The interrelation of Liquidity Risk, Default Risk, and Equity Returns

Maria Vassalou[*], Jing Chen[**], and Lihong Zhou[***]
Columbia University

First draft: May 4, 2005
This draft: December 7, 2005

[*] Corresponding Author. Associate Professor of Finance, Graduate School of Business, Columbia University, 416 Uris Hall, 3022 Broadway, New York, NY 10027. tel: 212-854 4104, e-mail: maria.vassalou@columbia.edu.

[**] Ph.D Candidate, Graduate School of Business, Columbia University. e-mail: jc2017@columbia.edu

[***] PhD Candidate, Graduate School of Business, Columbia University, e-mail: lz2004@columbia.edu

The relation between liquidity risk and default risk in equity returns

Abstract

As proxies for liquidity risk we consider the Pastor-Stambaugh measure, as well as the turnover and illiquidity measures. The default measure of choice is the one based on Merton's (1974) contingent claims approach. The alternative liquidity measures contain very different information about liquidity and share low correlations. However, they are all related to our default measure. Vector autoregressive tests reveal the existence of a two-way causal relation between default risk and stock market returns. Liquidity risk does not affect the future path of stock market returns. These relations hold, even when we take into account the correlation of the default and liquidity measures with aggregate stock market volatility. Low liquidity stocks earn higher returns than high liquidity stocks, only if these stocks also have high default risk, but in no other case. In contrast, high default risk stocks always earn higher returns than low default risk stocks, independently of their liquidity level. The inclusion of default and liquidity variables in popular asset pricing specifications improves the model's performance, but the improvement is larger in the case of the inclusion of the default variable. Finally, in the presence of the default variable, the inclusion of a liquidity proxy in the specification results in a marginal improvement of the model's performance, but the opposite is not true. Our findings regarding the interrelation of default and liquidity risk and their effects on equity returns are independent of the liquidity proxy considered.

JEL Classification: G11, G12.

Keywords: liquidity, default, risk, equity returns.

Investors are concerned about liquidity risk. It affects their ability to trade the quantity of stocks they want to buy or sell within their desired time-framework. Most importantly, investors fear that in the event of a financial crisis, they may not be able to exit the market fast enough to contain their losses. These considerations may lead them to shy away from illiquid securities, or require a liquidity-related risk premium to hold them.

Given the importance that liquidity risk has in trading assets, it is no surprise that it has received a large amount of attention in academic research. One of the main concerns in this literature is the construction of a liquidity measure that adequately captures this multifaceted phenomenon. While there are several available, none of them is unambiguously considered the dominant or preferred one so far. This fact, however, should not prevent us from trying to understand the causes and effects that liquidity may have on asset returns.

The current study aims to improve our understanding on the sources of liquidity risk and the effects that it has on one particular asset class: equities. To that end, we study the interrelation of liquidity risk, defined in alternative ways, with default risk.

There are good reasons why one should study the interrelation of liquidity and default risk. It is well-known that both vary with the business cycle. Both are of high concern to the investors. Low liquidity can be viewed as a deterioration of the terms of trade investors face, while high default risk, and in particular bankruptcies, render worthless any holdings of equities affected by them. Besides, it is economically intuitive to hypothesize that the two notions can be related. For instance, when default risk is high, it is plausible to expect that liquidity will be low, as there may be fewer buyers in the market willing to hold stocks with high default risk. Similarly, it could be the case that low liquidity increases the probability of firms to go bankrupt, leading to an increase in default risk in the market by reducing the firms' ability to raise capital.

As proxies for liquidity risk, we consider three alternative and popular measures. They are Pastor and Stambaugh's (2003) return reversal measure, Amihud's (2002) illiquidity ratio, and Amihud and Mendelson's (1986) turnover ratio. While we use three measures to proxy for liquidity risk, we consider only one to capture default risk. It is a measure based on Merton's (1974) contingent claims approach. This is a rather simple measure, but commercial versions of it are widely used by practitioners. All four measures used in this study are discussed in detailed in Section 1.

Our decision to limit our tests to only one measure of default risk was motivated by two factors. First, Merton's model is simple and easy to implement, and it does have significant ability to predict future defaults (see for instance, Vassalou and Xing (2004)), although critics may argue that more sophisticated versions of it may be able to do it better. Second, the results of this study show that even on the basis of this simple default measure we employ, we find strong two-way causal relations between default risk and stock market returns that go beyond the relation of our default measure with stock market volatility. Given the nature of our empirical results, and the scope of this study, we limit ourselves to studying only the relation of the alternative liquidity measures with our default measure and stock market returns.

We start our analysis by examining the commonality in the information contained in the three liquidity measures and our default risk proxy. We show that all three liquidity measures are correlated with our default measure, but they are not highly correlated among themselves. Regression and Vector Autoregressive (VAR) tests confirm this result. We then examine in detail the interrelation of the alternative liquidity proxies with our default measure. Despite the fact that the three liquidity measures are not highly correlated, our results regarding the interrelation of default and liquidity risks with stock market returns are largely consistent across the alternative liquidity proxies examined. Our tests show the existence of a strong two-way causal relation between default risk and stock market returns. Default risk Granger-causes stock market returns, and the reverse is also true. However, none of the liquidity proxies has the ability to Granger-cause future stock market returns.

Tests of the effects that liquidity risk has on equity returns, conditional on the level of default risk, reveal that low liquidity stocks earn higher returns than high liquidity stocks, only if the stocks involved also exhibit high default risk. In contrast, high default risk stocks earn higher returns than low default risk stocks, independently of how liquid they are. It appears that the liquidity premium earned by equities is conditional on default risk, but the reverse is not true.

Multifactor inefficiency tests, along the lines proposed by Avramov, Chao, and Chordia (2002) show that both the liquidity and default factors help improve the efficiency of the model, when used to augment either the Capital Asset Pricing Model (CAPM) or the Fama-French (1993) specification. However, the improvement resulting from the inclusion of the default factor is greater than that obtained based on any of the alternative liquidity factors. Furthermore, in the presence of the default factor in the specification, the addition of the liquidity factor has a rather marginal effect on improving the efficiency of the market portfolio, while the reverse is again not true. These results are also shown to be independent of the state of the economy, in the sense that they hold regardless of whether the economy experiences an expansion or contraction.

The bottom line obtained from this study is that, although liquidity risk is a legitimate concern in trading equities, it really does matter most when the level of default risk is high. In contrast, default risk affects equity returns, independently of the level of liquidity in the market.

The rest of the paper is organized as follows. Section 1 details the alternative liquidity measures and the default proxy considered. Section 2 discusses the data and provides summary statistics, as well as results on the interrelation of the liquidity and default measures based on simple regression analysis. In Section 3 we use the VAR methodology to examine the interrelation of liquidity risk, default risk, and stock market returns. In Section 4 we repeat some of the tests in Section 3 using the components of the default and liquidity measures which are orthogonal to stock market volatility. The purpose of this section is to verify that the relations we uncover between default, liquidity, and stock returns are not spurious and due to the potential correlation of default and liquidity risks with stock market volatility. Section 5 presents results of conditional tests using a portfolio sorting procedure. In particular, we test whether low liquidity stocks earn higher returns than high liquidity stocks, conditional on their default risk. In addition, we examine whether high default risk stocks earn higher returns than low default risk stocks, conditional on their liquidity level. Section 6 provides evidence on the effects of liquidity and default risks on the cross-section of equity returns. The multifactor inefficiency measure is discussed and tests based on it are presented. We conclude in Section 7 with a summary of our results.

1. Liquidity and Default Risk: The Proxies

Liquidity is an elusive concept. It cannot be observed directly and generally denotes the ability to trade large quantities quickly, at low cost, and without moving the price. Since liquidity has many dimensions, it is hard to proxy it with a single measure. In the literature, there are several alternative measures of liquidity. Here, we will review and consider in our analysis three of them, which are also the most widely cited.

1.1 The Pastor Stambaugh (PS) (2003) return-reversal measure

This measure reflects order flow-induced temporary price fluctuations. Lower liquidity is represented by stronger volume-related return reversals. This measure is motivated by the Campbell, Grossman, and Wang (1993) model. In their symmetric information setting, risk-averse market makers accommodate trades from liquidity or non-informational traders. In providing liquidity, market makers demand compensation in the form of a lower (higher) stock price and a higher expected stock return, when facing selling (buying) order from liquidity traders. Such trades thus cause higher volume return reversals when current trading volume is high.

The firm-specific PS measure for stock i in month t is given by the ordinary least square estimate $ps_{i,t}$ obtained from the following regression:

$$r^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + ps_{i,t} \cdot sign(r^e_{i,d,t}) v_{i,d,t} + \varepsilon_{i,d+1,t} \tag{1}$$

where $r_{i,d,t}$ is the return on stock i on day d in month t; $r^e_{i,d,t}$ is the excess return given by $r_{i,d,t} - r_{m,d,t}$, where $r_{m,d,t}$ is the return on the CRSP value-weighted market return on day

d in month t; and $v_{i,d,t}$ is the dollar volume for stock i on day d in month t. The market-wide PS proxy is then the cross-sectional average of these monthly firm-specific return reversal measures $ps_{i,t}$. To ensure stationarity, the one used in our study is the scaled market-wide proxy PS, which is given by:

$$PS_t = (m_t / m_1) \cdot (1/N_t) \sum_{i=1}^{N_t} ps_{i,t} \tag{2}$$

where m_t is the total dollar value at the end of month $t-1$ of the stocks included in the cross-sectional average in month t, m_1 is the corresponding value for August 1962, and N_t is the number of available stocks in month t. For ease of exposition, we use hereafter lower case notation for firm-specific measures and upper case for the corresponding aggregate market-wide measures.

1.2 Illiquidity ratio

The illiquidity ratio proposed by Amihud (2002) is a proxy for the price impact of a trade. The firm-specific illiquidity ratio $iliq_{i,t}$ for stock i in month t is given by the average daily ratio of the absolute return of a stock to its dollar trading volume over a month.

$$iliq_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|r_{i,d,t}|}{v_{i,d,t}} \tag{3}$$

where $r_{i,d,t}$ and $v_{i,d,t}$ are the return and dollar volume (measured in millions of dollars) for stock i on day d in month *t,* respectively, and $D_{i,t}$ is the number of observations for stock i in month *t*. In our study, the illiquidity ratio measure is computed for stocks with at least 15 return and volume observations during a month and with beginning-of-month stock prices in the range of \$5 and \$1,000. The market-wide illiquidity ratio is then the cross-sectional average of these monthly firm-specific $iliq_{i,t}$. Again, to ensure stationarity, our study uses the scaled market-wide price impact measure, $ILIQ_t$, which is given by:

$$ILIQ_t = \left(m_t \big/ m_1 \right) \cdot \left(1 \big/ \mathrm{N}_t \right) \sum_{i=1}^{\mathrm{N}_t} iliq_{i,t} \tag{4}$$

where m_t is the total dollar value at the end of month *t-1* of the stocks included in the cross-sectional average in month *t,* and m_1 is the corresponding value for August 1962. N_t is the number of available stocks in month *t*.

The illiquidity ratio of Amihud (2002) is a low-frequency analog to the high frequency illiquidity measure of Kyle's (1985) market microstructure model. It corresponds to the response of price to order flow resulting from adverse selection. Amihud (2002) documents that expected stock returns are an increasing function of expected illiquidity, both in cross-sectional and time-series tests. Moreover, he finds that the illiquidity ratio is positively and strongly related to both the price impact and the fixed cost component estimates of Brennan and Subrahmanyam (1996). Hasbrouck (2003) finds that the illiquidity ratio is a valuable price-impact proxy constructed from daily data. In his work, he uses market microstructure data to estimate a measure of Kyle's (1985) lambda and finds that its correlation with Amihud's illiquidity ratio is 0.47 for individual stocks and 0.90 for portfolios. In addition, Amihud (2002) finds that his measure predicts excess market returns, whereas Acharya and Pedersen (2003) show that the innovation in the illiquidity ratio significantly affects the cross-section of stock returns.

1.3 Share Turnover Ratio

The share turnover ratio for a stock is given by the ratio of its trading volume to the number of shares outstanding. It measures the trading activity of a stock. Amihud and Mendelson's (1986) model implies that an asset's return is a decreasing function of its turnover rate. In an intertemporal setting with zero transaction costs, investors will continuously rebalance their portfolios in response to changes in the investment opportunity set. In the presence of transaction costs, such rebalancing will be performed more infrequently, resulting in reduced liquidity for the assets involved. Indeed, a number of studies (Haugen and Baker, 1996; Datar et al., 1998; Hu, 1997a; Rouwenhorst, 1998; Chordia et al., 2001) show that in a cross-sectional comparison, stock returns are a decreasing function of turnover.

The share turnover for stock i in month *t*, $stov_{it}$ is given by the average daily turnover over the month

$$stov_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} stov_{i,d,t} \tag{5}$$

where $stov_{i,d,t}$ is the share turnover for stock i on day *d* in month *t,* and D_{it} is the number of observations for stock i in month *t*. The market-wide turnover is just the cross-sectional average of individual securities' share turnover $stov_{it}$. Again, we use the scaled market-wide turnover TO given by:

$$TO_t = \left(\upsilon_1 / \upsilon_t \right) \left(1 / \mathrm{N}_t \right) \sum_{i=1}^{\mathrm{N}_t} stov_{i,t} \qquad (6)$$

where υ_t is the 24-month moving average of the market turnover through month t-24 to t-1, υ_1 is the value of the market turnover for August 1962, and N_t is the number of stocks included in the average for month *t*.

1.4 Default risk measure

As a proxy for default risk, we use the default measure based on Merton's (1974) contingent claims approach, and recently employed in Vassalou and Xing (2004).

