncratic volatility suggest that there is some latent bad regime in which all these variables not only have higher means but also higher standard deviations.

3.4.3. *Univariate Regime-Switching with time-varying probability*

For each of these series, we also estimate more sophisticated regime-switching models with time-varying transition probabilities in order to examine if the probability of switching regimes varies significantly with the other two parameters. For instance, take the case of a univariate regime-switching model on market volatility, estimated in equation (3-7). In the previous section, we assumed q and p to be constants. Now, instead of constraining the q and p to be constants, we follow specify time-varying transition probabilities as follows:

$$\begin{aligned} q_t &= P(S_t^0 | S_{t-1}^0) = \frac{\exp(q_0 + q_1 \cdot ILLIQ_t)}{1 + \exp(q_0 + q_1 \cdot ILLIQ_t)} \\ p_t &= P(S_t^1 | S_{t-1}^1) = \frac{\exp(p_0 + p_1 \cdot ILLIQ_t)}{1 + \exp(p_0 + p_1 \cdot ILLIQ_t)} \end{aligned} \tag{3-10}$$

where q_0 , q_1 , p_0 and p_1 are the parameters to be estimated. Note that we use the contemporaneous value for illiquidity ($ILLIQ_t$). This allows us to examine whether illiquidity at time t is associated with different transition probabilities of shifting regimes between t and $t-1$. If volatility and illiquidity are responding to similar market shocks, then one would expect that high values should lower the probability of being regime-zero (a negative q_1) and should increase the probability of being in regime-one (a positive p_1).

With three variables, one can have a total of six models. Table 3-3 provides results from estimation from all six of them. We find that q_1 is negative and statistically significant in all six cases. With regards to p_1 , it is positive in all cases and is statistically significant in three cases. These findings further suggest that these variables are substantially responding to same underlying conditions in the economy.

3.4.4. *Bivariate Regime-Switching Model*

We next estimate bivariate regime-switching models which simultaneously estimate the correlations, means and variance of the two variables. If the three variables are substantially responding to the same underlying economic conditions, one would expect means, the standard deviations, and the pair-wise correlations to show a similar trend as in case of univariate analysis.

The bivariate regime-switching model estimated on market volatility and illiquidity is given by:

$$\begin{aligned}
\ln MKT_t &= \mu_{\ln MKT}^{S_t} + \sigma_{\ln MKT}^{S_t} \cdot \varepsilon_t \\
ILLIQ_t &= \mu_{ILLIQ}^{S_t} + \sigma_{ILLIQ}^{S_t} \cdot \eta_t \\
(\varepsilon_t, \eta_t) &\sim N(0, \Sigma_{\ln MKT, ILLIQ}) \quad \text{where} \quad \Sigma_{\ln MKT, ILLIQ} = \begin{vmatrix} 1 & \rho_{\ln MKT, ILLIQ}^{S_t} \\ \rho_{\ln MKT, ILLIQ}^{S_t} & 1 \end{vmatrix}
\end{aligned} \tag{3-11}$$

where $\rho_{\ln MKT, ILLIQ}^{S_t}$ is the regime-specific correlation between the two variables; the rest of the parameters are defined earlier. Note that the model simultaneously estimates the regime-specific correlations, means and variances. The results are reported in Group 1 of Table 3-4. Panel A presents the estimation results and Panel B reports the regime-specific characteristics once the months are classified into regimes based on the filtered probability from the estimation. The corresponding filtered probability of being in the bad regime is drawn in Plot A of Figure 3-3. In a bivariate model, it can be tough to define the bad regime as the two characterizing variables may have higher mean values in different regimes. Fortunately, we don't face this problem because the regime with higher mean volatility is also associated with higher mean illiquidity. We refer to this regime as the bad regime.

As earlier, for all three variables, the bad regime is not only associated with higher mean values but also with higher standard deviations. Also, the differences-in-the-means and differences-in-the-variances across the two regimes is statistically significant. Note that the cross-regime difference in the standard deviations of the $\ln MKT$ ($\ln IV$) are lower than similar differences in MKT (IV) or in $sd MKT$ ($sd IV$). This is so because the log value dampens the effect of outliers. In any case, it is clear that the standard deviation of volatility and of idiosyncratic volatility (and of illiquidity) is substantially higher during the bad regime. However, the findings related to pair-wise correlations are mixed.

Consistent with results from univariate estimations, we find that the bad regime has meaningfully higher correlation between illiquidity and idiosyncratic volatility, has slightly higher correlation between market volatility and illiquidity, and has insignificant or no clear trend in the correlation between volatility and idiosyncratic volatility. Finally, we find that the bad regime is associated with the lower stock returns.

We next estimate a bivariate regime-switching model on volatility and idiosyncratic volatility. The model is given by:

$$\begin{aligned}
\ln MKT_t &= \mu_{\ln MKT}^{S_t} + \sigma_{\ln MKT}^{S_t} \cdot \varepsilon_t \\
\ln IV_t &= \mu_{\ln IV}^{S_t} + \sigma_{\ln IV}^{S_t} \cdot \xi_t
\end{aligned} \tag{3-12}$$

$$(\varepsilon_t, \xi_t) \sim N(0, \Sigma_{\ln MKT, \ln IV}) \quad \text{where} \quad \Sigma_{\ln MKT, \ln IV} = \begin{vmatrix} 1 & \rho_{\ln MKT, \ln IV}^{S_t} \\ \rho_{\ln MKT, \ln IV}^{S_t} & 1 \end{vmatrix}$$

The results are in Group 2 of Table 3-4. Panel A documents the estimation results and Panel B presents the regime-specific characteristics obtained from classification of the months. The corresponding filtered probability of being bad regime is drawn in Plot B of Figure 3-3. The bad regime is easily identified as both volatility and idiosyncratic volatility have higher means in same regime. This regime is the bad regime. As expected, for all three variables, the bad regime is not only associated with higher mean values but also with higher standard deviations. In relation to pair-wise correlation, once again we find that the bad regime has higher correlation between illiquidity and idiosyncratic volatility. However, in this case, unlike the earlier results, the correlation between volatility and illiquidity is not so different across regimes. Finally, as earlier, there is no significant difference in the correlation between volatility and idiosyncratic volatility.

Finally, we use illiquidity and idiosyncratic volatility to estimate a bivariate regime-switching model, given by:

$$\begin{aligned}
ILLIQ_t &= \mu_{ILLIQ}^{S_t} + \sigma_{ILLIQ}^{S_t} \cdot \eta_t \\
lnIV_t &= \mu_{lnIV}^{S_t} + \sigma_{lnIV}^{S_t} \cdot \xi_t \\
(\eta_t, \xi_t) &\sim N(0, \Sigma_{ILLIQ, lnIV}) \quad \text{where} \quad \Sigma_{ILLIQ, lnIV} = \begin{vmatrix} 1 & \rho_{ILLIQ, lnIV}^{S_t} \\ \rho_{ILLIQ, lnIV}^{S_t} & 1 \end{vmatrix}
\end{aligned} \tag{3-13}$$

Table 3-4 Group 3 presents the results. Panel A reports on estimated coefficients and Panel B on the regime-specific characteristics obtained from classification of the months. Figure 3-3 Plot C plots the corresponding filtered probability. Both the characterizing variables have higher mean values in the same regime, which we call as the bad regime. Once again, all the three variables have higher standard deviations in the bad regime. Interestingly, all three pair-wise correlations are also higher in the bad regime. The market returns are also substantially lower.

Overall, the bivariate models, confirm that all the three series have higher means and higher uncertainties during at the same regime. we get similar results from trivariate regime-switching models reported in the Appendix B. This supports our notion that these measures may be capturing the same information regarding the underlying state of the financial markets.

3.5. Granger-Causality Tests

The previous sections document the contemporaneous relationship between these variables. In this section, we take a forward looking perspective and ask whether these variables help to forecast each other. Table 3-5 investigates this question using Granger-causality tests. Panel A reports p-values for bivariate VARs and Panel B uses trivariate

VAR including all three series. The VAR lag length was chosen using the Akaike information criterion. This section follows from CLMX (2001) who study the Granger-causality in MKT and IV. However, as mentioned earlier, they don't study the causality of these two series with illiquidity.

In bivariate VARs, we find both MKT and IV Granger-cause each other at very high significance level. Further, both MKT and IV help predict ILLIQ only at 10% significance level. However, in the reverse causality, ILLIQ helps significantly to forecast both MKT and IV. In terms of R-squared, we find that the MKT is least predictable and both that ILLIQ and IV can be predicted with R-squared of about 0.8.

In the trivariate VARs, MKT and IV continue to Granger-cause each other at very high significance level. Both MKT and IV now help significantly predict ILLIQ (the significant levels are much higher than that in bivariate case). ILLIQ continue to help forecast IV (at high significance level) but it loses any ability in predicting MKT. Among the three series, the MKT has the lowest R-squared.

Overall, our granger-causality tests suggest that each of these series have some ability in forecasting the other two series. This further supports our claim that these variables are closely related and may be responding to the same latent shocks to financial markets.

3.6. Implications on Stocks Returns

In this section, we show how our findings may have important bearing on research that show that these variables affect stock market returns. In the first paragraph of the Introduction, we cite several papers that study such a relationship. These studies examine whether one or two of these variables are related to stock returns, but not all three

jointly. For instance, the French, Schwert and Stambaugh (1987) examine the relation of stock excess return with expected and unexpected market volatility. Amihud (2002) borrows their framework and substitutes illiquidity for market volatility in order to examine the relation of stock excess return with expected and unexpected illiquidity. In our test, we use the expected and the unexpected values of both market volatility and illiquidity in explaining the variation in stock returns. We are interested in comparing the joint explanatory power (R-square) of these two variables with that of each variable alone. Note that we don't include idiosyncratic volatility in the test as we find that idiosyncratic volatility has no power in explaining stock returns.