This is a rather simple measure, but one that has been shown to capture at least some of the default-related information in equity returns. Note that so long as we can reject the hypothesis that the liquidity measures considered contain more information about equity returns than the default measure employed, we do not need to search for more informative default proxies. Of course, if we fail to reject the above hypothesis, we will be unable to tell whether the rejection is due to liquidity risk being more dominant in equity returns, or to the inadequacy of our default measure to capture default risk. This case, however does not present itself in our study. In effect, our choice to examine three popular alternative measures of liquidity risk, but only one relatively simple measure of default risk could be viewed as designing the tests to provide an advantage on the onset to the liquidity risk hypothesis. In our view, this adds to the robustness of our results on default risk, as they will be discussed in the sections to follow.

In Merton's model, a firm's equity is viewed as a call option on its assets. In particular, using the Black-Scholes (1973) model, the equity value V_E of the firm is given by

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2), \tag{7}$$

$$d_1 = \frac{ln(V_A / X) + (r + \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}}, d_2 = d_1 - \sigma_A \sqrt{T}$$

where V_A is the market value of firm's assets, X is the exercise price which is proxied by the book value of the debt, r is the risk free rate, N(.) is the cumulative density function of the standard normal distribution, and σ_A is the volatility of the firm's assets.

The distance to default (DD) defines by how many standard deviations should the log of the ratio of the firm's assets to its book value of debt deviate from its mean for default to occur. It is given by:

$$DD_t = \frac{\ln(V_{A,t} / X_t) + (\mu - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}} \tag{8}$$

where μ is the instantaneous mean of the firm's asset returns. The default likelihood indicator (*dli*) of a firm i in month t is then defined by

$$dli_{i,t} = N(-DD) = N(-\frac{\ln(V_{A,i,t} / X_{i,t}) + (\mu - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}}) \tag{9}$$

Note that similarly to Vassalou and Xing (2004), we define the market-wide DLI as the equally-weighted average of all the firms' dli:

$$DLI_t = \frac{1}{N_t} \sum_{i=1}^{N_t} dli_{i,t} \tag{10}$$

where N_t is the number of firms for which dli can be calculated in month t. The market-wide survival rate SV is just one minus DLI.

Vassalou and Xing's default likelihood indicator (DLI) provides the likelihood with which a firm's market value of assets are expected to be below the book value of the firm's liabilities over the next year. The main advantages of the measure over accounting-based alternatives are that it uses market-based information, and can be updated frequently. Details and references on the properties of the measure and its performance are provided in Vassalou and Xing (2004, 2005).

2. Data and Summary Statistics

All individual stock data, that is stock returns, prices, trading volume and market capitalization, are obtained from the CRSP daily stock files. We thank Pastor and Stambaugh for providing us with their market-wide return reversal measure PS. The DLI data are available on Vassalou's website.

Table 1 reports the summary statistics for the three alternative liquidity measures, as well as for the default measure. As Panel B shows, all measures considered are highly autocorrelated, with the least autocorrelated being the PS measure. Panel A reports time-series means and standard deviations. The cross-sectional moments of the four measures are reported in Panel C.

2.1 Simple comparisons among the alternative liquidity measures

Panel A of Table 2 reports the correlation coefficients among the three alternative market-wide liquidity measures examined. Recall that low liquidity is denoted by a high value for $ILIQ$ and low values for PS and TO. As a result, the correlations between $ILIQ$ and PS, as well as $ILIQ$ and TO are negative.

Note that the correlation between TO and PS is only 0.11, which means that the two measures have very little information in common. In addition, the correlation between $ILIQ$ and PS is -0.44 whereas that between $ILIQ$ and TO is -0.48.

Panel B and C report firm-level average correlations. Panel B presents average time series correlations across firms, whereas Panel C contains average cross-sectional correlations across time. In both cases, the correlation coefficients obtained are quite small, and indeed smaller than those referring to the market-wide measures.

The results of Table 2 suggest that the three measures contain markedly different information about liquidity at a firm level.

In Table 3 we report results from regressions of each market-wide liquidity measure on a constant and the other two market-wide liquidity measures. Consistent with our previous evidence, we find that only $ILIQ$ has a statistically significant ability to explain part of the time-series variation of the other two market-wide liquidity measures.

Given that the three liquidity measures are quite distinct in their information content, it may be worthwhile to examine their behavior in more detail within the framework of a Vector Autoregressive (VAR) system. To avoid diverting attention from the main purpose of the paper, which is to examine the interrelation of liquidity and default risk as well as their relative impact on equity returns, this draft presents the liquidity VAR results in Appendix A.

2.2 Contemporaneous relationship between market default risk and market liquidity

It is known that liquidity and default risks vary with the business cycle. During recessions, market default risk tends to rise while market liquidity may be reduced. This implies a potential close relation between market default risk and market liquidity risk which we aim to explore. In this section, we provide some first tests of this hypothesis based on regression analysis.

Table 4 presents results from univariate regressions of each market-wide liquidity proxy (PS, TO, $ILIQ$) on a constant and the market-wide survival rate proxy SV. The sample period runs from January 1971 to December 1998. The end date of our sample is dictated to us by the availability of the PS measure.

Notice that SV helps explain all three market-wide liquidity measures, although they are all quite different from each other, as shown in the previous section and Appendix A. The coefficients on SV are economically intuitive. They suggest that when market default risk is high, and therefore the survival rate is low, market liquidity is low. Recall that low market liquidity is represented by a low TO, low PS, and high $ILIQ$. Note also that the R^2 from the regression of $ILIQ$ on SV is of the order of 31%, indicating that SV explains a substantial proportion of the time-series variation in $ILIQ$. In contrast SV explains just under 5% of the time series variation in the PS measure and 13% of the time series variation of TO.

The results of Table 4 confirm that the default risk measure is contemporaneously correlated with the liquidity measures considered. In the following section, we examine the dynamic interrelation of these two types of risk in the context of a VAR methodology.

2.3 Does default measure capture the same information about liquidity as a volatility variable?

Since there is evidence in the literature of a relation between volatility and liquidity, the default measure we used may simply capture the same information about liquidity as a volatility variable. To address this concern, we explore the relationship among liquidity, default, and volatility in this section.

We first compute the correlations among the three liquidity measures, default measure, and market volatility. The monthly market volatility (noted as VOL) is computed as daily standard deviation of the value-weighted market returns within a month.

The results are reported in Panel A of Table 2. Note that there does exist high correlations between volatility and liquidity. The correlation of VOL with PS is pretty high (-63%), implying that they are closely related to each other. It is also significantly correlated with $ILIQ$ with a correlation coefficient of 43%. The correlation between VOL and TO is quite small, only 2%. This evidence shows that with the exception of TO, liquidity has a high correlation with VOL. As for the relation between market default and market liquidity, the highest correlation is between SV and $ILIQ$, which is -56%. In addition, the correlation between SV and PS is 22%, and 36% between SV and TO. This result confirms the contemporaneous relationship between market default risk and market liquidity in Section 2.2. Note that the correlation between VOL and SV is -41%. These correlation results indicate that both market volatility and market default are related to market liquidity, and SV has some information in common with VOL.

To further examine the relation among liquidity, default, and volatility, we regress market liquidity on both market default and market volatility. Table 4 reports the results. Note that even when we take into account the effect of VOL on market liquidity, the coefficient on the default risk measure is still significant. This implies that market default captures information about liquidity beyond the market volatility effect. The only exception is the PS regression. We see from the correlation table that PS has the highest correlation with VOL. Therefore, PS may largely capture a volatility effect, rather than a liquidity effect.

In conclusion, although there exists a relation among market default, market liquidity and market volatility, market default does not capture the same information about liquidity as a volatility variable.

3. Effects of liquidity and default risk on market returns: A VAR approach

The tests of this section allow us to observe potential causal relations between the liquidity and default variables in the system, as well as quantify the effects that a shock on one variable may have on itself and the others.

For each market-wide liquidity measure, we estimate a three-variable VAR model which includes the liquidity measure itself, SV, and the excess return on the value-weighted market index, $EMKT$. The market index includes all NYSE, AMEX, and NASDAQ stocks (obtained from CRSP), and it is in excess of the one-month Treasury bill rate available from Ibbotson Associates. The lag structure for the VAR is chosen based on the Schwartz Information Criterion.

Table 5 reports three sets of VAR estimation results, one for each of the three market-wide liquidity proxies. The significantly negative coefficients of SV in the three $EMKT$ equations show that high default risk, which is indicated by low SV, consistently Granger-cause high market return next period. This implies that when default risk is high, investors require on average higher equity returns next period. In contrast, the liquidity effects on next period's market return are generally of much smaller order of magnitude, and at best statistically significant at the 10% level. The significantly positive coefficients of $EMKT$ in the three SV equations suggest that high market returns Granger-cause low default risk next period.

There exist strong contemporaneous correlations between the VAR innovations reported in Table 6. In particular, the shocks to SV and PS have a correlation of 23%, those of SV and TO a correlation of 15%, whereas SV and $ILIQ$ have a correlation of -34%. In addition, the shocks to SV and $EMKT$ are 59% correlated, while the correlations of shocks to $EMKT$ and the liquidity measures range between 33% and 52%. These results reveal the existence of important dynamic interrelations among the variables in the VAR system.

Table 7 presents pair-wise Granger-causality test results between the VAR variables. We test the null hypothesis of no causality running from a row variable to a column variable, and report the Chi-square statistics and associated significance levels. The results clearly show that there exists significant two-way Granger-causality relation between SV and $EMKT$ at the 5% level. $EMKT$ Granger-causes PS at the 10% level, and Granger-causes TO at the 1% level. On the other hand, market liquidity does not Granger-cause $EMKT$. The direction of Granger-causality relation generally goes from market liquidity to market default. With the exception of PS, both TO and $ILIQ$ strongly Granger-cause SV at the 1% level. SV does not generally Granger-cause any of the liquidity variables, with the exception of PS, where the causality is significant at the 10% level. Overall, the message emerging from our analysis is that there exist significant two-way causal relations between market default and market return, and one-way causality from market return to market liquidity. In addition, market liquidity tends to Granger-cause market default risk.

In light of the results in Table 7, it is instructive to investigate the direction, magnitude, and persistence by which innovations in any of the variables in question affect the others. To that end, we study the impulse response functions (IRFs) and variance decompositions (VDs) implied from the VARs. Since the variable innovations are correlated, they need to be orthogonalized, and the ordering of the VAR variables matters. One approach to decide the ordering is to order the variables according to the order in which they influence the other variables. The Granger-causality test results reported in Table 7 suggest that $EMKT$ is likely to be the first, SV to be the last, and the liquidity measures in the middle. The only exception applies to the case of PS, where we put PS to be the last variable and SV to be the middle one.

Figure 1 plots the IRFs over a 5-year period, subsequent to each VAR innovation, along with the two standard error bands. The left column of plots gives the impulse responses of SV. The middle plots depict the impulse responses of market liquidity, whereas the right set of plots show the impulse responses of $EMKT$.

In Figure 1A, the liquidity measure considered is PS. Note that a positive unit standard deviation shock in SV leads to a 0.7% increase in SV in the following month, and the impact remains significant for more than 19 months. A positive unit standard deviation of $EMKT$ shock leads to a 0.8% increase in SV in the following month, and this impact remains significant for at least 20 months. Shocks of PS appear to have no impact on SV. In the case of the PS impulse responses, shown in the middle column of plots, a positive unit standard deviation shock in SV leads to a 0.2% increase in PS in the initial month, and the effect lasts only 1 month. Shocks of PS and $EMKT$ have a two to three months worth of positive effect on PS. For $EMKT$, shocks from SV and $EMKT$ itself have impacts that are significant and persistently negative, with a positive unit standard deviation shock in SV leading to a 0.14% decrease in $EMKT$ in the first month. The impact from such a shock remains significant for over 30 months. A positive unit standard deviation of $EMKT$ shock leads to a 0.14% decrease in $EMKT$ in the fourth month, and this impact remains significant for about 32 months, indicating slowly mean-reverting behavior. Note that a shock from PS has no effect on $EMKT$.

Figure 1B presents equivalent results based on the TO liquidity measure. As can be seen from the plots, the results are qualitatively the same as those in the case of PS. Notice again that a shock from the liquidity measure – in this case TO, has no effect on $EMKT$, while SV shocks have long-lasting impact on it.

Figure 1C contains the results for $ILIQ$. A positive unit standard deviation shock in $ILIQ$ leads to a 0.1% decrease in SV in the following month, and the impact remains significant for 18 months. In the case of the $ILIQ$ impulse responses, shown in the middle column of plots, both $EMKT$ and $ILIQ$ shocks have significant effects on it. A positive unit standard deviation shock in $ILIQ$ leads to a 27% increase in $ILIQ$ in the following month, and the impact remains significant for over 13 months. A positive unit standard deviation shock in $EMKT$ leads to a 15% decrease in $ILIQ$ in the following month, and this impact lasts 9 months. Shocks in SV appear to have no impact on $ILIQ$. Once again, $ILIQ$ shocks have no significant effect on $EMKT$, while SV shocks have persistent effect on it.

Table 8 reports the results from variance decompositions over the forecasting horizons of $1, 3, 6, 12,$ and 24 months.

Panel A presents the results for PS. While much of PS's time variation is explained by its own past shock, $EMKT$ shocks account for around 14% of the variation in PS across various horizons. Interestingly enough, $EMKT$ shocks explain as high as 60% of the time variation in SV at 2-year horizon, which is of much greater order of magnitude than that of SV on itself. Both SV and PS shocks account for a little part of the variation in $EMKT$.

The results in the case of TO are reported in Panel B of Table 8, and they are very similar to those for PS in Panel A. The same applies in the case of $ILIQ$. The only difference is that $ILIQ$ shocks have a higher ability to explain SV's time variation than the other two liquidity measures. Shocks to $ILIQ$ account for 14.7% of SV's time variations at the two-year horizon.