More specifically, we examine the variation in R-squares in the different specifications of the following regression

$$R_{M,t} - R_{f,t} = \alpha_0 + \beta_0 \cdot ILLIQ_t^E + \beta_1 \cdot ILLIQ_t^U + \delta_0 \cdot MKT_t^E + \delta_1 \cdot MKT_t^U + \varepsilon_t \quad (3-14)$$

where $R_{M,t}$ and $R_{f,t}$ is the return on market portfolio and risk-free asset, respectively; $ILLIQ_t^E$ and $ILLIQ_t^U$ are the expected and unexpected aggregate stock market illiquidity from the trivariate VAR model in the previous section; Similarly, MKT_t^E and MKT_t^U are the expected and the unexpected volatility of market portfolio, respectively, obtained from the same trivariate VAR model. Table 3-6 presents the results from estimation.

In the specification [1] to [3], we find that the excess stock returns have negative and significant relation with both the innovations in illiquidity and with innovations in market

volatility. Surprisingly, we don't have any significant relationship of stock returns with expected illiquidity or with expected market volatility⁹.

Examining the explanatory power of these regressors (as indicated by the R-square of the respective regressions) reveals an interesting result. When illiquidity is the only regressor, the R-squared is 22.11%. When both illiquidity and volatility are the regressors, the R-squared is only marginally higher at 23.12%. This suggests that though volatility may be individually informative of the stock returns but does not add any incremental explanatory power. This point is further illustrated by regressing the residuals from illiquidity-only-regression¹⁰ (residuals are denoted by ε_t^{ILLIQ}) on the expected and unexpected volatility. We find the R-square of the regression is only 1.36% (specification [4] in the table). This further confirms that the volatility has very little power beyond that in illiquidity in terms of explaining stock returns.

We also test our results in Table 3-6 for the first-half and the second-half period of our sample. The results are consistent with the results in the full sample period. For instance, for the period 1963:07 – 1984:09, the R-square of the illiquidity-only-regression for the period is 31.39%, whereas that of the illiquidity-and-volatility-regression is 31.78% .

3.7. Conclusion

This paper presents a statistical description, rather than a structural economic model, of movements and co-movements in stock market volatility, illiquidity and idiosyncratic

⁹ Our insignificant sign on expected illiquidity is at odds with Amihud (2002) who finds a positive and significant sign on this coefficient. There are several reasons that may explain this difference. First, Amihud's sample period is 1962-1996 whereas ours is 1963-2006. Second, to estimate expected and unexpected illiquidity, he uses an AR(1) process whereas we use a trivariate VAR on market volatility, illiquidity and idiosyncratic volatility. Third, he doesn't scale his aggregate illiquidity series in the manner in which we do (see Section 3.3.3 for details on scaling).

¹⁰ The residuals from illiquidity-only-regression, ε_t^{ILLIQ} , represents the stock returns unexplained by the illiquidity related measures.

volatility. We use daily stock data from 1963 to 2006 to construct realized monthly values for the three variables, which we then use as observables. In our study, market volatility is the variance of the daily returns on a value-weighted market portfolio, illiquidity measure is the Amihud's (2002) illiquidity ratio for the aggregate market, and the idiosyncratic volatility is the value-weighted cross-sectional average of individual stocks' variance of daily residuals from Fama and French three factor model.

We find that the three variables of interest, as expected, are highly correlated. In our two-state, univariate and multivariate regime-switching models, we find strong evidence that the three variables have both higher means and higher standard deviations during the bad regime. The result holds irrespective of the information set used to classify the regimes. That is, we get regimes with similar characteristics from the univariate and bivariate (and also the results from trivariate) regime-switching models. Our findings suggest that these measures contain much of the same information about the underlying condition of the market economy. These results are further supported by Granger-causality tests, in which we find that each of these series have some ability in forecasting the other two series.

With respect to the regime-specific pair-wise correlations in these variables, the results are mixed. While we find strong evidence that the correlation between illiquidity and idiosyncratic volatility is higher in the bad regime, we find no clear regime-specific trend in correlation between market volatility and illiquidity, and between market volatility and idiosyncratic volatility.

We provide a simple illustration how our findings may have important bearing on research that show that variables affect stock market returns. We find that the joint explanatory power of the market volatility and illiquidity (in explaining the variation in

stock returns) is not much different than that of illiquidity alone. This suggest that the study that only examines the relation between returns and market volatility may attribute a return pattern to price-volatility effects, when it might be more of price-liquidity effect (or some combination of the two effects).

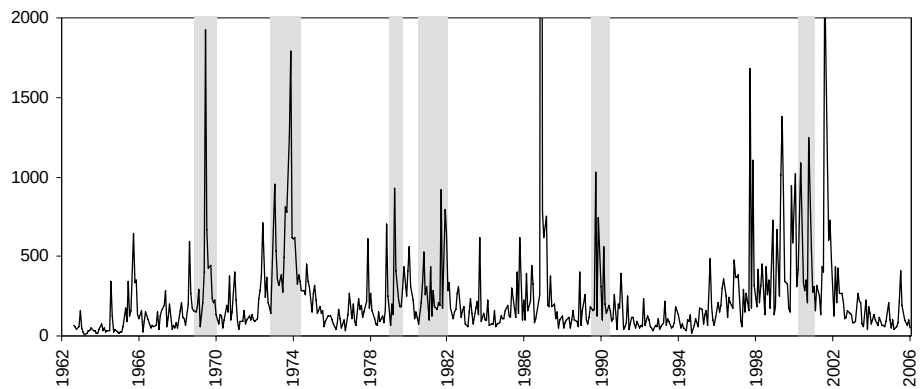
Another implication from this paper stems from the finding that the state with higher mean values is also the state with higher standard deviation of these measures. In an asset pricing framework, it would be interesting to study the incremental effect on the stock returns of the levels of these measures and of their standard deviations. For instance, this paper finds that both the level and volatility of volatility is higher during bad times. A natural research question to ask is: do the investors care about market volatility or the volatility of market volatility?

Figures

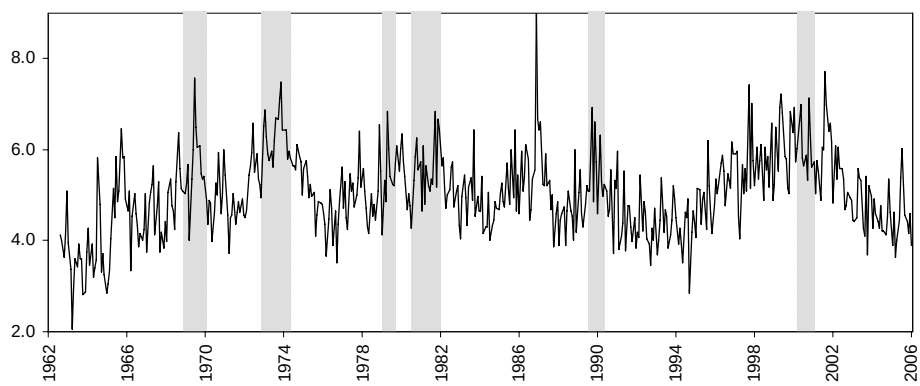
Figure 3-1: Time Series Plots

This figure displays the time-series plots of market volatility (Plot A and Plot B), illiquidity (Plot C), and idiosyncratic volatility (Plot D and Plot E) for the period July 1963 to December 2006. The shaded region in all graphs represents NBER recessions.

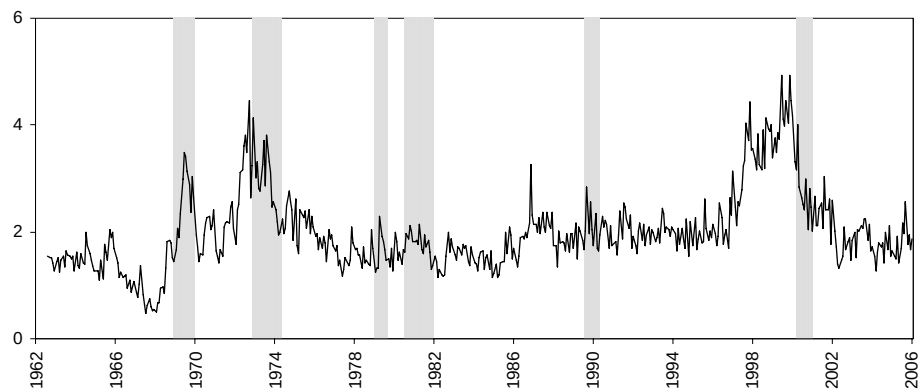
Plot A: Market Volatility (MKT)



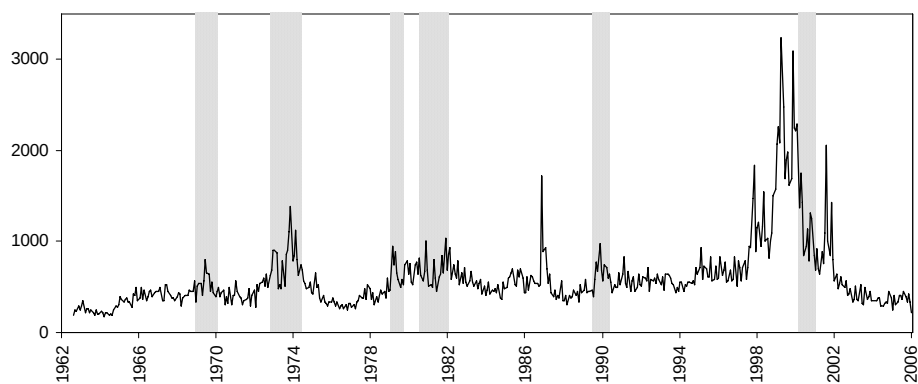
Plot B: Log of Market Volatility (lnMKT)



Plot C: Illiquidity



Plot D: Idiosyncratic Volatility



Plot E: Log of Idiosyncratic Volatility

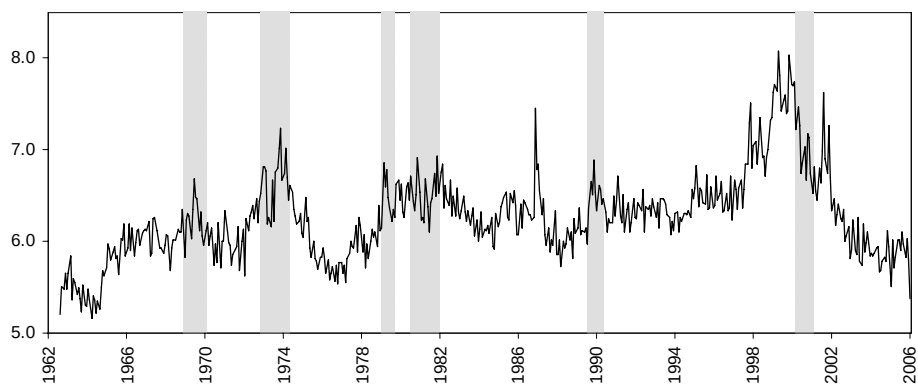
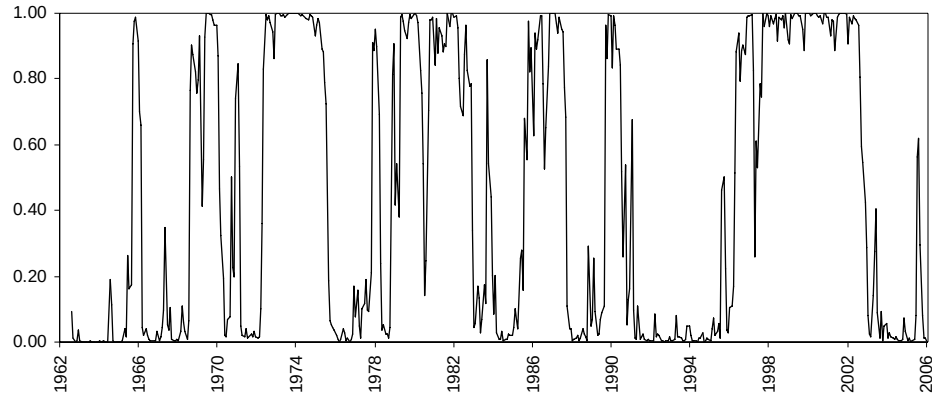


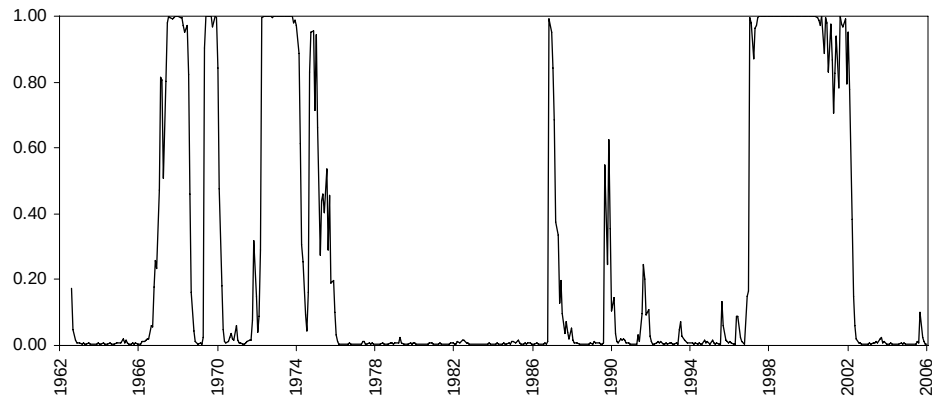
Figure 3-2: Filtered Probabilities from Univariate Estimation

This figure displays the time-series of the filtered probability of being in bad regime, $P(S_t^1 | I_{t-1})$, estimated from univariate regime-switching models on market volatility (Plot A), on illiquidity (Plot B), and on idiosyncratic volatility (Plot C).

Plot A: Filter probability of univariate regime-switching estimation on lnMKT



Plot B: Filter probability of univariate regime-switching estimation on ILLIQ



Plot C: Filter probability of univariate regime-switching estimation on $\ln IV$

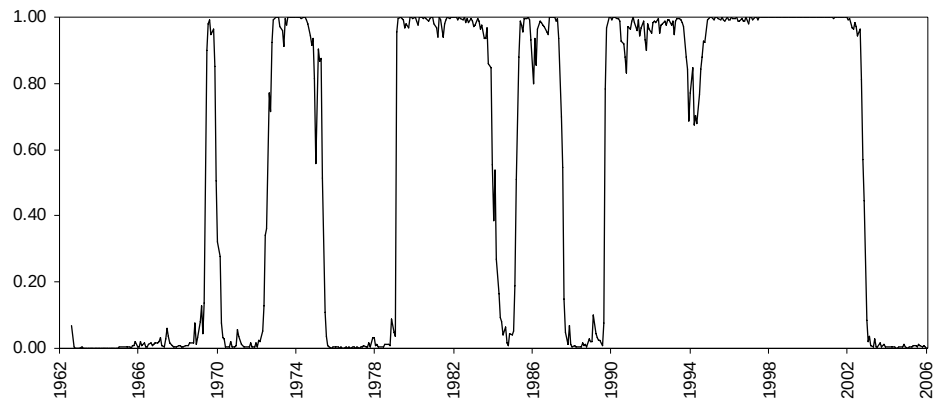
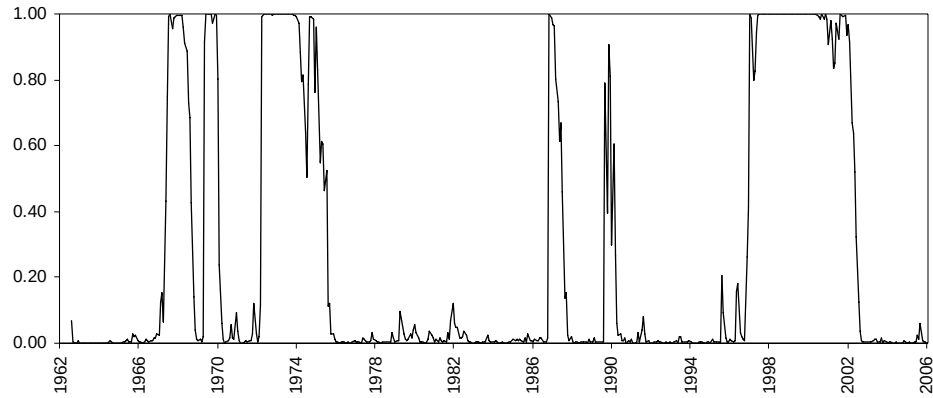


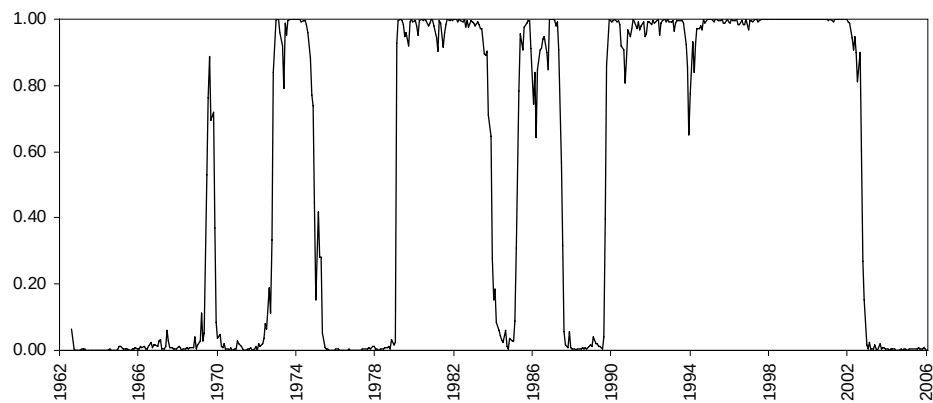
Figure 3-3: Filtered Probabilities from Bivariate Estimation

This figure displays the time-series of the filtered probability of being in bad regime, $P(S_t^1 | I_{t-1})$, estimated from bivariate regime-switching models on market volatility and illiquidity (Plot A), on market volatility and idiosyncratic volatility (Plot B), and on illiquidity and idiosyncratic volatility (Plot C).

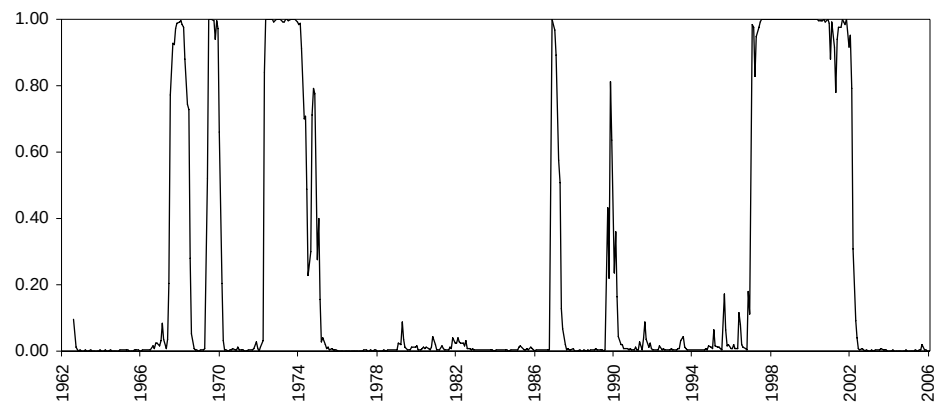
Plot A: Filter probability of bivariate regime-switching estimation on lnMKT and ILLIQ



Plot B: Filter probability of bivariate regime-switching estimation on lnMKT and lnIV



Plot C: Filter probability of bivariate regime-switching estimation on ILLIQ and lnIV



Tables

Table 3-1: Descriptive Statistics

This table presents the descriptive statistics for market volatility, illiquidity, and idiosyncratic volatility. MKT is measured as the variance of the daily returns on CRSP value-weighted NYSE/AMEX/NASDAQ portfolio. sdMKT and lnMKT, in column 3 and 4, is the standard deviation and natural log of MKT, respectively. ILLIQ is the Amihud (2002) inspired measure of aggregate stock market illiquidity. IV is measured as the value-weighted cross-sectional average of individual stocks' variance of daily residuals from Fama and French (1989) three factor model. sdIV and lnIV, in column 7 and 8, is the standard deviation and natural log of IV, respectively. Both market volatility and idiosyncratic volatility are computed using returns expressed in percentage units (i.e. 1.59% return is expressed as 1.59 instead of 0.0159), and both measures are annualized. Panel B of the table reports the correlations between the various measures. The sample period is from July, 1963 to December, 2006.