The conclusion that emerges from this section is that there is a substantial interrelation between default risk and stock market returns. Shocks to one of these variables affects significantly the path of the other, but liquidity risk, independently of how it is proxied, has a marginal or no effect on future stock market returns.

4. Is it Default and Liquidity Risk, or Simply Volatility?

The results of Section 3 establish some clear patterns of interrelation between default risk, liquidity risk, and stock market returns. However, an important question still remains. Since the default and liquidity risk measures are related and affected by stock market volatility, are the relations presented in Section 3 due indeed to default and liquidity risks, or simply to the correlations that these measures may have with stock market volatility?

To address this potential concern, we perform the following test. We regress the monthly default and liquidity measures on monthly stock market volatility, computed as the daily standard deviation of the value-weighted market returns within a month. We then repeat the tests of Table 5, using the residuals of SV and liquidity in the VAR systems. To conserve space, we only report the results referring to the use of PS as the liquidity proxy. They are reported in Table 9a. Furthermore, Table 9b reports the results from the Granger-causality tests using the orthogonalized default and liquidity measures.

Note that the main relations identified in Section 3 still hold. There is again a two-way causality between stock market returns and the orthogonalized default measure, as previously identified. Therefore, the relations we identify are unlikely to be due solely to the effects of volatility, and not on default- and liquidity-related information. Given the above results, we will proceed our analysis in the following sections using the original default and liquidity measures of the previous sections, rather than their orthogonal-to-market volatility components used here.

5. Conditional Tests

Vassalou and Xing (2004) show that the size effect can be viewed as a default effect, and that this is also largely true for the book-to-market effect. They also provide evidence that default risk is systematic risk, and that stocks with higher default risk tend to command higher expected returns.

The effects of liquidity risk on asset returns have been widely examined too. For instance, Amihud and Mendelson (1986), and Brennan, Chordia and Subrahmanyam (1998) among others, find that less liquid stocks have higher average stock returns. Pastor and Stambaugh (2003) provide evidence for the existence of a systematic component in liquidity. They show that assets whose returns highly co-vary with their PS measure earn higher expected returns than assets which exhibit low covariation with PS.

In this section, we aim to synthesize the previous findings, by simultaneously considering the effects of liquidity and default risk on the cross-section of equity returns. To that end, we examine the returns of portfolios sorted on both default and liquidity risk.

5.1 Default effect conditional on liquidity

Table 10 presents results from sequential sorts of stocks on the basis of our default and liquidity measures. From January 1971 to December 1998, and at the beginning of each month, stocks are first sorted into five quintiles on the basis of their individual liquidity measures. Subsequently, each portfolio is sorted into quintiles on the basis of their past month's change in their stocks' default likelihood indicators, Δdli. As previously, we examine in turn all three liquidity measures, but at a firm level. Recall that the firm-level turnover measure is denoted by $stov$, the Pastor-Stambaugh individual liquidity beta by β^L, while the firm-level illiquidity measure is given by $iliq$. To avoid look-ahead bias, all sortings use measures computed on the basis of past month's information.

The procedure described above produces 25 portfolios in total. In what follows, we examine whether the default effect exists in all liquidity quintiles, as well as in the whole sample.

Panel A of Table 10 presents the results based on the $stov$ liquidity measure. We can see that high default risk firms earn higher returns than low default risk firms, independently of the $stov$ quintile in which they belong. The same result is found when the whole sample is used. This implies that not only the default effect exists at the whole sample level, with a spread return of 1.26% per month and a t-value of 9.6, but it is also not subsumed by the liquidity effect as represented here by $stov$. Across the $stov$ quintiles, the default spread varies between 0.82% and 1.94% per month, and it is always statistically significant.

The results based on the Pastor-Stambaugh liquidity beta β^L measure are reported in Panel B of Table 10. Again, our findings are qualitatively the same as those in Panel A, in the sense that the default spread is present across all liquidity-sorted quintiles.

Panel C reports the results for the $iliq$ measure. Once more, the default spread is significant across the $iliq$ quintiles, with the exception of the lowest $iliq$ quintile, where it is not.

There are obviously slight differences in the results presented in Table 10, depending on the liquidity measure used. These differences can be understood in light of the results presented earlier in the paper, which show that the informational content of the three liquidity measures is quite different. Despite this fact, the message that emerges from

Table 10 is clear. Accounting for liquidity differences across stocks cannot subsume the default effect previously documented in the cross-section of equity returns.

5.2 Liquidity effect conditional on default

We now reverse the sorting order so that we can examine whether the liquidity effect prevails when the differences in the default characteristics of stocks are taken into account. For this experiment, we first sort stocks into five portfolios according to their default risk characteristics. We subsequently test whether stocks that share the same default characteristics but have different liquidity characteristics earn statistically different returns. The results are reported in Table 11.

Panel A refers to the tests when the liquidity risk is proxied by $stov$. In this case, the liquidity effect is significant only at the highest default quintile, in the sense that only in that quintile stocks with low liquidity earn a higher return than stocks with high liquidity. The difference in returns is of the order of 1.5% per month. In all other quintiles, the spread in returns is statistically equal to zero. A significant spread is also found in the case of the whole sample, but the magnitude of the spread is only 0.5% per month.

The results for the Pastor-Stambaugh and $iliq$ measures are reported in Panels B and C of Table 11, respectively. The findings are consistent with those of Panel A. In particular, the liquidity effect is present in the whole sample, but once it is controlled by default, it appears significant only within the high default risk quintile.

The sequential sorts of this section reveal that while the liquidity effect exists in the whole sample, and more prominently when it is proxied by $stov$ or $iliq$, it is subsumed by the default measure in all quintiles except the one with the highest default risk. This means that liquidity considerations are additive to any default considerations only when default risk is high, and in no other case. In contrast, the default effect is prevalent across all liquidity quintiles and independently of the liquidity proxy used. Note that this result is obtained despite the fact that we use a rather simple proxy for default risk. In short, it appears that liquidity risk is conditional on the level of default risk, but the reverse is not true.

6. Liquidity and Default Risk in the Cross-Section of Equity Returns

This section, investigates further the relative importance of liquidity and default risk in the cross-section of equity returns using the multifactor inefficiency measure presented in Avramov, Chao and Chordia's (2002).

6.1 Methodology: The multifactor inefficiency measure

The model on which the multifactor inefficiency measure is based is Merton's (1973) intertemporal CAPM. According to Merton's model, risk-averse investors are concerned about changes in the investment opportunity set, and they are willing to hold "hedge" portfolios to insure themselves against adverse changes in that investment opportunity set.

In the ICAPM framework, the expected excess return of a risky asset is given by:

$$\mathrm{E}\left(r_i\right)-r_f=\beta_{im}\left[\mathrm{E}\left(r_m\right)-r_f\right]+\sum_{s=1}^{S}\beta_{is}\left[\mathrm{E}\left(r_s\right)-r_f\right] \tag{11}$$

where $E(r_i)$ is the expected return of asset *i*, r_f is the riskless rate, β_{im} is the beta of asset *i* with respect to the market portfolio, and r_s, with $s=1,\ldots,S$, are the returns on the state variable mimicking portfolios. The sensitivity of asset's i with a state variable s is given by β_{is} .

The corresponding return generating process is given by:

$$r_t^e = \alpha_r + \beta_m r_{mt}^e + \sum_{s=1}^{S} \beta_s r_{st}^e + \varepsilon_t \tag{12}$$

where r_{st}^e is the excess return of the s state-variable's mimicking portfolio, and r_{mt}^e is the excess return on the market portfolio. Note that ε_t has zero mean and variance matrix Ω, whereas α_r should equal to zero if asset prices conform to the return generating process specified. The dynamics of the market portfolio are given by

$$r_{mt}^e = \alpha_m + \sum_{s=1} \beta_{ms} r_{st}^e + \mu_t \tag{13}$$

where μ_t has mean of zero and variance equal to σ_m^2.

Assume that the vector of excess returns (N testing assets plus market return) has a multivariate normal distribution, with $(N+1)\times 1$ mean vector E and $(N+1)\times(N+1)$ covariance matrix V. The corresponding return loading vector is $\beta = \left[\tilde{\beta}_1, \tilde{\beta}_2, \ldots, \tilde{\beta}_s\right]$ with $\tilde{\beta}s = \left[\beta_s', \beta_{ms}\right]'$. Fama (1996) builds Merton's ICAPM on the multifactor efficiency concept. Multifactor efficient portfolios are defined as portfolios with the smallest possible return variances, given their expected returns and sensitivities to the state variables. According to Merton's ICAPM, investors hold a multifactor-efficient portfolio, which is a combination of mean-variance-efficient portfolios and hedge portfolios that mimic uncertainty about future consumption-investment state variables. In equilibrium, market-clearing prices imply that the market portfolio is multifactor efficient. The corresponding portfolio weights vector ω_m whose first N elements are zero and the (N + 1)th element is 1, solves the problem

$$\{\min \omega' V \omega \ st.\ \omega' E = \omega_m^{'} E,\ \beta' \omega = \beta' \omega_m, \omega' \mathbf{1} = 1\}. \tag{14}$$

The multifactor inefficiency measure defined in Avramov, Chao and Chordia (2002) is given by

$$\psi\left(\mathrm{E}, V, \beta\right) = \max_{\omega}\left(\omega'\mathrm{E} - \omega'_m \mathrm{E} \ \middle| \omega' V \omega = \omega'_m V \omega_m, \beta'\omega = \beta'\omega_m, \sum_{i=1}^{N+1} \omega_i = 1 \right) \tag{15}$$

The above expression says that the multifactor inefficiency measure ψ is the loss in expected returns resulting from holding the market portfolio rather than the multifactor efficient portfolio with the same variance and the same sensitivities to the state variables. Essentially, the market portfolio will be multifactor efficient if and only if $\psi = 0$.

Note that the portfolio weights are unconstrained. To compute the measure, we first identify the portfolios whose variance and state variable sensitivities are identical to those of the market portfolio. Subsequently, we compute the difference in expected returns between these portfolios and the market portfolio. The multifactor inefficiency measure ψ corresponds to the maximization of these differences. By comparing the multifactor inefficiency measure across different model specifications that may contain a liquidity factor, the default factor, or both, we can obtain an understanding of whether liquidity, default, or both can play the role of state variables that investors would want to hedge against in the context of the ICAPM.

Since ψ is a nonlinear function of E, V, and β, we do not have analytical expressions for the posterior distribution of ψ. Therefore, similarly to Avramov, Chao, and Chordia (2002), we follow a Bayesian approach.

The return generating process can be rewritten as

$$R = XB + \varepsilon \tag{16}$$

$$R_m = YC + U \tag{17}$$

Where $X=\left[\iota_{T,}\ R_{m,}\ R_s\right]$, $B=\left[\alpha_r,\ \beta_{\text{m}},\ B_{\text{s}}'\right]'$, $Y=\left[\iota_T,\ R_s\right]$, $C=\left[\alpha_m,\ B_{ms}{}'\right]'$, ι_T is a $T\times 1$ vector of ones, $R=\left[r_1^e, r_2^e, \ldots, r_T^e\right]'$, $R_m=\left[r_{m1}^e, r_{m2}^e, \ldots, r_{mT}^e\right]'$, $B_s=\left[\beta_1, \beta_2, \ldots, \beta_s\right]'$, and $B_{\text{ms}}=\left[\beta_{m1}, \beta_{m2}, \ldots, \beta_{ms}\right]'$. We assume $vec(\varepsilon) \sim N\left(0, \Omega \otimes I_T\right)$ and $U \sim N\left(0, \sigma_m^2 I_T\right)$, where vec is the vectorization operator, and I_T is an identity matrix of order T. The dynamics of the hedging portfolios are modeled as $R_s = \iota_T \mu_s{}' + \eta$, where μ_s is an $S\times 1$ vector of unconditional means of the state variable excess returns, and $vec\left(\eta\right) \sim N\left(0, V_s \otimes I_T\right)$.

In each simulation, we first draw a random sample V_s from the inverted Wishart distribution with parameter matrix L and degrees of freedom equal to $T-S-1$. Then, a random sample μ_s is drawn from the multivariate normal distribution with mean $\hat{\mu}_s$ and variance V_s / T. As a third step, σ_m^2 is drawn from the inverted Gamma distribution with parameter matrix Q and degrees of freedom equal to $T-1$. The fourth step involves drawing a random sample C from the multivariate normal distribution with mean $\hat{C}$ and variance $\sigma_m^2 (Y'Y)'$. Subsequently, we draw Ω from the inverted Wishart distribution with parameter matrix P and degrees of freedom $T-S-2$. Finally, a random sample $vec(B)$ is drawn from a multivariate normal distribution with mean $vec(\hat{B})$ and variance $\Omega \otimes (X'X)^{-1}$. A detailed description of the above symbols and the simulation is provided in Appendix B.

Once we have drawn all the random parameters from their joint posterior density, we can obtain the moments E, V, and β. Note that ω is computed by solving the above constrained optimization problem. In this manner, we obtain a draw from the posterior density of ψ. The above procedure is repeated 5000 times so that 5000 independent random samples of ψ from its posterior distribution are generated.

6.2 The MWW test

Following Avramov, Chao and Chordia's (2002), we use the Mann-Whitney-Wilcoxon (MWW) test to assess the relative performance of the different model specifications considered.

The MWW test is a nonparametric test that makes virtually no assumptions about the form of the sampled distribution. The only assumption made is that the population has a continuous distribution. The test is used to determine whether two populations are identical.