Panel A:

	MKT	sdMKT	lnMKT	ILLIQ	IV	sdIV	lnIV
Mean	246.83	13.89	5.05	2.00	597.39	23.64	6.27
25th percentile	87.96	9.38	4.48	1.54	391.59	19.79	5.97
50th percentile	153.84	12.40	5.04	1.86	514.95	22.69	6.24
75th percentile	271.03	16.46	5.60	2.24	647.38	25.44	6.47
Minimum	7.74	2.78	2.05	0.48	174.64	13.22	5.16
Maximum	8103.79	90.02	9.00	4.94	3238.22	56.91	8.08
Standard Deviation	431.25	7.36	0.90	0.73	375.15	6.23	0.47
Skewness	12.35	3.22	0.28	1.28	3.16	1.89	0.79
Kurtosis	213.33	23.36	0.67	2.15	13.40	5.40	1.55

Panel B:

	Market Volatility & Illiquidity		Market Volatility & Idiosyncratic Volatility		Illiquidity & Idiosyncratic Volatility	
Correlations	Correl (MKT, ILLIQ)	0.359	Correl (MKT, IV)	0.456	Correl (ILLIQ, IV)	0.671
	Correl (sdMKT, ILLIQ)	0.509	Correl (sdMKT, sdIV)	0.614	Correl (ILLIQ, sdIV)	0.671
	Correl (lnMKT, ILLIQ)	0.518	Correl (lnMKT, lnIV)	0.633	Correl (ILLIQ, lnIV)	0.638

Table 3-2: Univariate Regime-Switching Models with Constant Transition Probabilities

This table reports results related to estimation on univariate regime-switching model with constant transition probabilities. The table is divided into two panels (Panel A and Panel B) and into three groups within each panel. Panel A reports the estimated model, and the coefficients obtained from the estimation. Panel B reports the regime-specific characteristics obtained from classifying the months into good state (bad state) if the filtered probability of being in good state (bad state) is more than 0.8. The univariate regime-switching model is estimated separately on market volatility, on illiquidity, and on idiosyncratic volatility. The results from each of these three estimations are reported in the three groups (Group-1, Group-2, and Group-3), respectively. In the Panel A, superscript S_t denotes the regime for the regime-specific parameters, with $S_t = 0$ for good regime and $S_t = 1$ for bad regime; $\lnMKT$ is natural log of volatility of market portfolio; $ILLIQ$ is measure of aggregate market illiquidity inspired from Amihud (2002); $\lnIV$ is natural log of aggregate idiosyncratic volatility (for details on $\lnMKT$, $ILLIQ$ and $\lnIV$, see Table 1 discussion); $\mu_{\lnMKT}^{S_t}$, $\mu_{ILLIQ}^{S_t}$ and $\mu_{\lnIV}^{S_t}$ are regime-specific means; $\sigma_{\lnMKT}^{S_t}$, $\sigma_{ILLIQ}^{S_t}$, and $\sigma_{\lnIV}^{S_t}$ are regime-specific standard deviations; and the residuals ε_t , η_t and ξ_t are modelled as univariate, standard, normally distributed, random variables. The state variable S_t is modelled with constant transition probabilities, $q = P(S_t^0 | S_{t-1}^0)$ and $p = P(S_t^1 | S_{t-1}^1)$. The regime-specific means, regime-specific standard-deviations, and the transition probabilities are parameters to be estimated. The models are estimated by maximizing the log-likelihood function for the univariate normal density while allowing for regime-switching. In Panel B, the parameters MKT and $sMKT$, IV and $\lnIV$ are alternative measures of market volatility and idiosyncratic volatility, respectively (see Table 1 discussion); and r_M is the returns on market portfolio. The test of differences refers either to the test of differences-in-means across regimes (in context of the levels of the three parameters) or to difference-in-variances across regimes (in context of uncertainty about these parameters). The statistical significance of the test-of-differences is indicated by ***, **, * for p-values at the 0.1%, 1%, and 5%, respectively. The sample period is from July, 1963 to December, 2006.

Panel A: Estimated Model									
	Group 1 (Estimation on Market Volatility)			Group 2 (Estimation on Illiquidity)			Group 3 (Estimation on Idiosyncratic Volatility)		
Univariate Regime Switching Model	$\lnMKT_t = \mu_{\lnMKT}^{S_t} + \sigma_{\lnMKT}^{S_t} \cdot \varepsilon_t$			$ILLIQ_t = \mu_{ILLIQ}^{S_t} + \sigma_{ILLIQ}^{S_t} \cdot \eta_t$			$\lnIV_t = \mu_{\lnIV}^{S_t} + \sigma_{\lnIV}^{S_t} \cdot \xi_t$		
		coefficient	std. err.		coefficient	std. err.		coefficient	std. err.
	$\mu_{\lnMKT}^0$	4.537	0.048	μ_{ILLIQ}^0	1.769	0.021	$\mu_{\lnIV}^0$	5.921	0.021
	$\mu_{\lnMKT}^1$	5.697	0.058	μ_{ILLIQ}^1	2.674	0.110	$\mu_{\lnIV}^1$	6.569	0.026
Estimated Coefficients	$\sigma_{\lnMKT}^0$	0.652	0.029	σ_{ILLIQ}^0	0.334	0.015	$\sigma_{\lnIV}^0$	0.258	0.012
	$\sigma_{\lnMKT}^1$	0.724	0.034	σ_{ILLIQ}^1	1.072	0.068	$\sigma_{\lnIV}^1$	0.391	0.017
	q	0.965	0.013	q	0.985	0.007	q	0.979	0.010
	p	0.956	0.015	p	0.956	0.020	p	0.981	0.008

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Panel B: Regime-specific Characteristics									
	Group 1 (Estimation on Market Volatility)			Group 2 (Estimation on Illiquidity)			Group 3 (Estimation on Idiosyncratic Volatility)		
Regime-Specific Characteristics	<i>Good Regime (Regime=0)</i>	<i>Bad Regime (Regime=1)</i>	<i>Test of Differences</i>	<i>Good Regime (Regime=0)</i>	<i>Bad Regime (Regime=1)</i>	<i>Test of Differences</i>	<i>Good Regime (Regime=0)</i>	<i>Bad Regime (Regime=1)</i>	<i>Test of Differences</i>
N (# months)	255	195		374	114		227	269	
Levels									
Mean(MKT)	100.88	457.64	356.76***	160.60	521.47	360.87***	131.43	348.18	216.75***
Mean(sdMKT)	9.65	19.61	9.96***	11.82	20.21	8.40***	10.75	16.60	5.85***
Mean(lnMKT)	4.45	5.82	1.37***	4.80	5.80	1.01***	4.62	5.42	0.80***
Mean(IV)	428.38	845.43	417.05***	482.55	982.80	500.25***	379.81	791.01	411.20***
Mean(sdIV)	20.44	28.17	7.73***	21.67	30.10	8.43***	19.34	27.41	8.07***
Mean(lnIV)	6.01	6.62	0.61***	6.12	6.73	0.61***	5.91	6.58	0.67***
Mean(ILLIQ)	1.67	2.48	0.81***	1.75	2.81	1.06***	1.65	2.27	0.63***
Standard Deviations									
Std. Dev. (MKT)	56.88	645.70	588.82***	135.83	825.20	689.36***	106.62	570.88	464.26***
Std. Dev. (sdMKT)	2.79	8.57	5.79***	4.59	10.68	6.09***	3.99	8.54	4.55***
Std. Dev. (lnMKT)	0.61	0.69	0.08	0.76	0.90	0.14*	0.73	0.87	0.14**
Std. Dev. (IV)	135.88	494.81	358.93***	157.30	603.02	445.72***	92.65	432.24	339.59***
Std. Dev. (sdIV)	3.26	7.24	3.97***	3.59	8.79	5.20***	2.43	6.32	3.89***
Std. Dev. (lnIV)	0.32	0.46	0.13***	0.34	0.56	0.22***	0.26	0.39	0.13***
Std. Dev. (ILLIQ)	0.42	0.86	0.44***	0.33	1.08	0.75***	0.46	0.78	0.32***
Pair-wise Correlations									
Correl(MKT,ILLIQ)	0.147	0.230		0.214	0.206		0.346	0.304	
Correl(sdMKT,ILLIQ)	0.159	0.317		0.236	0.370		0.359	0.425	
Correl(lnMKT,ILLIQ)	0.168	0.340		0.249	0.508		0.346	0.433	
Correl(MKT,IV)	0.189	0.340		0.468	0.322		0.414	0.395	
Correl(sdMKT,sdIV)	0.240	0.448		0.487	0.470		0.456	0.530	
Correl(lnMKT,lnIV)	0.296	0.463		0.501	0.544		0.490	0.534	
Correl(ILLIQ,IV)	0.270	0.642		0.211	0.608		0.132	0.696	
Correl(ILLIQ,sdIV)	0.260	0.648		0.222	0.652		0.126	0.707	
Correl(ILLIQ,lnIV)	0.246	0.636		0.230	0.687		0.121	0.700	
Stock Returns									
Mean (r_M)	1.04	0.76	-0.27	1.34	-0.33	-1.67**	0.84	0.98	0.14

Table 3-3: Univariate Regime-Switching Models with Time-Varying Transition Probabilities

This table reports results related to estimation on univariate regime-switching model with time-varying transition probabilities. The univariate regime-switching model is estimated separately on market volatility, on illiquidity, and on idiosyncratic volatility. The results from each of these three estimations are reported in the three groups (Group-1, Group-2, and Group-3), respectively. For each group, we report the estimated model, and the coefficients obtained from the estimation. All the variables are explained in discussion for Table 2.

	Group 1 $\ln MKT_t = \mu_{\ln MKT}^{S_t} + \sigma_{\ln MKT}^{S_t} \cdot \varepsilon_t$	Group 2 $ILLIQ_t = \mu_{ILLIQ}^{S_t} + \sigma_{ILLIQ}^{S_t} \cdot \eta_t$	Group 3 $\ln IV_t = \mu_{\ln IV}^{S_t} + \sigma_{\ln IV}^{S_t} \cdot \zeta_t$						
Model I	$q_t = \frac{e^{q_0 + q_1 \cdot ILLIQ_t}}{1 + e^{q_0 + q_1 \cdot ILLIQ_t}}; p_t = \frac{e^{p_0 + p_1 \cdot ILLIQ_t}}{1 + e^{p_0 + p_1 \cdot ILLIQ_t}}$	$q_t = \frac{e^{q_0 + q_1 \cdot \ln MKT_t}}{1 + e^{q_0 + q_1 \cdot \ln MKT_t}}; p_t = \frac{e^{p_0 + p_1 \cdot \ln MKT_t}}{1 + e^{p_0 + p_1 \cdot \ln MKT_t}}$	$q_t = \frac{e^{q_0 + q_1 \cdot \ln MKT_t}}{1 + e^{q_0 + q_1 \cdot \ln MKT_t}}; p_t = \frac{e^{p_0 + p_1 \cdot \ln MKT_t}}{1 + e^{p_0 + p_1 \cdot \ln MKT_t}}$						
Estimated Coefficients	<u>coefficient</u> $\mu_{\ln MKT}^0$	<u>std. err.</u> 4.611	<u>std. err.</u> 0.050	<u>coefficient</u> μ_{ILLIQ}^0	<u>std. err.</u> 1.752	<u>std. err.</u> 0.020	<u>coefficient</u> $\mu_{\ln IV}^0$	<u>std. err.</u> 6.094	<u>std. err.</u> 0.017
	$\mu_{\ln MKT}^1$	5.840	0.068	μ_{ILLIQ}^1	2.816	0.110	$\mu_{\ln IV}^1$	6.554	0.043
	$\sigma_{\ln MKT}^0$	0.660	0.029	σ_{ILLIQ}^0	0.349	0.015	$\sigma_{\ln IV}^0$	0.240	0.010
	$\sigma_{\ln MKT}^1$	0.697	0.038	σ_{ILLIQ}^1	1.006	0.072	$\sigma_{\ln IV}^1$	0.591	0.034
	q_0	11.473	3.168	q_0	14.932	3.928	q_0	20.421	6.849
	q_1	-4.189	1.371	q_1	-2.005	0.669	q_1	-2.988	1.135
	p_0	-1.766	1.668	p_0	-0.414	3.437	p_0	1.745	1.851
	p_1	2.016	0.895	p_1	0.567	0.629	p_1	0.262	0.363
Model II	$q_t = \frac{e^{q_0 + q_1 \cdot \ln IV_t}}{1 + e^{q_0 + q_1 \cdot \ln IV_t}}; p_t = \frac{e^{p_0 + p_1 \cdot \ln IV_t}}{1 + e^{p_0 + p_1 \cdot \ln IV_t}}$	$q_t = \frac{e^{q_0 + q_1 \cdot \ln IV_t}}{1 + e^{q_0 + q_1 \cdot \ln IV_t}}; p_t = \frac{e^{p_0 + p_1 \cdot \ln IV_t}}{1 + e^{p_0 + p_1 \cdot \ln IV_t}}$	$q_t = \frac{e^{q_0 + q_1 \cdot ILLIQ_t}}{1 + e^{q_0 + q_1 \cdot ILLIQ_t}}; p_t = \frac{e^{p_0 + p_1 \cdot ILLIQ_t}}{1 + e^{p_0 + p_1 \cdot ILLIQ_t}}$						
Estimated Coefficients	<u>coefficient</u> $\mu_{\ln MKT}^0$	<u>std. err.</u> 4.554	<u>std. err.</u> 0.053	<u>coefficient</u> μ_{ILLIQ}^0	<u>std. err.</u> 1.750	<u>std. err.</u> 0.022	<u>coefficient</u> $\mu_{\ln IV}^0$	<u>std. err.</u> 5.985	<u>std. err.</u> 0.019
	$\mu_{\ln MKT}^1$	5.752	0.082	μ_{ILLIQ}^1	2.812	0.125	$\mu_{\ln IV}^1$	6.477	0.032
	$\sigma_{\ln MKT}^0$	0.645	0.030	σ_{ILLIQ}^0	0.352	0.017	$\sigma_{\ln IV}^0$	0.198	0.012
	$\sigma_{\ln MKT}^1$	0.710	0.037	σ_{ILLIQ}^1	0.996	0.078	$\sigma_{\ln IV}^1$	0.496	0.024
	q_0	26.340	11.247	q_0	28.371	9.022	q_0	9.325	2.678
	q_1	-3.797	1.778	q_1	-3.827	1.387	q_1	-2.826	1.165
	p_0	-41.651	18.553	p_0	-12.781	9.512	p_0	2.749	1.486
	p_1	7.004	3.051	p_1	2.424	1.528	p_1	0.496	0.729

Table 3-4: Bivariate Regime-Switching Models with Constant Transition Probabilities

This table reports results related to estimation on bivariate regime-switching model with constant transition probabilities. The Panel A reports the estimated model, and the coefficients obtained from the estimation. Panel B reports the regime-specific characteristics obtained from classifying the months into good state (bad state) if the filtered probability of being in good state (bad state) is more than 0.8. The bivariate regime-switching model is estimated separately on the pair of market volatility and illiquidity, on the pair of market volatility and idiosyncratic volatility, and on the pair of illiquidity and idiosyncratic volatility. The results from each of these three estimations are reported in the three groups (Group-1, Group-2, and Group-3), respectively. In the Panel A, superscript S_t denotes the regime for the regime-specific parameters, with $S_t = 0$ for good regime and $S_t = 1$ for bad regime; $\lnMKT$ is natural log of volatility of market portfolio; $ILLIQ$ is measure of aggregate stock market illiquidity inspired from Amihud (2002); $\lnIV$ is natural log of aggregate idiosyncratic volatility (for details on $\lnMKT$, $ILLIQ$ and $\lnIV$, see Table 1 discussion); $\mu_{\lnMKT}^{S_t}$, $\mu_{ILLIQ}^{S_t}$ and $\mu_{\lnIV}^{S_t}$ are regime-specific means; $\sigma_{\lnMKT}^{S_t}$, $\sigma_{ILLIQ}^{S_t}$, and $\sigma_{\lnIV}^{S_t}$ are regime-specific standard deviations; $\rho_{\lnMKT, ILLIQ}^{S_t}$, $\rho_{\lnMKT, \lnIV}^{S_t}$, and $\rho_{ILLIQ, \lnIV}^{S_t}$ are regime-specific pair-wise correlations, and the residuals ε_t , η_t and ξ_t are modelled as pair-wise bivariate, standard, normally distributed, random variables. The state variable S_t is modelled with constant transition probabilities, $q = P(S_t^0 | S_{t-1}^0)$ and $p = P(S_t^1 | S_{t-1}^1)$. The regime-specific means, regime-specific standard-deviations, regime-specific correlations, and the transition probabilities are the parameters to be estimated. The models are estimated by maximizing the log-likelihood function for the bivariate normal density while allowing for regime-switching. In Panel B, the parameters MKT and $sdMKT$, IV and $\lnIV$ are alternative measures of market volatility and idiosyncratic volatility, respectively (see Table 1 discussion); and r_M is the returns on market portfolio. The test of differences refers either to the test of differences-in-means across regimes (in context of the levels of the three parameters) or to difference-in-variances across regimes (in context of uncertainty about these parameters). The statistical significance of the test-of-differences is indicated by ***, **, * for p-values at the 0.1%, 1%, and 5%, respectively. The sample period is from July, 1963 to December, 2006.

Panel A: Estimated Model									
	Group 1			Group 2			Group 3		
	$\ln MKT_t = \mu_{\ln MKT}^{S_t} + \sigma_{\ln MKT}^{S_t} \cdot \varepsilon_t$ $ILLIQ_t = \mu_{ILLIQ}^{S_t} + \sigma_{ILLIQ}^{S_t} \cdot \eta_t$			$\ln MKT_t = \mu_{\ln MKT}^{S_t} + \sigma_{\ln MKT}^{S_t} \cdot \varepsilon_t$ $\ln IV_t = \mu_{\ln IV}^{S_t} + \sigma_{\ln IV}^{S_t} \cdot \xi_t$			$ILLIQ_t = \mu_{ILLIQ}^{S_t} + \sigma_{ILLIQ}^{S_t} \cdot \eta_t$ $\ln IV_t = \mu_{\ln IV}^{S_t} + \sigma_{\ln IV}^{S_t} \cdot \xi_t$		
Estimated Coefficients		coefficient	std. err.		coefficient	std. err.		coefficient	std. err.
	$\mu_{\ln MKT}^0$	4.797	0.041	$\mu_{\ln MKT}^0$	4.716	0.063	μ_{ILLIQ}^0	1.759	0.020
	$\mu_{\ln MKT}^1$	5.795	0.086	$\mu_{\ln MKT}^1$	5.382	0.059	μ_{ILLIQ}^1	2.844	0.116
	μ_{ILLIQ}^0	1.752	0.020	$\mu_{\ln IV}^0$	5.944	0.023	$\mu_{\ln IV}^0$	6.128	0.018
	μ_{ILLIQ}^1	2.722	0.103	$\mu_{\ln IV}^1$	6.587	0.027	$\mu_{\ln IV}^1$	6.760	0.058
	$\sigma_{\ln MKT}^0$	0.757	0.029	$\sigma_{\ln MKT}^0$	0.765	0.045	σ_{ILLIQ}^0	0.359	0.017
	$\sigma_{\ln MKT}^1$	0.850	0.056	$\sigma_{\ln MKT}^1$	0.891	0.040	σ_{ILLIQ}^1	1.013	0.064
	σ_{ILLIQ}^0	0.342	0.014	$\sigma_{\ln IV}^0$	0.268	0.014	$\sigma_{\ln IV}^0$	0.334	0.014
	σ_{ILLIQ}^1	1.019	0.072	$\sigma_{\ln IV}^1$	0.394	0.018	$\sigma_{\ln IV}^1$	0.526	0.031
	$\rho_{\ln MKT, ILLIQ}^0$	0.238	0.055	$\rho_{\ln MKT, \ln IV}^0$	0.558	0.056	$\rho_{ILLIQ, \ln IV}^0$	0.221	0.051
	$\rho_{\ln MKT, ILLIQ}^1$	0.487	0.073	$\rho_{\ln MKT, \ln IV}^1$	0.567	0.046	$\rho_{ILLIQ, \ln IV}^1$	0.658	0.034
	q	0.985	0.007	q	0.983	0.009	q	0.986	0.007
	p	0.956	0.018	p	0.983	0.007	p	0.952	0.021