The MWW statistic is constructed as follows. Let $\psi_1^{M_A}$, $\psi_2^{M_A}$, ……, $\psi_I^{M_A}$ and $\psi_1^{M_B}, \psi_2^{M_B}$, ……, $\psi_I^{M_B}$ be I draws of the inefficiency measure for models A and B respectively, drawn from their posterior distributions. If $F_A(x)$ and $F_B(x)$ denote the cumulative distribution functions for ψ^{M_A} and ψ^{M_B} separately, we test the following null and alternative hypotheses:

$$H_0 : F_A\left(x\right) = F_B\left(x\right) \text{ for all } x$$
$$H_1 : F_A\left(x\right) \prec F_B\left(x\right) \text{ for all } x$$

First, we define

$$Z_{ij}^{MA} = \begin{cases} 1 & if\,\psi_i^{MA} \prec \psi_j^{MB} \\ 0 & otherwise \end{cases} \tag{18}$$

for i = 1, 2, ……, I and j = 1, 2, ……, I.

$$U_{AB} = \sum_{j=1}^{I}\sum_{i=1}^{I} Z_{ij}^{AB} \tag{19}$$

The test statistic is then defined by

$$W_{AB} = \frac{U_{AB} - \frac{I^2}{2}}{\sqrt{\frac{I^2\left(2I+1\right)}{12}}} \tag{20}$$

Note that as $I \to \infty$, $W_{AB} \xrightarrow{d} N(0,1)$. The null hypothesis H_0 is rejected at 5% significant level if $W_{AB} < -1.645$. In this case we conclude that ψ^{M_A} is "stochastically smaller" than ψ^{M_B}.

6.3 State variable mimicking portfolio construction

The model specifications examined are the CAPM, the three-factor Fama and French (1993) (FF) model, the CAPM augmented by a liquidity factor, the CAPM augmented by the default factor, as well as the CAPM augmented by both a liquidity factor and the default factor. In addition, we examine versions of the FF model that include a liquidity and default factor. In particular, we augment the FF by a liquidity factor, the default factor, or both.

According to the definition of the multifactor inefficiency measure, the pricing factors should be mimicking portfolios of state variables. For that purpose, we create mimicking portfolios for the liquidity and default factors considered. The Fama-French factors $EMKT, SMB, HML$ are obtained from Kenneth French's website. The test assets are the 25 size and book-to-market portfolios whose returns are available again from French's website. The testing period is January 1971 to December 1998.

We denote by MPS the mimicking portfolio for the market-wide Pastor and Stambaugh (2003) liquidity proxy PS. The construction of market-wide PS proxy is described in Section 1. Pastor and Stambaugh first compute an individual stock's predicted liquidity beta by regressing its monthly returns on the innovation in their market-wide PS measure. At the end of each year, stocks are sorted into 10 portfolios based on their predicted liquidity betas. The mimicking portfolio MPS is just the spread in returns between the two extreme portfolios. In effect, it goes long the portfolio with the highest liquidity beta, and shorts the decile with the lowest liquidity beta. The mimicking portfolio data are again obtained from Pastor and Stambaugh.

We construct the mimicking portfolio for the $ILIQ$ measure in a similar fashion to that described above, and we denote it by $MILIQ$. Each month, stocks are sorted into ten portfolios based on their individual illiquidity ratio $iliq$. Recall that the construction of the individual illiquidity ratio $iliq$ is described in Section 1.2. $MILIQ$ is again the spread in returns between the portfolio with the highest level of $iliq$ and the portfolios with the lowest $iliq$.

To make our results comparable to those in Avramov, Chao, and Chordia (2002), we follow their methodology for the construction of the mimicking portfolio with respect to the turnover measure. We denote it by MTO. In particular, at the end of each June, six portfolios are formed from the intersection of 2 turnover-sorted portfolios and 3 book-to-market-sorted portfolios. Recall again that the individual stock's turnover rate $stov$ is described in Section 1.3. The mimicking portfolio MTO (low turnover minus high turnover) is the difference between the equally weighted average of the three low turnover portfolio returns and the three high turnover portfolio returns. We have tested the robustness of our results with respect to the turnover factor using instead the spread between the extreme portfolios from a simple sort into deciles on the basis of individual stocks' turnover rate. The results are the same as those reported below. To conserve space, we do not report them there.

Finally, the mimicking portfolio for the market-wide default factor is denoted by $MDLI$. To construct the portfolio, we use the firm-level default likelihood indicators available from Vassalou's website. As shown in Vassalou and Xing (2004), the DLI measure is intimately related to the market capitalization of firms. Therefore, in order to control for the size effect, we follow the procedure outlined below. At the beginning of each month, and using the previous month's information, the stocks are sorted into 5 size portfolios and 5 dli portfolios, using independent sorts. The $MDLI$ factor is then defined as the difference in returns between the equally weighted average return of the five high dli portfolios and the five low dli portfolios.

6.4 Results

Table 12 reports the posterior annualized means and standard deviations of the multifactor inefficiency measure ψ resulting from the model specifications considered. It is evident from the results presented, that none of the specifications considered represents the "correct" model. In other words, they are all mis-specified. However, our purpose here is not to propose the "correct" asset pricing model. Rather, we aim to evaluate the relative contribution of default and liquidity factors in improving the model performance. To that end, the results of Table 12 reveal that the multifactor inefficiency measure becomes smaller when either the liquidity or default factors are included in the asset pricing specification. More importantly, it further declines in magnitude when both a liquidity measure and the default factor are present. This implies that both liquidity and default factors contribute positively to the model's performance by making the market portfolio less inefficient.

A more detailed examination of the alternative specifications is provided in Table 13. The upper diagonal section of the table, and for the $(i, j)^{th}$ element, with $i < j$, reports the probability $\hat{p}_{ij}$ with which model i, M_i, generates a higher multifactor inefficiency measure than model j, M_j. Note that $\hat{p}_{ij} = \mathrm{U}_{\mathrm{ij}} / I^2$, where I = 5000. The way to understand the reported numbers is as follows. For instance, Panel A reports the results when MTO is used as a liquidity proxy. The number 0.52 reported in entries $(1, 2)$ and $(1, 3)$, shows that the $CAPM$ generates a higher multifactor inefficiency measure than $CAPM + MTO$ or $CAPM + MDLI$ with a probability of 0.52. Under the null hypothesis that M_i and M_j perform equally well, $P(\psi^{M_j} < \psi^{M_i}) = 0.5$. If the hypothesis is true, $\hat{p}_{ij}$ should be equal or at least very close to 0.5. The number 0.50 as reported in the (2, 3) entry, is an estimate of the probability that $CAPM + MTO$ generates a higher multifactor inefficiency measures than the model $CAPM + MDLI$, which means these two models perform equally well. On the other hand, $(i, j)^{th}$ element, i > j, in the lower diagonal section of the table reports the values of the MWW statistics for testing $H_0: \psi^{M_i} = \psi^{M_j}$ versus $H_1: \psi^{M_i} < \psi^{M_j}$. For example, the (7, 6) entry in *Panel A*, gives the value of the MWW statistic for testing the null hypothesis that $FF + MTO$ and $FF + MDLI$ perform equally well versus the alternative hypothesis that $FF + MDLI$ outperforms $FF + MTO$. From the MWW test statistics of 15.61, we conclude that $FF + MDLI$ significantly outperforms $FF + MTO$ at 0.1% level. And this is confirmed by the corresponding probability of 0.59 in the (6, 7) entry, which means that $FF + MTO$ performs worse than the model $FF + MDLI$ with probability of 59%. Note that the performance of the $FF + MDLI$ model comes close to that of $FF + MDLI + MTO$. Although the MWW test statistic for comparing these two models has a value of 3.54 in the (8, 7) entry, which is significant at 0.1% level, the probability P ($FF + MDLI + MTO$ out-performs $FF + MDLI$) is only 0.52 in the (7, 8) entry, which is not very different from the H_0 value of 0.5. Hence, the superiority of $FF + MDLI + MTO$ over $FF + MDLI$ is not overwhelming. On the contrary, $FF + MDLI + MTO$ outperforms $FF + MTO$ significantly both in terms of MWW tests (19.04 in the (8, 6) entry) and probability (0.61 in the (6, 8) entry). Therefore, the overall message from this table is that specifications that include the default factor outperform specifications that include only a liquidity factor, whereas in the presence of the default factor, any of the liquidity factors has a rather small incremental effect. This conclusion is consistent with the findings of the previous section where it is shown that liquidity risk affects the cross-section of equity returns *only* when default risk is high.

Panels B and C of Table 13 report the results when MPS and $MILIQ$ are used as liquidity proxies, respectively. Similarly to the tests conducted earlier in this paper, the results are qualitatively the same as those for MTO. By that we mean that, once again, specifications that include either the default factor or one of the liquidity factors outperform specifications that exclude them (that is, the CAPM or the FF model), and that models that include the default factor outperform models that include any of the liquidity factors alone. In addition, the incremental contribution of a liquidity factor when $MDLI$ is included in the specification is rather marginal.

As a robustness test for our results, we examine whether our results based on the MWW statistic differ across alternative states of the economy. For the purposes of this test, we define the state of the economy based on two alternative proxies: the market volatility and the leading economic indicator.

The monthly market volatility is computed as daily standard deviation of the value-weighted market returns within a month. We then assign as high volatility months those months with volatilities above the average monthly volatility during our sample period.

When the economic states are defined on the basis of the leading economic indicator (lei), we use the data provided by the Conference Board. Following McQueen and Roley (1993), we first regress the log of the indicator on a constant and a time trend to estimate the trend in the growth of the indicator. We then classify sample months as being in the low (high) growth state, if the indicator's growth during the month is below (above) the trend. The details of the economic state classification are provided in

Appendix C. Note that for the purpose of this exercise, we avoid using the NBER business-cycle dates, as our sample is relatively small to cover several recessions.

Table 14 presents the results. The conclusion that emerges from this exercise is that the findings in Tables 12 and 13 continue to hold and they are largely independent of the state of the overall economy.

7. Conclusions

This paper examines the relative importance of liquidity and default risk in the equity returns. We consider three alternative but popular liquidity measures, and one simple default measure. The liquidity measures considered are those based on the turnover ratio, the Pastor-Stambaugh measure, and the illiquidity measure. The default measure we use is that following from Merton's (1974) contingent claims approach.

One of the first results obtained is that the alternative liquidity measures examined contain very different information about liquidity and they share low correlations. However, they are all related to some extent with our default measure.

Vector autoregressive tests reveal that there is causality between the default measure and stock market returns. Shocks to one of these variables affects significantly the path of the other, but liquidity risk, independently of how it is proxied, has a marginal or no effect on future stock market returns. We verify that the presented relations among the default and liquidity measures and stock market returns are not the result of any correlation that the default and liquidity measures may share with aggregate stock market volatility.

In terms of the relative contribution of default and liquidity factors in the cross-section of equity returns, we find that when the default factor is present in the empirical specification, the incremental contribution of the liquidity factor is rather marginal. The converse is not true, however. The addition of the default factor significantly improves its multifactor efficiency. This result is consistent with our findings from the conditional tests, where the existence of a liquidity-related spread in equity returns is conditional on the stocks involved being of high default risk. Once again, the reverse is not true. There is a default-related spread in equity returns, independently of the liquidity level of the stocks considered. Our results clarify the roles of liquidity and default risk in equity returns, as well as their relative importance.

Appendix A. The interrelation of the three liquidity measures

To better understand the interrelation of the three liquidity measures, we estimate a three-variable VAR(2) model which includes $ILIQ$, TO, and PS. The lag structure for the VAR is chosen based on the Schwartz Information Criterion.

Table a.1 reports the VAR estimation results. The significant coefficients clearly indicate the existence of intertemporal relations among the three liquidity measures. The shocks to the three liquidity measures are correlated. Table a.2 presents the contemporaneous cross-correlations of innovations obtained from VAR estimation. The shocks to $ILIQ$ and TO have a correlation of –21.2%, those of $ILIQ$ and PS a correlation of –29.7%, whereas TO and PS have a small correlation of –6.6%. These estimation results strongly indicate the existence of a dynamic interrelation among these three liquidity measures.

Table a.3 presents pair-wise Granger-causality test results between the VAR variables. The null of no causality running from a row variable to a column variable is tested. The Chi-square statistics and associated significance levels are reported. The results clearly show that there exists significant two-way Granger-causality relation between $ILIQ$ and TO at 1% level, and between TO and PS at 5% level. $ILIQ$ Granger-causes PS at the 1% significance level, but the reverse is not true. Overall, the message is that there does exist significant causalities among these three liquidity measures.

To further investigate the dynamic relation among these three liquidity measures, we study the impulse response functions ($IRFs$) and variance decompositions (VDs) implied from the VARs. They are computed using standard Cholesky decompositions of the VAR residuals and assume that innovations in the variables placed earlier in the VAR have a greater effect than the variables that follow. We check different orders and find that our results are robust.

Figure a.1 plots the IRFs over a 5-year period, subsequent to each VAR innovation, along with the two standard error bands. A positive unit standard deviation shock in $ILIQ$ generates substantial reductions in TO and PS over extended periods of time. It leads to a 0.1% standard deviation drop in TO at the first month, and the impact remains significant for over 15 months. PS starts to fall by 0.57% standard deviation in response to the $ILIQ$ shock at the first month, and exhibits a significant decline in the following 16 months after the shock. A unit shock in $ILIQ$ initially produces a 35.8% standard deviation increase in itself, and its impact lasts significantly for the subsequent 18 months as it gradually tapers off to zero. Shocks of TO and PS don't have a significant effect on $ILIQ$, and there is no dynamic relation between TO and PS.

Table a.4 reports the results for the variance decomposition for five different forecast horizons, and in particular those of 1, 3, 6, 12, and 24 months ahead. Note that while the majority of TO and PS's time variation is explained by their own past shock, $ILIQ$ also makes important contributions. For example, the $ILIQ$ shocks account for 4% to 28% of the variation in TO, and 9% to 20% of the variation in PS. In general, the impact of these shocks increase with the forecast horizon. In contrast, TO and PS account for a small part of the time variation in $ILIQ$.

Table a.1 **The Coefficient Estimates of the VAR Model with Three Market Liquidity**

This table reports the coefficient estimates of the VAR(2) model consisting of three market-wide liquidity proxies $ILIQ$, TO , PS . The VAR lag length is chosen by the Schwartz Information Criterion. The estimated coefficients and their standard errors (in brackets) are reported. Significance at 10%, 5% and 1% levels is indicated by '*', '**', '***', respectively. The sample period is from Jan 1971 to Dec 1998.

	Dependent Variables		
	$ILIQ_t$	TO_t	PS_t
Constant	-0.0979	0.0086***	0.0473*
	(0.1931)	(0.0014)	(0.0280)
$ILIQ_{t-1}$	0.5543***	-0.0022***	-0.0070
	(0.0549)	(0.0004)	(0.0080)
TO_{t-1}	-12.0132	0.5100***	1.4737
	(7.5565)	(0.0551)	(1.0974)
PS_{t-1}	-0.6220	0.0010	0.1547***
	(0.3997)	(0.0029)	(0.0580)
$ILIQ_{t-2}$	0.3907***	0.0015***	-0.0170**
	(0.0572)	(0.0004)	(0.0083)
TO_{t-2}	27.2459***	0.0906*	-2.2868**
	(7.4016)	(0.0540)	(1.0749)
PS_{t-2}	0.9797**	0.0029	0.0741
	(0.4053)	(0.0030)	(0.0589)

Table a.2 **Contemporaneous Correlations between VAR Innovations**

This table reports the contemporaneous correlations between innovations from the VAR model consisting of three market-wide liquidity proxies $ILIQ$, TO, PS. VAR(2) is estimated and the VAR lag length is chosen by the Schwartz Information Criterion. The sample period is from Jan 1971 to Dec 1998.

	ε_{ILIQ}	ε_{TO}	ε_{PS}
ε_{ILIQ}	1.0000		
ε_{TO}	-0.2118	1.0000	
ε_{PS}	-0.2972	-0.0656	1.0000

Table a.3 **Granger Causality Tests**

This table reports the results of the Granger causality tests. The null of no causality running from a row variable to a column variable is tested using the VAR(2) models with $ILIQ$, TO, PS. $ILIQ$ is market-wide illiquidity ratio, TO is market-wide turnover, and PS is Pastor and Stambaugh market-wide liquidity. Chi-square statistics and associated p-values (in parentheses) are reported. The causal relationships being significant at 10, 5, and 1% are indicated by '*', '**', and '***' respectively. The sample period is from Jan 1971 to Dec 1998.

	$ILIQ$	TO	PS
$ILIQ$		39.08***	16.92***
		(0.00)	(0.00)
TO	10.87***		6.60**
	(0.00)		(0.04)
PS	4.42	8.58**	
	(0.11)	(0.01)	

Table a.4 **Variance Decomposition**

This table gives the results of the variance decomposition from the VAR model consisting of three market-wide liquidity proxies $ILIQ$, TO , PS . The VAR(2) is estimated and the VAR lag length is chosen by the Schwartz Information Criterion. The numbers in the table represent percentages of the forecast error variance in a row variable accounted for by innovations in each column variable at 1, 3, 6, 12, and 24 month horizons. 'Variable' denotes the variable for which the variance decomposition is computed. The sample period is from Jan 1971 to Dec 1998.

Variable	Horizon	$ILIQ$	TO	PS
$ILIQ$	1	100	0	0
	3	98.627	0.697	0.676
	6	97.028	2.275	0.697
	12	94.454	4.619	0.927
	24	93.280	5.684	1.036
TO	1	4.484	95.516	0
	3	16.959	82.489	0.552
	6	22.757	76.656	0.587
	12	26.634	72.784	0.582
	24	28.213	71.174	0.612
PS	1	8.832	1.729	89.439
	3	12.600	2.337	85.063
	6	15.596	2.744	81.661
	12	18.440	3.233	78.327
	24	19.787	3.459	76.754

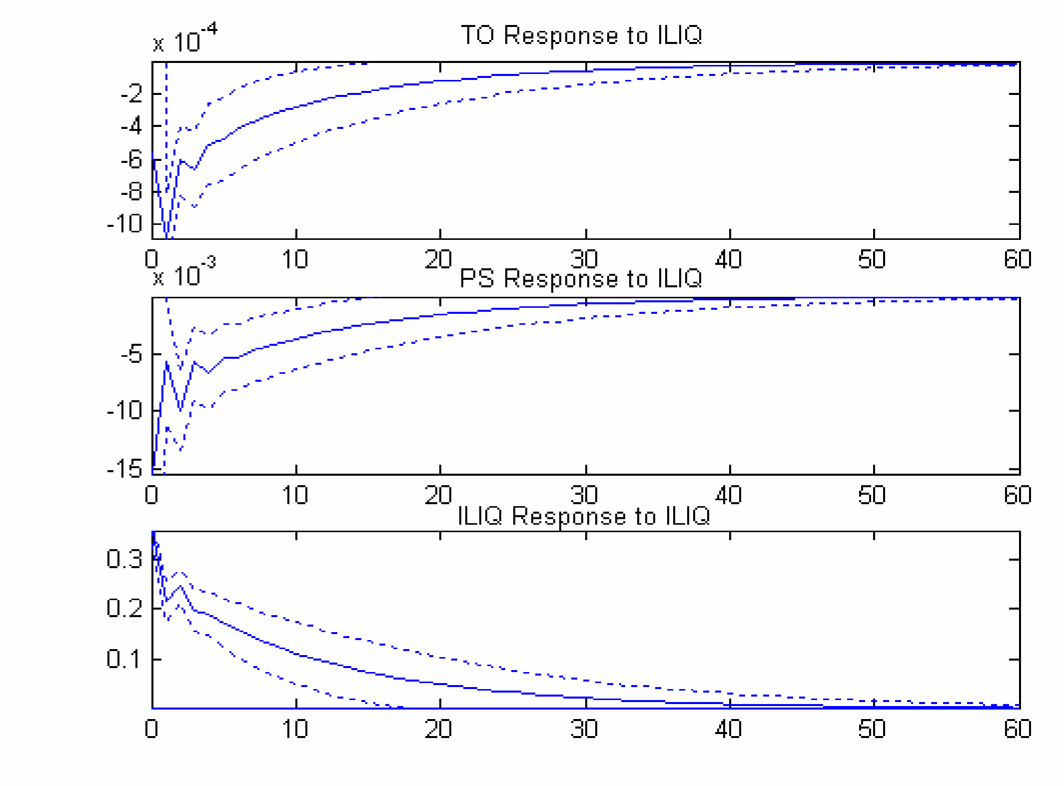

Figure a.1 **Orthogonalized Impulse Responses of** $ILIQ$**,** TO **and** PS. This figure shows impulse responses of $ILIQ$, TO and PS to a Cholesky one-standard-deviation innovation to $ILIQ$. The VAR lag length is chosen by the Schwartz Information Criterion. The top panel gives the impulse responses of TO. The middle panel reports the impulse responses of PS. The bottom panel documents the impulse responses of $ILIQ$. Dashed lines represent two-standard error bands. The sample period is from Jan 1971 to Dec 1998.

Appendix B

A. Posterior density of $E, V, and\,\beta$

The return generating process can be rewritten as

$$R = XB + \varepsilon \qquad (1)$$

$$R_m = YC + U \qquad (2)$$

where X= $\left[\iota_{T,}\ R_{m,}\ R_s\right]$, $B = \left[\alpha_r,\ \beta_{\mathrm{m}},\ B_{\mathrm{s}}'\right]'$, $Y = \left[\iota_T,\ R_s\right]$, $C = \left[\alpha_m,\ B_{ms}'\right]'$, ι_T is a $T \times 1$vector of ones, $R = \left[r_1^e, r_2^e, \ldots, r_T^e\right]'$, $R_m = \left[r_{m1}^e, r_{m2}^e, \ldots, r_{mT}^e\right]'$, $B_s = \left[\beta_1, \beta_2, \ldots, \beta_s\right]'$, and $B_{\mathrm{ms}} = \left[\beta_{m1}, \beta_{m2}, \ldots, \beta_{ms}\right]'$. We assume $vec(\varepsilon) \sim N\left(0, \Omega \otimes I_T\right)$and $U \sim N\left(0, \sigma_m^2 I_T\right)$, where vec is the vectorization operator, and I_T is an identity matrix of order T.The dynamics of the hedging portfolios are modeled as $R_s = \iota_T \mu_s' + \eta$, where $\mu_s$is an $S \times 1$vector of unconditional means of the state variable excess returns, and $vec\left(\eta\right) \sim N\left(0, V_s \otimes I_T\right)$.

The random parameters are $B, C, \mu_s, \Omega, \sigma_m^2, V_s$, and the sample data contains $R, R_m, and\ R_s$. The sample data is denoted as D. The resulting conditional and marginal posterior densities are standards (e.g, Zellner (1971)), and are given by

$$vec\left(B\right)\Big|\Omega, D \sim N\left(vec\left(\hat{B}\right), \Omega \otimes \left(X'X\right)^{-1}\right) \qquad (3)$$

$$\Omega\Big|D \sim IW\left(P, T - S - 2\right) \qquad (4)$$

$$C\Big|\sigma_m^2, D \sim N\left(\hat{C}, \sigma_m^2\left(Y'Y\right)^{-1}\right) \qquad (5)$$

$$\sigma_m^2\Big|D \sim IG\left(Q, T - 1\right) \qquad (6)$$

$$\mu_s \left| V_s, D \sim N\left(\hat{\mu}_s, \frac{V_s}{T}\right)\right. \tag{7}$$

$$V_s \left| D, \sim IW\left(L, T-S-1\right)\right. \tag{8}$$

where $\hat{B} = \left(X'X\right)^{-1} X'R$, $\hat{C} = \left(Y'Y\right)^{-1} Y'R_m$, $\hat{\mu}_s = {R_s}'\iota_T \big/ T$, $P = \left(R - X\hat{B}\right)'\left(R - X\hat{B}\right)$

$Q = \left(R_m - Y\hat{C}\right)'\left(R_m - Y\hat{C}\right)$, $L = \left(R_s - \iota_T {\hat{\mu}_s}'\right)'\left(R_s - \iota_T {\hat{\mu}_s}'\right)$, and IW and IG stand for the inverted Wishart and inverted Gamma distributions.

Once we draw random parameters from the joint posterior density, the moments E, V and β follows

$$E = \begin{bmatrix} \alpha_r + \beta_m \alpha_m + \left[\beta_m {B_{ms}}' + {B_s}'\right]\mu_s \\ \alpha_m + {B_{ms}}'\mu_s \end{bmatrix} \tag{9}$$

$$V = \begin{bmatrix} V_r & V_{rm} \\ {V_{rm}}' & V_m \end{bmatrix} \tag{10}$$

$$\beta = \left[B_{s,} B_{ms}\right] \tag{11}$$

where

$$\begin{aligned} V_r &= \beta_m {\beta_m}' V_m + \Omega + {B_s}' V_s B_s + \beta_m {B_{ms}}' V_s B_s + {B_s}' V_s B_{ms} {\beta_m}' \\ V_{rm} &= \beta_m V_m + {B_s}' V_s B_{ms} \\ V_m &= B_{ms}{}' V_s B_{ms} + \sigma_m^2 \end{aligned}$$

Appendix C.

C1. Economic States Based on the Leading Economic Indicator (LEI)

The economic high growth state and low growth state are determined by the leading economic indicator. The leading economic indicator is provided by the Conference Board. The index is computed using the following macroeconomic series: (1) average weekly hour in manufacturing, (2) average weekly initial claims for unemployment insurance, (3) manufacturers' new orders for consumer goods and materials, (4) vendor performance given by slower deliveries diffusion index, (5) manufacturers' new orders for non-defense capital goods, (6) building permits for new private housing units, (7) the Standard & Poor's 500 stock index, (8) money supply given by M2, (9) interest rate spread defined by the difference between the yield of 10-year Treasury bonds and the federal funds rate, and (10) the index of consumer expectations. The economic states are determined relative to the trend. Among the 336 months included in the sample, 187 months are classified as being in the high growth regimes and 149 months are identified as being in the contrary regimes.

High growth states		Low growth states	
Periods	Durations	Periods	Durations
03/71-05/74	39	01/71-02/71	2
02/76-03/79	38	06/74-01/76	20
07/83-07/83	1	04/79-06/83	51
10/83-08/90	83	08/83-09/83	2
07/91-07/91	1	09/90-06/91	10
12/92-12/92	1	08/91-11/92	16
03/94-03/94	1	01/93-02/94	14
02/97-12/98	23	04/94-01/97	34
total	*187*	*total*	*149*

C2. Volatility Regimes

Volatility regimes are determined by the market volatility. Months whose market volatility is above the average market volatility are defined as high volatility months. The following table lists the duration of each volatility regime. Among the 336 months in the sample, 129 months are classified as being in the high volatility regimes and 207 months are classified as being in the low volatility regimes.