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Panel B: Regime-specific Characteristics									
Regime-Specific Characteristics	Group 1 (Market Volatility and Illiquidity)			Group 2 (Mkt. Volatility and Idio. Volatility)			Group 3 (Illiquidity and Idio. Volatility)		
	Good Regime (Regime=0)	Bad Regime (Regime=1)	Test of Differences	Good Regime (Regime=0)	Bad Regime (Regime=1)	Test of Differences	Good Regime (Regime=0)	Bad Regime (Regime=1)	Test of Differences
N (# months)	370	119		240	255		388	105	
Levels									
Mean(MKT)	152.74	530.14	377.40***	136.65	344.07	207.42***	158.75	563.06	404.31***
Mean(sdMKT)	11.54	20.60	9.06***	10.94	16.45	5.50***	11.77	21.16	9.39***
Mean(lnMKT)	4.76	5.86	1.11***	4.65	5.39	0.74***	4.79	5.90	1.11***
Mean(IV)	476.27	986.99	510.72***	385.49	804.61	419.11***	478.01	1046.29	568.28***
Mean(sdIV)	21.53	30.26	8.73***	19.48	27.64	8.16***	21.58	31.21	9.63***
Mean(lnIV)	6.11	6.75	0.64***	5.92	6.60	0.67***	6.12	6.81	0.69***
Mean(ILLIQ)	1.74	2.83	1.09***	1.69	2.27	0.57***	1.75	2.94	1.19***
Standard Deviations									
Std. Dev. (MKT)	130.72	805.46	674.75***	112.49	577.33	464.83***	133.15	851.53	718.38***
Std. Dev. (sdMKT)	4.43	10.33	5.90***	4.12	8.60	4.48***	4.51	10.80	6.29***
Std. Dev. (lnMKT)	0.74	0.86	0.11*	0.74	0.89	0.15***	0.75	0.88	0.13**
Std. Dev. (IV)	155.04	584.87	429.83***	94.82	439.17	344.35***	153.82	596.96	443.15***
Std. Dev. (sdIV)	3.55	8.47	4.92***	2.47	6.38	3.92***	3.52	8.54	5.03***
Std. Dev. (lnIV)	0.34	0.53	0.19***	0.26	0.40	0.13***	0.33	0.53	0.20***
Std. Dev. (ILLIQ)	0.34	1.01	0.67***	0.54	0.78	0.24***	0.35	0.99	0.64***
Pair-wise Correlations									
Correl(MKT,ILLIQ)	0.162	0.189		0.419	0.293		0.161	0.158	
Correl(sdMKT,ILLIQ)	0.187	0.330		0.427	0.412		0.185	0.284	
Correl(lnMKT,ILLIQ)	0.206	0.451		0.402	0.418		0.205	0.404	
Correl(MKT,IV)	0.446	0.313		0.447	0.402		0.444	0.294	
Correl(sdMKT,sdIV)	0.467	0.450		0.483	0.550		0.465	0.427	
Correl(lnMKT,lnIV)	0.481	0.522		0.510	0.562		0.482	0.502	
Correl(ILLIQ,IV)	0.173	0.598		0.224	0.723		0.160	0.575	
Correl(ILLIQ,sdIV)	0.185	0.635		0.212	0.738		0.171	0.611	
Correl(ILLIQ,lnIV)	0.195	0.662		0.200	0.735		0.180	0.639	
Stock Returns									
Mean (r_M)	1.22	-0.03	-1.25*	0.93	0.96	0.03	1.30	-0.24	-1.54*

Table 3-5: Granger Causality

This table presents reports the p-values of Granger-causality VAR tests. In Panel A, only the row and column series are included in the VAR; in Panel B, all three series are included. The VAR is estimated with K lags and a constant term, and uses 522 observations. For the bivariate case, the number of lags is reported in parenthesis. For the trivariate case, we use 4 lags. The number of lags is chosen using the Akaike Information Criterion (AIC)., MKT is the market volatility and is measured as the variance of the daily returns on CRSP value-weighted NYSE/AMEX/NASDAQ portfolio. ILLIQ is the Amihud (2002) inspired measure of aggregate stock market illiquidity. IV is aggregate idiosyncratic volatility and is measured as the value-weighted cross-sectional average of individual stocks' variance of daily residuals from Fama and French (1989) three factor model. The sample period is from July, 1963 to December, 2006.

Panel A: Bivariate VAR			
	MKT_t	$ILLIQ_t$	IV_t
MKT_{t-1}	-	0.0616 R ² =0.80 [K=5]	0.0000 R ² =0.78 [K=4]
$ILLIQ_{t-1}$	0.0041 R ² =0.10 [K=5]	-	0.0000 R ² =0.79 [K=9]
IV_{t-1}	0.0001 R ² =0.11 [K=4]	0.0552 R ² =0.81 [K=9]	-
Panel B: Trivariate VAR			
	MKT_t	$ILLIQ_t$	IV_t
MKT_{t-1}	-	0.0007	0.0003
$ILLIQ_{t-1}$	0.3733	-	0.0003
IV_{t-1}	0.0006 R ² =0.11	0.0013 R ² =0.81	- R ² =0.79

Table 3-6: The effect of Market Volatility, Illiquidity on Expected Stock Returns

This table reports results from the regression $R_{M,t} - R_{f,t} = \alpha_0 + \beta_0 \cdot ILLIQ_t^E + \beta_1 \cdot ILLIQ_t^U + \delta_0 \cdot MKT_t^E + \delta_1 \cdot MKT_t^U + \varepsilon_t$ where $R_{M,t}$ and $R_{f,t}$ is the return on market portfolio and risk-free asset, respectively; $ILLIQ_t^E$ and $ILLIQ_t^U$ are the expected and unexpected aggregate stock market illiquidity from the trivariate VAR model in Table 3-5; Similarly, MKT_t^E and MKT_t^U are the expected and the unexpected volatility of market portfolio, respectively, obtained from the trivariate VAR model. ε_t^{ILLIQ} represents the residuals from the constrained regression in which excess returns are regressed against only aggregate market illiquidity (that is, $\beta_0 = \beta_1 = 0$). On similar lines, ε_t^{MKT} represents the residuals from the constrained regression in which excess returns are regressed against only market volatility (that is, $\delta_0 = \delta_1 = 0$). The period of estimation is from July, 1963 to December, 2006. The p-values are in parenthesis.

	[1]	[2]	[3]	[4]	[5]
	$R_{M,t} - R_{f,t}$	$R_{M,t} - R_{f,t}$	$R_{M,t} - R_{f,t}$	ε_t^{ILLIQ}	ε_t^{MKT}
α_0	1.063 [0.058]	0.462 [0.201]	1.257 [0.026]	-0.254 [0.449]	0.603 [0.273]
$ILLIQ_t^E$	-0.2962 [0.265]		-0.680 [0.081]		-0.301 [0.248]
$ILLIQ_t^U$	-5.947 [0.000]		-5.033 [0.000]		-4.521 [0.000]
MKT_t^E		0.299 x 10 ⁻⁴ [0.981]	23.10 x 10 ⁻⁴ [0.187]	10.11 x 10 ⁻⁴ [0.380]	
MKT_t^U		-35.55 x 10 ⁻⁴ [0.000]	-22.80 x 10 ⁻⁴ [0.000]	-20.49 x 10 ⁻⁴ [0.000]	
R^2	22.11%	10.54%	23.12%	1.26%	12.36%

Appendix A: Comparison of different measures of Idiosyncratic Volatility

In this appendix, we show that the idiosyncratic volatility measured with respect to different asset pricing models have very high correlations among themselves, and hence the choice of the asset pricing model is unlikely to affect the findings of the paper.

We know the return for each stock can be written as the sum of its systematic return component and its firm-specific return component. Idiosyncratic volatility of the security is computed as variance of the firm-specific residuals. The challenge is that while the return of the security is observable, the individual components are not. In practice, one uses an asset pricing model to decompose the security's return. In the literature, researchers have used one or more of the following models to proxy idiosyncratic volatility:

1. CLMX(2001) $R_{i,t} = R_{ind,t} + \varepsilon_{i,t}$
where $R_{ind,t}$ is the excess returns on the value-weighted portfolio of firms that belong to same industry as firm i .
2. Market Adjusted Model $R_{i,t} = R_{M,t} + \varepsilon_{i,t}$
3. Market Model $R_{i,t} = \beta_i R_{M,t} + \varepsilon_{i,t}$
4. 3-factor Model (FF) $R_{i,t} = \beta_{i,1} R_{M,t} + \beta_{i,2} SMB_t + \beta_{i,3} HML_t + \varepsilon_{i,t}$
5. 4-factor Model $R_{i,t} = \beta_{i,1} R_{M,t} + \beta_{i,2} SMB_t + \beta_{i,3} HML_t + \beta_{i,4} UMD_t + \varepsilon_{i,t}$
6. Variant of Market Adjusted $R_{i,t} = R_{M,t}^{ew} + \varepsilon_{i,t}$
where $R_{M,t}^{ew}$ is the excess returns on the equally-weighted market portfolio.

We compute the aggregate idiosyncratic volatility as the value-weighted average of the individual stock's variance of daily residual from each of the above six asset pricing model. The pair-wise correlations among the various measures are shown in the Table A1.

Table A1: Comparison of different measures of Idiosyncratic Volatility

	CLMX	MA	MM	3-factor	4-factor	MA (ew)
CLMX	1					
MA	0.995	1				
MM	0.990	0.988	1			
3-factor	0.982	0.978	0.987	1		
4-factor	0.975	0.968	0.978	0.992	1	
MA (ew)	0.992	0.996	0.984	0.969	0.956	1

Appendix B: Trivariate Regime-Switching Model

This table reports results related to estimation on trivariate regime-switching model with constant transition probabilities. The table is divided into two panels (Panel A and Panel B). Panel A reports the estimated model, and the coefficients obtained from the estimation. Panel B reports the regime-specific characteristics obtained from classifying the months into good state (bad state) if the filtered probability of being in good state (bad state) is more than 0.8. The trivariate regime-switching model is estimated on the market volatility illiquidity, and idiosyncratic volatility. In the Panel A, superscript S_t denotes the regime for the regime-specific parameters, with $S_t = 0$ for good regime and $S_t = 1$ for bad regime; $\ln\text{MKT}$ is natural log of volatility of market portfolio; ILLIQ is Amihud inspired measure of illiquidity; $\ln\text{IV}$ is natural log of aggregate idiosyncratic volatility (for details on $\ln\text{MKT}$, ILLIQ and $\ln\text{IV}$, see Table 1 discussion); $\mu_{\ln\text{MKT}}^{S_t}$, $\mu_{\text{ILLIQ}}^{S_t}$ and $\mu_{\ln\text{IV}}^{S_t}$ are regime-specific means; $\sigma_{\ln\text{MKT}}^{S_t}$, $\sigma_{\text{ILLIQ}}^{S_t}$, and $\sigma_{\ln\text{IV}}^{S_t}$ are regime-specific standard deviations; $\rho_{\ln\text{MKT},\text{ILLIQ}}^{S_t}$, $\rho_{\ln\text{MKT},\ln\text{IV}}^{S_t}$, and $\rho_{\text{ILLIQ},\ln\text{IV}}^{S_t}$ are regime-specific pair-wise correlations, and the residuals ε_t , η_t and ξ_t are modelled as trivariate, standard, normally distributed, random variables. The state variable S_t is modelled with constant transition probabilities, $q = P(S_t^0 | S_{t-1}^0)$ and $p = P(S_t^1 | S_{t-1}^1)$. The regime-specific means, standard-deviations, correlations, and the transition probabilities are regime-specific parameters to be estimated. The models are estimated by maximizing the log-likelihood function for the trivariate normal density while allowing for regime-switching. In Panel B, the parameters MKT and sdMKT , IV and $\ln\text{IV}$ are alternative measures of market volatility and idiosyncratic volatility, respectively (see Table 1 discussion); and r_M is the returns on market portfolio. The test of differences refers either to the test of differences-in-means across regimes (in context of the levels of the three parameters) or to difference-in-variances across regimes (in context of uncertainty about these parameters). The statistical significance of the test-of-differences is indicated by ***, **, * for p-values at the 0.1%, 1%, and 5%, respectively. The sample period is from July, 1963 to December, 2006.

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Panel A:

Trivariate Regime Switching Model	$\ln MKT_t = \mu_{\ln MKT}^S + \sigma_{\ln MKT}^S \cdot \varepsilon_t$ $ILLIQ_t = \mu_{ILLIQ}^S + \sigma_{ILLIQ}^S \cdot \eta_t$ $\ln IV_t = \mu_{\ln IV}^S + \sigma_{\ln IV}^S \cdot \xi_t$		
	coefficient	std. err.	
Estimated Coefficients	$\mu_{\ln MKT}^0$	4.827	0.037
	$\mu_{\ln MKT}^1$	6.018	0.080
	μ_{ILLIQ}^0	1.734	0.020
	μ_{ILLIQ}^1	3.144	0.082
	$\mu_{\ln IV}^0$	6.128	0.015
	$\mu_{\ln IV}^1$	6.871	0.055
	$\sigma_{\ln MKT}^0$	0.762	0.027
	$\sigma_{\ln MKT}^1$	0.773	0.053
	σ_{ILLIQ}^0	0.403	0.014
	σ_{ILLIQ}^1	0.712	0.050
	$\sigma_{\ln IV}^0$	0.332	0.011
	$\sigma_{\ln IV}^1$	0.482	0.038
	$\rho_{\ln MKT, ILLIQ}^0$	0.273	0.039
	$\rho_{\ln MKT, ILLIQ}^1$	0.126	0.090
	$\rho_{\ln MKT, \ln IV}^0$	0.506	0.037
	$\rho_{\ln MKT, \ln IV}^1$	0.359	0.083
	$\rho_{ILLIQ, \ln IV}^0$	0.230	0.040
	$\rho_{ILLIQ, \ln IV}^1$	0.492	0.073
	q	0.990	0.004
	p	0.957	0.020

Panel B:

Regime-Specific Characteristics	Good Regime (Regime=0)	Bad Regime (Regime=1)	Test of Differences
N (# months)	412	92	
Levels			
Mean(MKT)	159.33	619.15	459.81***
Mean(sdMKT)	11.79	22.50	10.71***
Mean(lnMKT)	4.80	6.07	1.27***
Mean(IV)	477.84	1126.27	648.43***
Mean(sdIV)	21.58	32.57	10.98***
Mean(lnIV)	6.12	6.91	0.79***
Mean(ILLIQ)	1.72	3.18	1.46***
Standard Deviations			
Std. Dev. (MKT)	132.89	893.45	760.56***
Std. Dev. (sdMKT)	4.50	10.68	6.18***
Std. Dev. (lnMKT)	0.75	0.76	0.01
Std. Dev. (IV)	152.23	591.98	439.74***
Std. Dev. (sdIV)	3.47	8.15	4.67***
Std. Dev. (lnIV)	0.33	0.48	0.15***
Std. Dev. (ILLIQ)	0.40	0.72	0.33***
Pair-wise Correlations			
Correl(MKT, ILLIQ)	0.203	0.046	
Correl(sdMKT, ILLIQ)	0.224	0.060	
Correl(lnMKT, ILLIQ)	0.234	0.053	
Correl(MKT, IV)	0.455	0.247	
Correl(sdMKT, sdIV)	0.471	0.325	
Correl(lnMKT, lnIV)	0.483	0.332	
Correl(ILLIQ, IV)	0.198	0.497	
Correl(ILLIQ, sdIV)	0.203	0.482	
Correl(ILLIQ, lnIV)	0.204	0.453	
Stock Returns			
Mean (r _M)	1.25	-0.44	-1.68*

CHAPTER 4

CONCLUSION

This dissertation consists of two essays. In the first paper, we study how the correlations between stock portfolios and Treasury bonds vary jointly with the stock's volatility and the stock's illiquidity. In a time series, we find that the tendency of the bonds and stocks to move together on day t as well as the stock-bond correlation over days $t+1$ to $t+22$ decreases with the realized market volatility and the market illiquidity estimated over the previous 22-trading-days ($t-22$ to $t-1$). Both the price impact and return reversal measure of illiquidity are informative at an individual level. However, only Amihud's price impact measure is incrementally informative once we control for stock volatility. We also find the lagged market volatility remains informative even after controlling either of the lagged illiquidity measures. Our results are qualitatively similar across alternate empirical frameworks and across different sample periods (including the 1986-2004 subperiod over which inflation has been fairly constant). Further, our findings results are not only statistically significant but also appear to be economically significant.

In the cross-section of stocks, both a stock's illiquidity and stock's volatility is informative about the variation in correlation of bonds with stock portfolios. We find that the negative relation between illiquidity and stock-bond correlation is visible across all volatility quintiles, and both during uncertain and stable market conditions. Our results also indicate that during times of stress, a stock's illiquidity is more informative about the cross-sectional variation in the correlation changes than is a stock's volatility.

From our time series and cross sectional analysis, market volatility appears better at identifying the times when stock-bond correlations become more negative, but illiquidity appears better at identifying which stocks have stronger correlation variation.

Finally, with respect to the information the two illiquidity measures contain regarding future stock-bond comovements, the results for Pastor and Stambaugh measure are in sharp contrast to the results for Amihud measure. Amihud measure is informative even after controlling for volatility both at aggregate and cross-sectional level, whereas Pastor and Stambaugh measure has no information at cross-section level and is uninformative at aggregate level once one controls for volatility. Therefore, in this setting, the Amihud (2002) price impact measure of illiquidity performs better than Pastor and Stambaugh (2003) return reversal measure of illiquidity.

This paper presents a statistical description, rather than a structural economic model, of movements and co-movements in stock market volatility, illiquidity and idiosyncratic volatility. We use daily stock data from 1963 to 2006 to construct realized monthly values for the three variables, which we then use as observables. In our study, market volatility is the variance of the daily returns on a value-weighted market portfolio, illiquidity measure is the Amihud's (2002) illiquidity ratio for the aggregate market, and the idiosyncratic volatility is the value-weighted cross-sectional average of individual stocks' variance of daily residuals from Fama and French three factor model.

We find that the three variables of interest, as expected, are highly correlated. In our two-state, univariate and multivariate regime-switching models, we find strong evidence that the three variables have both higher means and higher standard deviations during the bad regime. The result holds irrespective of the information set used to classify the regimes.

That is, we get regimes with similar characteristics from the univariate and bivariate (and also the results from trivariate) regime-switching models. Our findings suggest that these measures contain much of the same information about the underlying condition of the market economy. These results are further supported by Granger-causality tests, in which we find that each of these series have some ability in forecasting the other two series.

With respect to the regime-specific pair-wise correlations in these variables, the results are mixed. While we find strong evidence that the correlation between illiquidity and idiosyncratic volatility is higher in the bad regime, we find no clear regime-specific trend in correlation between market volatility and illiquidity, and between market volatility and idiosyncratic volatility.

We provide a simple illustration how our findings may have important bearing on research that show that variables affect stock market returns. We find that the joint explanatory power of the market volatility and illiquidity (in explaining the variation in stock returns) is not much different than that of illiquidity alone. This suggests that the study that only examines the relation between returns and market volatility may attribute a return pattern to price-volatility effects, when it might be more of price-liquidity effect (or some combination of the two effects).

Another implication from this paper stems from the finding that the state with higher mean values is also the state with higher standard deviation of these measures. In an asset pricing framework, it would be interesting to study the incremental effect on the stock returns of the levels of these measures and of their standard deviations. For instance, this paper finds that both the level and volatility of volatility is higher during bad times. A

natural research question to ask is: do the investors care about market volatility or the volatility of market volatility?