High volatility periods		Low volatility periods	
Periods	Durations	Periods	Durations
08/71-08/71	1	01/71-07/71	7
11/71-11/71	1	09/71-10/71	2
02/73-07/73	6	12/71-01/73	14
11/73-05/75	19	08/73-10/73	3
08/75-10/75	3	06/75-07/75	2
12/75-02/76	3	11/75-11/75	1
11/77-11/77	1	03/76-10/77	20
10/78-12/78	3	12/77-09/78	10
09/79-11/79	3	01/79-08/79	8
01/80-05/85	5	12/79-12/79	1
08/80-03/81	8	06/80-07/80	2
08/81-11/81	4	04/81-07/81	4
01/82-03/82	3	12/82-12/81	1
06/82-06/82	1	04/82-05/82	2
08/82-02/83	7	07/82-07/82	1
06/83-07/83	2	03/83-05/83	3
02/84-02/84	1	08/83-01/84	6
06/84-06/84	1	03/84-05/84	3
08/84-08/84	1	07/84-07/84	1
01/86-01/86	1	09/84-12/85	16
04/86-04/86	1	02/86-03/86	2
07/86-07/86	1	05/86-06/86	2
09/86-09/86	1	08/86-08/86	1
11/86-11/86	1	10/86-10/86	1
01/87-01/87	1	12/86-12/86	1
03/87-05/87	3	02/87-02/87	1
08/87-02/88	7	06/87-07/87	2
04/88-06/88	3	03/88-03/88	1
10/89-10/89	1	07/88-09/89	15
01/90-01/90	1	11/89-11/89	2
08/90-11/90	4	02/90-07/90	6
01/91-02/91	2	12/90-12/90	1
04/91-04/91	1	03/91-03/91	1
08/91-08/91	1	05/91-07/91	3
11/91-12/91	2	09/91-10/91	2
04/92-04/92	1	01/92-03/92	3
02/93-02/93	1	05/92-01/93	9
04/94-04/94	1	03/93-03/94	13
03/96-03/96	1	05/94-02/06	22
07/96-07/96	1	04/96-06/96	3
12/96-12/96	1	08/96-11/96	4
02/97-05/97	4	01/97-01/97	1
07/97-01/98	7	06/97-06/97	1
04/98-04/98	1	02/98-03/98	2
06/98-12/98	7	05/98-05/98	1
total	129	*Total*	207

References

Acharya, Viral V., and Pederson, Lasse H., 2003. Asset pricing with liquidity risk, working paper, London Business School.

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

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31-56.

Avramov, Doron, Naik, John Chao, and Chordia, Tarun, 2002. Hedging Against Liquidity Risk and Short Sale Constraints. Social Science Research Network Electronic Library.

Black,Fischer, and Scholes, Myron, 1973, The pricing of options and corporate liabilities. Journal of Political Economy 81, 637-659.

Brennan, M.J., Subrahmanyam, A., 1996. Market microstructure and asset pricing: on the compensation for illiquidity in stock returns. Journal of Financial Economics 41, 441-464.

Brennan, M..,Chordia, T., and Subrahmanyam, A., 1998. Alternative factor specification,security characteristics, and the cross-section of expected stock return. Journal of Financial Economics 49, 345-373.

Campbell, John Y., Grossman, Sanford J., and Wang , Jiang, 1993. Trading volume and serial correlation in stock returns. Quarterly Journal of Economics 108(4), 905-939.

Chordia, T., and Subrahmanyam, A., 1996. Market microstructure and asset pricing: on the compensation for illiquidity in stock returns. Journal of Financial Economics 41, 441-464.

Chordia, Tarun, Roll, Richard, and Subrahmanyam, Avanidhar, 2001. Market liquidity and trading activity. Journal of Finance 56(2), 501-530.

Cooper, Michael, 1999. Filter rule based on price and volume in individual security overreaction. Review of Financial Studies 12(4), 901-935.

Datar, Vinay T., Naik, Narayan Y., Radcliffe, Robert, 1998. Liquidity and stock returns: an alternative test. Journal of Financial Markets 1(2), 203-219.

Eckbo, Espen B., and Norli, Oyvind, 2002. Pervasive liquidity risk, working paper, Dartmouth College.

Fama, E. F., and French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E. F., and French, K. R., 1996. Multifactor Explanations of Asset Pricing Anomalies. Journal of Finance 51, 55-84.

Hasbrouck, Joel, 2003, Trading costs and returns for US equities: the evidence from daily data, working paper, New York University.

Haugen, Robert A., Baker, Nardin L., 1996. Commonality in the determinants of expected stock returns. Journal of Financial Economics 41(3), 401-439.

Hu, Shing-Yang, 1997a. Trading turnover and expected stock returns: the trading frequency hypothesis and evidence from the Tokyo stock exchange. Working paper, National Taiwan University.

Kyle, Albert S., 1985, Continuous auctions and insider trading, Econometrica 53 (6), 1315-1335.

Vassalou, Maria, and Xing, Yuhang, 2004. Default risk in equity returns. J*ournal of Finance,* LIX(2): 831-68.

Vassalou , Maria, and Xing, Yuhang, 2005.Abnormal equity returns following downgrades. Working paper, Columbia University

McQueen, Grant, and Roley , V. Vance, 1993. Stock Prices, News, and Business Conditions. Review of Financial Studies 6(3), 683-707.

Merton, R. C., 1973, An Intertemporal Capital Asset Pricing Model. Econometrica 41, 867-887.

Merton, R. C., 1974, On the pricing of corpoteate debt: The risk structure of interest rates. Journal of Fianance 29, 449-470.

Pastor, Lubos, and Stambaugh, Robert F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642-685.

Rouwenhorst, K. Geert, 1998. Local return factors and turnover in emerging stock markets. Working paper, Yale School of Management.

Table 1 **Summary Statistics**

$Panel\ A$ and $Panel B$ shows the descriptive statistics for market-wide liquidity proxies and market-wide default risk proxy. TO is market-wide turnover, PS is Pastor and Stambaugh market-wide liquidity, $ILIQ$ is market-wide illiquidity ratio, and SV is market-wide survive rate. $Panel C$ shows the descriptive statistics for the cross-section of firm-specific liquidity measures. Firm-specific liquidity measures for NYSE/AMEX common stocks are used in $Panel C$. We compute the mean and standard deviations using time-series data for each firm, and then average the statistics across firms. The sample period is from Jan 1971 to Dec 1998.

Panel A: Descriptive Statistics for Scaled market-wide Series				
	TO	PS	$ILIQ$	SV
Mean	0.0166	-0.0313	2.4270	0.9495
Std. Dev.	0.0036	0.0559	0.6682	0.0310
Panel B: Autocorrelations for Scaled market-wide Series				
1	0.6412	0.2503	0.8108	0.9382
2	0.4673	0.2340	0.7452	0.8561
3	0.3137	0.2060	0.6857	0.7745
4	0.1694	0.1481	0.5916	0.6878
5	0.1628	0.1968	0.5575	0.6121

Panel C:Descriptive Statistics for the cross-section of firm-specific liquidity measures			
	$\overline{stov}$	$\overline{ps}$	$\overline{iliq}$
Mean	0.0495	-0.0237	13.0658
Std. Dev.	0.0435	0.3363	17.966

Table 2 **Correlations**

Panel A reports the correlations among three aggregate market-level liquidity measures, default measure and market volatility. TO is market-wide turnover, PS is Pastor and Stambaugh market-wide liquidity, $ILIQ$ is market-wide illiquidity ratio, SV is market-wide survive rate, and VOL is the market volatility. *Panel B* reports the average time-series correlations. Firm-specific liquidity measures for NYSE/AMEX common stocks are used in *Panel B*. We first compute the time-series correlation between each pair of variables across time for each firm, and then average these time-series correlations cross-sectionally across firms. *Panel C* reports the average cross-sectional correlations. Firm-specific liquidity measures for NYSE/AMEX common stocks are used in *Panel C*. We first compute the cross-sectional correlation between each pair of variables in each month t, and then average over time to obtain the average cross-sectional correlations. The sample period is from Jan 1971 to Dec 1998.

Panel A: Correlations among three aggregate market-level liquidity measures

	TO	PS	$ILIQ$	SV	VOL
TO	1.00				
PS	0.11	1.00			
$ILIQ$	-0.48	-0.44	1.00		
SV	0.36	0.22	-0.56	1.00	
VOL	0.02	-0.63	0.43	-0.41	1.00

Panel B: Average time-series correlations

	$\overline{stov}$	$\overline{ps}$	$\overline{iliq}$
$\overline{stov}$	1.00		
$\overline{ps}$	0.03	1.00	
$\overline{iliq}$	-0.33	-0.07	1.00

Panel C: Average cross-sectional correlations

	$\overline{stov}$	$\overline{ps}$	$\overline{iliq}$
$\overline{stov}$	1.00		
$\overline{ps}$	0.01	1	
$\overline{iliq}$	-0.09	-0.05	1.00

Table 3 **Regression Results on Three Market-wide Liquidity Proxies:** PS **,** TO **and** $ILIQ$

PS is Pastor and Stambaugh market-wide liquidity, TO is market-wide turnover, $ILIQ$ is market-wide illiquidity ratio. T-values in square brackets are calculated from Newey-West standard errors. The sample period is from Jan 1971 to Dec 1998.

Panel A**:** MODEL1 regress PS on constant**,** $ILIQ$ and TO				
	Constant	$ILIQ$	TO	Adj R^2
Estimates	0.1020	-0.0415	-1.9600	0.1982
t-value	[2.42]	[-4.33]	[-1.42]	

Panel B: MODEL2 regress TO on constant, PS and $ILIQ$				
	Constant	PS	$ILIQ$	Adj R^2
Estimates	0.0232	-0.0078	-0.0028	0.2326
t-value	[16.78]	[-1.71]	[-4.90]	

Panel C: MODEL3 regress $ILIQ$ on constant, PS and TO				
	Constant	PS	TO	Adj R^2
Estimates	3.6115	-4.6520	-80.2160	0.3713
t-value	[12.85]	[-4.77]	[-5.22]	

Table 4 **Regression Results of Three Market-wide Liquidity Proxies on Market-wide Default Risk, and Volatility**

SV is market-wide survival rate. PS , TO and $ILIQ$ are scaled market-wide liquidity proxies. VOL is the market volatility. $T-$values in square brackets are calculated from Newey-West standard errors. The sample period is from Jan 1971 to Dec 1998.

$Panel\ A$: regress PS on constant, SV				
	Constant	SV	VOL	Adj R^2
Estimates	-0.4129	0.4019		0.0497
$t-$value	[-2.4202]	[2.2667]		
Estimates	0.1124	-0.0759	-9.4366	0.3923
$t-$value	[0.8263]	[-0.5382]	[-13.4957]	
$Panel\ B$: regress TO on constant, SV				
	Constant	SV	VOL	Adj R^2
Estimates	-0.0232	0.0419		0.1302
$t-$value	[-2.8310]	[4.8139]		
Estimates	-0.0340	0.0517	0.1950	0.1655
$t-$value	[-3.7334]	[5.4560]	[3.4395]	
$Panel\ C$: regress $ILIQ$ on constant, SV				
	Constant	SV	VOL	Adj R^2
Estimates	13.8573	-12.0384		0.3122
$t-$value	[6.3637]	[-5.3170]		
Estimates	11.5104	-9.9038	42.1606	0.3601
$t-$value	[5.4561]	[-4.5378]	[3.3436]	

Table 5 **The Coefficient Estimates of the VAR Model with Market Default Risk, Market Liquidity and Market Return**

Table 5 reports the coefficient estimates of the VAR (1) model consisting of market-wide default risk SV, market-wide liquidity (PS, TO, $ILIQ$) and market return $EMKT$. The VAR lag length is chosen by the Schwartz Information Criterion. The estimated coefficients and their standard errors (in brackets) are reported. Significance at 10%, 5% and 1% levels is indicated by '*', '**', '***', respectively. The sample period is from Jan 1971 to Dec 1998.

Panel A: SV, PS and $EMKT$

	Dependent Variables		
	SV_t	PS_t	$EMKT_t$
Constant	0.0607***	-0.1830**	0.1906**
	(0.0169)	(0.0929)	(0.0781)
SV_{t-1}	0.9351***	0.1652*	-0.1922**
	(0.0177)	(0.0974)	(0.0818)
PS_{t-1}	-0.0067	0.1985***	0.0639
	(0.0104)	(0.0572)	(0.0481)
$EMKT_{t-1}$	0.0863***	0.1314*	0.0263
	(0.0125)	(0.0687)	(0.0577)

Panel B: SV, TO and $EMKT$

	Dependent Variables		
	SV_t	TO_t	$EMKT_t$
Constant	0.0684***	-0.0002	0.1953**
	(0.0168)	(0.0046)	(0.0777)
SV_{t-1}	0.9228***	0.0077	-0.2219***
	(0.0184)	(0.0051)	(0.0855)
TO_{t-1}	0.2533	0.5626***	1.2996*
	(0.1645)	(0.0454)	(0.7630)
$EMKT_{t-1}$	0.0787***	0.0153***	0.0247
	(0.0122)	(0.0034)	(0.0567)

Panel C: SV, $ILIQ$ and $EMKT$

	Dependent Variables		
	SV_t	$ILIQ_t$	$EMKT_t$
Constant	0.1026***	0.7089	0.2823***
	(0.0211)	(0.8383)	(0.0986)
SV_{t-1}	0.8990***	-0.3115	-0.2687***
	(0.0206)	(0.8202)	(0.0965)
$ILIQ_{t-1}$	-0.0030***	0.8311***	-0.0087*
	(0.0010)	(0.0405)	(0.0048)
$EMKT_{t-1}$	0.0715***	0.4608	0.0152
	(0.0124)	(0.4929)	(0.0580)

Table 6 **Contemporaneous Correlations between VAR Innovations**

Table 6 reports the contemporaneous correlations between innovations from the VAR model consisting of market-wide default risk SV, market-wide liquidity (PS, TO, $ILIQ$) and excess market return $EMKT$. VAR(1) is estimated and the VAR lag length is chosen by the Schwartz Information Criterion. The sample period is from Jan 1971 to Dec 1998.

Panel A: SV, PS and $EMKT$			
	ε_{SV}	ε_{PS}	ε_{EMKT}
ε_{SV}	1.00000		
ε_{PS}	0.22543	1.00000	
ε_{EMKT}	0.59475	0.32886	1.00000
Panel B: SV, TO and $EMKT$			
	ε_{SV}	ε_{TO}	ε_{EMKT}
ε_{SV}	1.00000		
ε_{TO}	0.15163	1.00000	
ε_{EMKT}	0.58698	0.34040	1.00000
Panel C: SV, $ILIQ$ and $EMKT$			
	ε_{SV}	ε_{ILIQ}	ε_{EMKT}
ε_{SV}	1.00000		
ε_{ILIQ}	-0.34420	1.00000	
ε_{EMKT}	0.58468	-0.52000	1.00000

Table 7 **Granger Causality Tests**

Table 7 reports the results of the Granger causality tests. The null of no causality running from a row variable to a column variable is tested using the VAR model consisting of market-wide default risk SV, market-wide liquidity (PS, TO, $ILIQ$) and excess market return $EMKT$. VAR(1) is estimated and the VAR lag length is chosen by the Schwartz Information Criterion. Chi-Square statistics are reported. The causal relationships being significant at 10, 5, and 1% are indicated by '*', '**', and '***', respectively. The sample period is from Jan 1971 to Dec 1998.