REFERENCES

- Acharya, V. and L. H. Pedersen, 2005, "Asset pricing with liquidity risk," *Journal of Financial Economics*, 77, 375-410.
- Admati, A., and P. Pfleiderer, 1988, "A theory of intraday patterns: Volume and price variability," *Review of Financial Studies* 1, 3-40.
- Amihud, Y., 2002, "Illiquidity and stock returns: Cross-section and time-series effects," *Journal of Financial Markets*, 5, 31-56.
- Amihud, Y., and H. Mendelson, 1980, "Dealership market: Market-making with inventory," *Journal of Financial Economics* 8, 31-53.
- Ang A. and J. Chen, 2002, "Asymmetric Correlations of Equity Portfolios," *Journal of Financial Economics*, 63, 3, 443-494.
- Baker, M. and J. Wurgler, 2005, "Government bond and cross-section of stock returns," Working Paper.
- Bali, T., N. Cakici, X. Yan, and Z. Zhang, 2005, "Does Idiosyncratic Risk Really Matter?" *Journal of Finance*, 60, 905-929.
- Barsky, R.B., 1989, "Why Don't the Prices of Stocks and Bonds Move Together?" *American Economic Review*, 79, 1132-1145.
- Beber, A., M. W. Brandt and K. A. Kavajecz, 2007, "Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market," Working paper available at SSRN: <http://ssrn.com/abstract=891736>
- Bekaert, G., and S.R. Grenadier, 2001, "Stock and Bond Pricing in an Affine Economy," Working Paper, Columbia Business School.
- Benston, G., and R. Hagerman, 1974, "Determinant of Bid-Asked Spreads in the Over-the-Counter Market," *Journal of Financial Economics*, 1(4), 353-364.
- Bollerslev, T. and J. Wooldridge, 1992, "Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances," *Econometric Reviews*, 11, 143-172.
- Brandt, M., A. Brav, and J. Graham, 2005, "The idiosyncratic volatility puzzle: Time trend or speculative episodes?" Fuqua School of Business working paper.

- Brennan, M.J. and A. Subrahmanyam, 1996, "Market microstructure and asset pricing: On the compensation for illiquidity in stock returns," *Journal of Financial Economics*, 41, 441-464.
- Brunnermeier, M. and L. H. Pedersen, 2007, "Market Liquidity and Funding Liquidity," NBER Working Paper No. W12939, Available at SSRN: <http://ssrn.com/abstract=965131>
- Campbell, J. Y., and J. Ammer, 1993, "What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns," *Journal of Finance*, 48, 3-37.
- Campbell, J., M. Lettau, B. Malkiel, and Y. Xu, 2001, "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," *Journal of Finance*, 56, 1-43.
- Carlin, B. I., M. S. Lobo, and S. Viswanathan, 2007, "Episodic liquidity crises: Cooperative and predatory trading," *Journal of Finance*, forthcoming.
- Chordia, T., R. Roll, and A. Subrahmanyam, 2001, "Market liquidity and trading activity," *Journal of Finance*, 56, 501-530.
- Chordia, T., A. Sarkar, and A. Subrahmanyam, 2005, "An empirical analysis of stock and bond market liquidity," *Review of Financial Studies*, 18, 87-129.
- Connolly, R., C. Stivers, and L. Sun, 2005, "Stock market uncertainty and the stock-bond return relation," *Journal of Financial and Quantitative Analysis*, 40, 161-194.
- Connolly, R., C. Stivers, and L. Sun, 2007, "Commonality in the Time-variation of Stock-Stock and Stock-Bond Return Comovements," *Journal of Financial Markets*, 10, 192-218.
- Deuskar, P., 2006, "Extrapolative Expectations: Implications for Volatility and Liquidity," Working Paper Available at SSRN: <http://ssrn.com/abstract=891539>
- Fleming, J., C. Kirby, and B. Ostdiek, 1998, "Information and volatility linkages in the stock, bond, and money markets," *Journal of Financial Economics*, 49, 111-137.
- Fleming, J., C. Kirby, and B. Ostdiek, 2001, "The economic value of volatility timing," *Journal of Finance*, 56, 329-352.
- Fleming, J., C. Kirby, and B. Ostdiek, 2003, "The economic value of volatility timing using 'realized' volatility," *Journal of Financial Economics*, 67, 473-509.
- Forbes, K. and R. Rigobon, 2002, "No Contagion. Only Interdependence: Measuring Stock Market Comovements," *Journal of Finance*, 57, 2223-2261.
- Foster, F.D., and S. Viswanathan, 1990, "A theory of intraday variations in volumes, variances and trading costs in securities markets," *Review of Financial Studies*, 3, 593-624.

French, K., G. Schwert and R. Stambaugh, 1987, "Expected Stock Returns and Volatility," *Journal of Financial Economics*, 19, 3-30.

Fujimoto, A., 2004, "Macroeconomic Sources of Systematic Liquidity," Working paper.

Ghysels, E., P. Santa-Clara and R. Valkanov, 2005, "There is a Risk Return Tradeoff After All," *Journal of Financial Economics*, 76, 509-548.

Glosten, L., R. Jagannathan and D. Runkle, 1993, "On the Relation Between Expected Value and the Volatility of the Nominal Excess Return on Stocks," *Journal of Finance*, 48, 1779-1801.

Goldreich, D., B. Hanke and P. Nath, 2005, "The price of future liquidity: Time-varying liquidity in the U.S. Treasury market," *Review of Finance*, 9, 1-32.

Goyal, A. and P. Santa-Clara, 2003, "Idiosyncratic Risk Matters!" *Journal of Finance*, 58, 975-1007.

Goyenko, R., 2006, "Stock and Bond Pricing with Liquidity Risk," Working Paper Available at SSRN: <http://ssrn.com/abstract=669921>

Goyenko, R. and A. Ukhov, 2007, "Stock and Bond Market Liquidity: A Long-Run Empirical Analysis," Working Paper Available at SSRN: <http://ssrn.com/abstract=669942>

Grossman, S. J. and M. H. Miller, 1988, "Liquidity and Market Structure," *Journal of Finance*, 43(3), 617-633.

Gulko, L., 2002, "Decoupling," *Journal of Portfolio Management*, 28, 59-66.

Guo, H. and R. Savickas, 2007, "Average Idiosyncratic Volatility in G7 Countries," *Review of Financial Studies*, forthcoming.

Hartmann, P., S. Straetmans, and C. Devries, 2004, "Asset Market Linkages in Crisis Periods," *Review of Economics and Statistics*, 86, 313-326.

Hasbrouck, J., 2006, "Trading costs and returns for US equities: The evidence from daily data," Working paper, New York University.

Henry, T. R. and J. T. Scruggs, 2007, "Expected Returns and Markov-Switching Illiquidity," Available at SSRN: <http://ssrn.com/abstract=967462>

Ho, T.S.Y. and H.R. Stoll, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial Economics* 9, 47-73.

Jones, C. M., O. Lamont, and R. Lumsdaine, 1998, "Macroeconomic News and Bond Market Volatility," *Journal of Financial Economics*, 47, 315-337.

- Kim, C., J.C. Morley, and C.R. Nelson, 2004, "Is there a positive relationship between stock market volatility and the equity premium," *Journal of Money, Credit, and Banking*, 36, 339-360.
- Kodres, L. and M. Pritsker, 2002, "A Rational Expectations Model of Financial Contagion," *Journal of Finance*, 57 (2), 769-799.
- Kyle, A. S., 1985, "Continuous Auctions and Insider Trading," *Econometrica*, 53 (6), 1315-1335.
- Li, L., 2002, "Macroeconomic Factors and the Correlation of Stock and Bond Returns," Yale ICF Working Paper No. 02-46.
- Longstaff, F., 2004, "The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices," *Journal of Business*, 77, 511-526.
- Lundblad C., 2007, "The Risk Return Tradeoff in the Long-Run: 1836-2003," *Journal of Financial Economics*, 85, 123-150.
- Mamaysky, H., 2002, "Market Prices of Risk and Return Predictability in a Joint Stock-Bond Pricing Model," Working Paper, Yale University.
- Mayfield, S., 2004, "Estimating the Market Risk Premium," *Journal of Financial Economics*, 73, 465-496.
- Merton, R., 1987, "A Simple Model of Capital Market Equilibrium with Incomplete information," *Journal of Finance*, 42(3), 483-510.
- Newey, W. and K. West, 1987, "A Simple Positive Semi-Definite. Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703-708.
- Pastor, L. and R. F. Stambaugh, 2003, "Liquidity risk and expected stock returns," *Journal of Political Economy*, 111, 642-685.
- Scholes, M., 2000, "Crisis and Risk Management," *American Economic Review, Papers and Proceedings*, 90, 17-21.
- Scruggs, J., 1998, "Resolving the Puzzling Intertemporal Relation Between the Market Risk Premium and Conditional Market Variance: A Two-Factor Approach," *Journal of Finance*, 53, 575-603.
- Scruggs, J. and P. Glabadanidis, 2003, "Risk premia and the dynamic covariance between stock and bond returns," *Journal of Financial and Quantitative Analysis*, 38, 295-316.
- Shiller, R. and A. Beltratti, 1992, "Stock prices and bond yields: Can their comovements be explained in terms of present value models?" *Journal of Monetary Economics*, 6, 405-434.

Shleifer, A. and R. Vishny, 1997, "The Limits to Arbitrage," *Journal of Finance*, 52, 35-55.

Spiegel, M. and X. Wang, 2005, "Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk," Working Paper, Yale University.

Stoll, H.R., 1978a, "The pricing of security dealer services: An empirical study of NASDAQ stocks," *Journal of Finance* 33, 1153–1172.

Stoll, H.R., 1978b, "The supply of dealer services in securities markets," *Journal of Finance* 33, 1133–1151.

Stoll, H. R., 2000, Friction, *Journal of Finance* 55, 1479 – 1514.

Stoll, H.R., 2003, Market microstructure, in G.M. Constantinides, M. Harris, and R. Stulz (eds), vol. 1A of *Handbook of the Economics of Finance*, chap. 9.

Tinic, S., 1972, "The economics of liquidity services," *Quarterly Journal of Economic*, 86, 79–93.

Turner, C., R. Startz, C. Nelson, 1989, "A Markov Model of Heterskedasticity, Risk, and Learning in the Stock Market," *Journal of Financial Economics*, 25, 3-22.

Underwood, S., 2006, "The Cross-Market Information Content of Stock and Bond Order Flow," Available at SSRN: <http://ssrn.com/abstract=686969>

Vayanos, D., 2004, "Flight to Quality, Flight to Liquidity, and the Pricing of Risk," NBER Working Paper No. W10327. Available at SSRN: <http://ssrn.com/abstract=509858>

Whitelaw, R. 2000, "Stock Market Risk and Return: An Equilibrium Approach," *Review of Financial Studies*, 13, 521-547.