Panel A: SV, PS and $EMKT$

	SV	PS	$EMKT$
SV		3.00*	4.52**
PS	2.38		0.77
$EMKT$	50.40***	3.78*	

Panel B: SV, TO and $EMKT$

	SV	TO	$EMKT$
SV		2.03	4.52**
TO	10.30***		0.70
$EMKT$	50.40***	20.36***	

Panel C: SV, $ILIQ$ and $EMKT$

	SV	$ILIQ$	$EMKT$
SV		0.24	4.52**
$ILIQ$	24.55***		0.10
$EMKT$	50.40***	0.97	

Table 8 **Variance Decomposition**

*Table 8*gives the results of the variance decomposition from the VAR model consisting of market-wide default risk SV , market-wide liquidity (PS , TO , $ILIQ$) and excess market return $EMKT$. The VAR(1) is estimated and the VAR lag length is chosen by the Schwartz Information Criterion. The numbers in the table represent percentages of the forecast error variance in a row variable accounted for by innovations in each column variable at 1, 3, 6, 12, and 24 month horizons. 'Variables' denotes the variable for which the variance decomposition is computed. The sample period is from Jan 1971 to Dec 1998.

Panel A : the Results for the Case of PS Measure

Variable	Horizon	$EMKT$	SV	PS
$EMKT$	1	100	0	0
	3	99.280	0.179	0.541
	6	99.092	0.367	0.541
	12	98.918	0.544	0.538
	24	98.836	0.627	0.537
SV	1	35.373	64.627	0
	3	54.649	45.315	0.036
	6	58.030	41.948	0.022
	12	59.361	40.623	0.016
	24	59.758	40.228	0.014
PS	1	10.815	0.138	89.047
	3	13.916	0.278	85.806
	6	14.123	0.393	85.484
	12	14.264	0.500	85.237
	24	14.330	0.550	85.121

Panel B : the Results for the Case of TO Measure

Variable	Horizon	$EMKT$	TO	SV
$EMKT$	1	100	0	0
	3	99.000	0.731	0.268
	6	98.709	0.785	0.507
	12	98.507	0.786	0.707
	24	98.421	0.791	0.787
TO	1	11.587	88.413	0
	3	24.882	75.055	0.064
	6	26.532	73.327	0.141
	12	26.820	72.958	0.222
	24	26.870	72.874	0.257
SV	1	34.455	0.263	65.283
	3	54.664	0.259	45.076
	6	59.401	0.825	39.773
	12	61.479	1.313	37.208
	24	62.054	1.471	36.476

Panel C: the Results for the Case of *ILIQ* Measure

	Horizon	*EMKT*	*ILIQ*	*SV*
EMKT	1	100	0	0
	3	99.052	0.559	0.389
	6	98.616	0.696	0.688
	12	98.416	0.711	0.873
	24	98.301	0.777	0.923
ILIQ	1	27.040	72.960	0
	3	24.823	75.167	0.011
	6	24.946	74.997	0.057
	12	25.515	74.329	0.157
	24	25.789	73.984	0.227
SV	1	34.185	0.221	65.594
	3	54.050	2.136	43.814
	6	57.506	6.222	36.272
	12	57.622	11.753	30.625
	24	56.998	14.696	28.306

Table 9a **The Tests of Table 5 Using the Orthogonal-to-market-volatility Components of the Default and Liquidity Measures.**

The coefficient estimates of the VAR (1) model consist of the market-wide default risk orthogonal to market volatility RSV, market-wide liquidity measure orthogonal to market volatility RPS, and the market return $EMKT$. The VAR lag length is chosen by the Schwartz Information Criterion. The standard errors are reported in parentheses below the coefficient estimates. Statistical significance at 10%, 5% and 1% levels is indicated by '*', '**', '***', respectively. The sample period is from Jan 1971 to Dec 1998.

Panel A: RSV, RPS, and $EMKT$

	Dependent Variables		
	RSV_t	RPS_t	$EMKT_t$
Constant	-0.0007	-0.0003	0.0062**
	(0.0001)	(0.0024)	(0.0025)
RSV_{t-1}	0.8717***	-0.0378	-0.1715*
	(0.0261)	(0.0838)	(0.0877)
RPS_{t-1}	-0.0182	0.1687***	0.0088
	(0.0173)	(0.0555)	(0.0581)
$EMKT_{t-1}$	0.1000***	0.0218	0.0209
	(0.0165)	(0.0530)	(0.0555)

Table 9b **Granger Causality Tests**

Table 9b reports the results of the Granger causality tests. The null of no causality running from a row variable to a column variable is tested using the VAR model consisting of the market-wide default risk orthogonal to market volatility RSV , market-wide liquidity measure orthogonal to market volatility RPS , and the market return $EMKT$. VAR(1) is estimated and the VAR lag length is chosen by the Schwartz Information Criterion. Chi-Square statistics are reported. The causal relationships being significant at 10, 5, and 1% are indicated by '*', '**', and '***', respectively. The sample period is from Jan 1971 to Dec 1998.

RSV , RPS and $EMKT$			
	RSV	RPS	$EMKT$
RSV		0.21	4.13**
RPS	0.01		2.57
$EMKT$	35.61***	0.18	

Table 10 **Default Risk Effect Controlled by Liquidity**

Panel A presents the **default effect (Δdli) controlled by turnover ($stov$):** From Jan 1971 to Dec 1998, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their turnover $stov$ in the previous month. Within each portfolio, stocks are then sorted into 5 portfolios, based on past month's change in default likelihood indicators (Δdli). Equally weighted average portfolio returns are reported in percentage terms. "High-Low" is the return difference between the highest and lowest Δdli portfolios within each $stov$ quintile. T-values are calculated from Newey-West standard errors. The value of the truncation parameter q was selected in each case to be equal to the number of autocorrelation in returns that are significant at the 5% level. The row labeled 'Whole sample' report results using all stocks in our sample. *Panel B presents the* **default effect (Δdli) controlled by Pastor-Stambaugh liquidity beta β^L:** From Jan 1971 to Dec 1998, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their historical liquidity beta β^L (estimated by $r_{i,t} = \beta_i^0 + \beta_i^L L_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \varepsilon_{i,t}$ using monthly data over the previous 5 years). Within each portfolio, stocks are then sorted into 5 portfolios, based on past month's change in default likelihood indicators (Δdli). Equally weighted average portfolio returns are reported in percentage terms. "High-Low" is the return difference between the highest and lowest Δdli portfolios within each quintile. *Panel C presents the* **default effect (Δdli) controlled by illiquidity ratio ($iliq$)**: From Jan 1971 to Dec 1998, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their illiquidity ratio $iliq$ in the previous month. Within each portfolio, stocks are then sorted into 5 portfolios, based on past month's change in default likelihood indicators (Δdli). Equally weighted average portfolio returns are reported in percentage terms. "High-Low" is the return difference between the highest and lowest Δdli portfolios within each $iliq$ quintile.

Panel A: default effect (Δdli) controlled by turnover ($stov$)

	Low Δdli 1	2	3	4	High Δdli 5	High-Low	$t-$stat
Low $stov$ 1	0.63%	1.42%	1.30%	1.33%	2.57%	1.94%	9.1723
2	0.79%	1.37%	1.28%	1.23%	2.34%	1.55%	8.3743
3	0.88%	1.41%	1.27%	1.26%	1.97%	1.09%	6.1351
4	0.63%	1.35%	1.21%	1.20%	1.73%	1.10%	6.2254
High $stov$ 5	0.20%	1.11%	1.01%	1.15%	1.02%	0.82%	4.7360
Whole sample	0.63%	1.36%	1.21%	1.26%	1.88%	1.26%	9.5652

Panel B: default effect (Δdli) controlled by Pastor-Stambaugh liquidity beta β^L

	Low Δdli 1	2	3	4	High Δdli 5	High-Low	$t-$stat
Low β^L 1	0.41%	1.27%	1.39%	1.35%	2.39%	1.98%	9.7202
2	0.95%	1.31%	1.24%	1.29%	1.87%	0.92%	4.6703
3	1.27%	1.32%	1.19%	1.40%	1.89%	0.62%	3.7782
4	1.02%	1.42%	1.33%	1.32%	1.90%	0.88%	5.1911
High β^L 5	0.84%	1.48%	1.47%	1.53%	2.19%	1.35%	7.2188
Whole Sample	0.85%	1.45%	1.31%	1.37%	2.05%	1.20%	9.3772

Panel C: default effect (Δdli) controlled by illiquidity ratio ($iliq$)

	Low Δdli 1	2	3	4	High Δdli 5	High-low	$t-$stat
Low $iliq$ 1	1.10%	1.24%	0.98%	1.24%	1.20%	0.10%	0.7708
2	1.01%	1.41%	1.20%	1.42%	1.35%	0.33%	2.5791
3	0.57%	1.11%	1.28%	1.30%	1.47%	0.90%	6.2069
4	0.14%	1.42%	1.29%	1.27%	1.56%	1.42%	7.7579
High $iliq$ 5	0.18%	1.24%	1.41%	1.82%	3.75%	3.57%	10.2785
Whole sample	0.64%	1.37%	1.22%	1.27%	1.89%	1.25%	9.5013

Table 11 **Liquidity Effect Controlled by Default Risk Effect**

Panel A presents the **turnover ($stov$) effect controlled by default effect (Δdli)*:*** From Jan 1971 to Dec 1998, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their change in default likelihood indicators (Δdli) in the previous month. Within each portfolio, stocks are then sorted into 5 portfolios, based on past month's turnover $stov$. Equally weighted average portfolio returns are reported in percentage terms. "Low-High" is the return difference between the lowest and highest $stov$ portfolios within each Δdli quintile. T-values are calculated from Newey-West standard errors. The value of the truncation parameter q was selected in each case to be equal to the number of autocorrelation in returns that are significant at the 5% level. The row labeled 'Whole sample' report results using all stocks in our sample. *Panel B* presents **the Pastor-Stambaugh liquidity beta β^L effect controlled by default effect (Δdli)*:*** From Jan 1971 to Dec 1998, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their change in default likelihood indicators (Δdli) in the previous month. Within each portfolio, stocks are then sorted into 5 portfolios, based on past month's Pastor-Stambaugh liquidity beta β^L. Equally weighted average portfolio returns are reported in percentage terms. "High-Low" is the return difference between the highest and lowest β^L portfolios within each Δdli quintile. *Panel C presents the* **illiquidity ratio ($iliq$) effect controlled by default effect (Δdli)*:*** From Jan 1971 to Dec 1998, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their change in default likelihood indicators (Δdli) in the previous month. Within each portfolio, stocks are then sorted into 5 portfolios, based on past month's illiquidity ratio $iliq$. Equally weighted average portfolio returns are reported in percentage terms. "High-Low" is the return difference between the highest and lowest $iliq$ portfolios within each Δdli quintile.

Panel A: Turnover ($stov$) effect controlled by default effect (Δdli)

	Low $stov$ 1	2	3	4	High $stov$ 5	Low-High	$t-$stat
Low Δdli 1	0.69%	0.87%	0.66%	0.66%	0.24%	0.45%	1.8539
2	1.41%	1.45%	1.39%	1.43%	1.11%	0.30%	1.2672
3	1.25%	1.27%	1.29%	1.22%	1.04%	0.21%	0.9740
4	1.32%	1.26%	1.34%	1.22%	1.14%	0.18%	0.7604
High Δdli 5	2.44%	2.32%	2.10%	1.65%	0.92%	1.52%	5.6377
Whole sample	1.45%	1.40%	1.36%	1.23%	0.90%	0.55%	2.5576

Panel B: Pastor-Stambaugh liquidity beta β^L effect controlled by default effect (Δdli)

	Low β^L 1	2	3	4	High β^L 5	High-Low	$t-$stat
High Δdli 1	0.63%	0.76%	1.02%	0.84%	1.05%	0.43%	1.9231
2	1.41%	1.44%	1.50%	1.48%	1.47%	0.06%	0.4239
3	1.31%	1.20%	1.24%	1.36%	1.40%	0.09%	0.851
4	1.30%	1.33%	1.43%	1.31%	1.45%	0.15%	1.1166
Low Δdli 5	2.33%	1.93%	1.97%	2.06%	2.08%	-0.25%	-1.3321
Whole sample	1.37%	1.34%	1.40%	1.40%	1.51%	0.14%	1.4273

Panel C: illiquidity ratio ($iliq$) effect controlled by default effect (Δdli)

	Low $iliq$ 1	2	3	4	5	6	7	8	9	High $iliq$ 10	High-Low	$t-$stat
Low Δdli 1	0.91%	0.85%	0.69%	0.36%	0.57%	0.33%	0.59%	0.56%	0.86%	0.70%	-0.21%	-0.481
2	1.23%	1.45%	1.35%	1.62%	1.45%	1.36%	1.30%	1.23%	1.37%	1.33%	0.10%	0.3499
3	1.17%	1.26%	1.07%	1.21%	1.16%	1.29%	1.26%	1.30%	1.32%	1.18%	0.01%	0.0333
4	1.23%	1.17%	1.38%	1.19%	1.20%	1.22%	1.29%	1.27%	1.41%	1.30%	0.07%	0.2405
High Δdli 5	1.19%	1.28%	1.14%	1.08%	1.52%	1.75%	1.59%	2.10%	2.79%	4.53%	3.33%	7.2115
Whole sample	1.15%	1.16%	1.20%	1.16%	1.06%	1.04%	1.07%	1.10%	1.06%	1.97%	0.82%	2.1805

Table 12 **The Multifactor Inefficiency Measure**

This table presents posterior means and standard deviations of multifactor inefficiency measure ψ, which is the loss in expected return due to holding the market portfolio instead of a multifactor efficient portfolio with the same variance and sensitivities to state variables, for several asset pricing models. The sample period is from Jan 1971 to Dec 1998. Means and standard deviation are presented in annual percentage terms.

	CAPM	CAPM+ MTO	CAPM+ MPS	CAPM+ MILIQ	CAPM+ MDLI	CAPM+MTO+ MDLI	CAPM+MPS+ MDLI	CAPM+MILIQ+ MDLI
Inefficiency measure	23.99	23.79	23.72	23.70	23.73	22.29	23.28	23.41
Standard error	3.56	3.65	3.63	3.68	3.66	3.63	3.65	3.67

	FF	FF+MTO	FF+MPS	FF+MILIQ	FF+MDLI	FF+MTO+MDLI	FF+MPS+MDLI	FF+MILIQ+MDLI
Inefficiency measure	23.55	22.42	22.51	23.34	21.29	21.04	21.05	21.10
Standard error	3.79	3.66	3.64	3.70	3.57	3.59	3.59	3.56

Table 13 **Evaluating the Performance of Asset Pricing Models**

The $(i, j)^{th}$ element, $i < j$ reports the statistic, $\hat{p}_{ij} = \mathrm{U}_{ij}/I^2$ (I = 5000), which is an unbiased estimator of $p_{ij} = P(\psi^{M_j} < \psi^{M_i})$, the probability that model i, M_i, will generate a higher multifactor inefficiency measure than model j, M_j. On the other hand, $(i, j)^{th}$ element, i > j, in the lower diagonal section of the table reports the values of the MWW statistics for testing H_0: $\psi^{M_i} = \psi^{M_j}$ versus H_1: $\psi^{M_i} < \psi^{M_j}$.

Panel A: Using MTO as Market Liquidity Proxy

	CAPM	CAPM+MTO	CAPM+MDLI	CAPM+MTO+MDLI	FF	FF+MTO	FF+MDLI	FF+MTO+MDLI
CAPM		0.52	0.52	0.63	0.54	0.62	0.70	0.72
CAPM+MTO	2.78		0.50	0.62	0.52	0.61	0.69	0.70
CAPM+MDLI	3.61	0.82		0.61	0.52	0.60	0.69	0.70
CAPM+MTO+MDLI	22.85	19.97	19.37		0.41	0.49	0.58	0.60
FF	5.99	3.22	2.41	-16.36		0.58	0.67	0.68
FF+MTO	21.82	18.80	17.95	-1.59	15.22		0.59	0.61
FF+MDLI	37.92	34.66	33.78	13.74	30.72	15.61		0.52
FF+MTO+MDLI	41.31	38.03	37.14	16.85	37.14	19.04	3.54	

Panel B: Using MPS as Market Liquidity Proxy

	CAPM	CAPM+MPS	CAPM+MDLI	CAPM+MPS+MDLI	FF	FF+MPS	FF+MDLI	FF+MPS+MDLI
CAPM		0.52	0.52	0.56	0.54	0.62	0.70	0.72
CAPM+MPS	3.65		0.50	0.54	0.51	0.59	0.68	0.70
CAPM+MDLI	3.31	-0.31		0.54	0.52	0.60	0.69	0.70
CAPM+MPS+MDLI	9.81	6.99	6.41		0.48	0.57	0.65	0.67
FF	6.06	2.46	2.75	-3.53		0.58	0.67	0.68
FF+MPS	19.98	16.30	16.54	11.52	13.56		0.59	0.61
FF+MDLI	35.47	31.91	32.04	26.43	29.08	16.39		0.52
FF+MPS+MDLI	38.07	34.58	34.69	29.32	31.76	19.35	3.14	

Panel C: Using MILIQ as Market Liquidity Proxy

	CAPM	CAPM+MILIQ	CAPM+MDLI	CAPM+MILIQ+MDLI	FF	FF+MILIQ	FF+MDLI	FF+MILIQ+MDLI
CAPM		0.52	0.52	0.55	0.54	0.55	0.70	0.72
CAPM+MILIQ	4.23		0.50	0.52	0.51	0.53	0.68	0.69
CAPM+MDLI	3.31	-0.87		0.53	0.52	0.53	0.69	0.70
CAPM+MILIQ+MDLI	8.03	3.79	4.66		0.50	0.51	0.66	0.67
FF	6.06	1.91	2.75	-1.83		0.52	0.68	0.68
FF+MILIQ	8.85	4.64	5.48	0.88	2.66		0.65	0.67
FF+MDLI	35.47	31.39	32.04	27.81	29.08	26.81		0.51
FF+MILIQ+MDLI	37.76	33.72	34.34	30.18	31.40	29.16	2.54	

Table 14 **Evaluating the performance of asset pricing models across different market volatility states and economic states**

Table 14.A: MWW tests on the same models across high market volatility periods during Jan 1971 to Dec 1998. We use within-month daily standard deviation of the value-weighted market return as monthly market volatility and define high volatility months to be those with greater than average volatility over the sample period. There are in total 129 observations classified as high market-volatility state.

Panel A: Using MTO as Market Liquidity Proxy

	CAPM	CAPM+MTO	CAPM+MDLI	CAPM+MTO+MDLI	FF	FF+MTO	FF+MDLI	FF+MTO+MDLI
CAPM		0.50	0.52	0.56	0.49	0.54	0.63	0.65
CAPM+MTO	-0.13		0.52	0.56	0.49	0.54	0.63	0.65
CAPM+MDLI	3.55	3.63		0.54	0.47	0.52	0.61	0.63
CAPM+MTO+MDLI	9.92	9.97	6.30		0.43	0.49	0.58	0.59
FF	-2.49	-2.38	-6.02	-12.33		0.56	0.65	0.66
FF+MTO	7.38	7.48	3.76	-2.60	9.83		0.59	0.61
FF+MDLI	23.06	23.09	19.44	13.32	25.26	15.84		0.52
FF+MTO+MDLI	25.69	25.69	22.14	16.15	27.80	18.63	3.00	

Panel B: Using MPS as Market Liquidity Proxy

	CAPM	CAPM+MPS	CAPM+MDLI	CAPM+MPS+MDLI	FF	FF+MPS	FF+MDLI	FF+MPS+MDLI
CAPM		0.52	0.52	0.56	0.49	0.55	0.63	0.64
CAPM+MPS	2.81		0.50	0.54	0.47	0.53	0.62	0.63
CAPM+MDLI	3.58	0.79		0.54	0.47	0.52	0.61	0.62
CAPM+MPS+MDLI	9.84	7.06	6.25		0.43	0.49	0.58	0.59
FF	-2.49	-5.28	-6.02	-12.17		0.56	0.65	0.66
FF+MPS	7.90	5.12	4.30	-1.94	10.24		0.59	0.60
FF+MDLI	23.10	20.36	19.48	13.18	25.27	15.14		0.51
FF+MPS+MDLI	25.10	22.43	21.56	15.41	27.16	17.34	2.52	

Panel C: Using MILIQ as Market Liquidity Proxy

	CAPM	CAPM+MILIQ	CAPM+MDLI	CAPM+MILIQ+MDLI	FF	FF+MILIQ	FF+MDLI	FF+MILIQ+MDLI
CAPM		0.52	0.52	0.52	0.49	0.51	0.63	0.65
CAPM+MILIQ	3.13		0.50	0.51	0.47	0.50	0.62	0.63
CAPM+MDLI	3.55	0.39		0.50	0.47	0.49	0.61	0.63
CAPM+MILIQ+MDLI	4.25	1.08	0.65		0.46	0.49	0.61	0.63
FF	-2.49	-5.60	-6.02	-6.74		0.53	0.65	0.66
FF+MILIQ	2.40	-0.73	-1.17	-1.84	4.85		0.62	0.64
FF+MDLI	23.06	19.92	19.44	18.84	25.26	20.46		0.52
FF+MILIQ+MDLI	26.37	23.26	22.76	22.19	28.47	23.77	3.43	

Table 14.B: MWW tests on the same models across low market volatility periods during Jan 1971 to Dec 1998. We use within-month daily standard deviation of the value-weighted market return as monthly market volatility and define low volatility months to be those with smaller than average volatility over the sample period. There are in total 207 observations classified as low market-volatility state.

Panel A: Using MTO as market liquidity proxy

	CAPM	CAPM+MTO	CAPM+MDLI	CAPM+MTO+MDLI	FF	FF+MTO	FF+MDLI	FF+MTO+MDLI
CAPM		0.52	0.51	0.58	0.53	0.66	0.66	0.61
CAPM+MTO	4.00		0.49	0.55	0.51	0.64	0.64	0.67
CAPM+MDLI	2.45	-1.64		0.56	0.52	0.65	0.65	0.68
CAPM+MTO+MDLI	13.19	9.18	10.73		0.45	0.58	0.59	0.62
FF	5.53	1.46	3.03	-7.83		0.63	0.63	0.66
FF+MTO	27.52	23.75	25.21	14.60	22.24		0.50	0.54
FF+MDLI	28.55	24.80	26.26	15.62	23.28	0.85		0.53
FF+MTO+MDLI	33.42	29.78	31.19	20.77	28.28	6.23	5.36	

Panel B: Using MPS as market liquidity proxy

	CAPM	CAPM+MPS	CAPM+MDLI	CAPM+MPS+MDLI	FF	FF+MPS	FF+MDLI	FF+MPS+MDLI
CAPM		0.51	0.51	0.54	0.53	0.59	0.67	0.69
CAPM+MPS	2.29		0.50	0.52	0.52	0.58	0.65	0.68
CAPM+MDLI	2.54	0.24		0.52	0.52	0.58	0.65	0.68
CAPM+MPS+MDLI	6.39	4.13	3.89		0.50	0.56	0.63	0.66
FF	5.62	3.34	3.11	-0.82		0.56	0.63	0.66
FF+MPS	15.93	13.74	13.51	9.52	10.42		0.58	0.61
FF+MDLI	28.63	26.57	26.34	22.41	23.36	13.23		0.53
FF+MPS+MDLI	33.30	31.32	31.08	27.32	28.25	18.57	5.74	

Panel C: Using MILIQ as market liquidity proxy

	CAPM	CAPM+MILIQ	CAPM+MDLI	CAPM+MILIQ+MDLI	FF	FF+MILIQ	FF+MDLI	FF+MILIQ+MDLI
CAPM		0.52	0.51	0.59	0.53	0.55	0.66	0.67
CAPM+MILIQ	3.84		0.49	0.57	0.51	0.53	0.64	0.65
CAPM+MDLI	2.45	-1.52		0.58	0.52	0.54	0.65	0.66
CAPM+MILIQ+MDLI	15.66	11.52	13.22		0.44	0.46	0.58	0.58
FF	5.53	1.53	3.03	-10.28		0.52	0.63	0.64
FF+MILIQ	9.02	5.02	6.58	-6.53	3.52		0.61	0.62
FF+MDLI	28.55	24.41	26.26	13.49	23.28	19.49		0.51
FF+MILIQ+MDLI	29.24	25.18	26.96	14.50	24.07	20.41	1.19	

Table 14.C: MWW tests on the same models across high economic growth states during Jan 1971 to Dec 1998. We use leading economic indicator (lei) provided by Conference Board. We first estimate the trend in the growth of this indicator by regressing the log of the indicator on a constant and a time trend, following McQueen and Roley (1993). We then classify each sample month as being in the low (high) growth state if the indicator's growth during the month is below (above) the trend. There are in total 187 observations classified as high economic growth state.

Panel A: Using MTO as Market Liquidity Proxy

	CAPM	CAPM+MTO	CAPM+MDLI	CAPM+MTO+MDLI	FF	FF+MTO	FF+MDLI	FF+MTO+MDLI
CAPM		0.51	0.50	0.54	0.50	0.56	0.61	0.63
CAPM+MTO	1.23		0.50	0.53	0.49	0.56	0.60	0.62
CAPM+MDLI	0.66	-0.63		0.53	0.49	0.56	0.60	0.62
CAPM+MTO+MDLI	6.25	5.04	5.57		0.46	0.53	0.57	0.59
FF	-0.87	-2.15	-1.58	-7.16		0.57	0.61	0.63
FF+MTO	11.12	9.94	10.49	4.83	11.92		0.54	0.56
FF+MDLI	18.73	17.62	18.13	12.54	19.49	7.73		0.52
FF+MTO+MDLI	21.99	20.92	21.41	15.85	22.73	11.04	3.23	

Panel B Using MPS as Market Liquidity Proxy

	CAPM	CAPM+MPS	CAPM+MDLI	CAPM+MPS+MDLI	FF	FF+MPS	FF+MDLI	FF+MPS+MDLI
CAPM		0.51	0.50	0.53	0.50	0.59	0.61	0.63
CAPM+MPS	2.22		0.49	0.52	0.48	0.58	0.60	0.62
CAPM+MDLI	0.71	-1.53		0.53	0.49	0.58	0.61	0.63
CAPM+MPS+MDLI	5.98	3.82	5.30		0.46	0.55	0.57	0.60
FF	-0.82	-3.04	-1.53	-6.79		0.59	0.61	0.63
FF+MPS	15.06	12.99	14.43	9.09	15.85		0.52	0.54
FF+MDLI	18.78	16.75	18.18	12.84	19.54	3.82		0.52
FF+MPS+MDLI	22.36	20.39	21.78	16.52	23.11	7.62	3.80	

Panel C: Using MILIQ as Market Liquidity Proxy

	CAPM	CAPM+MILIQ	CAPM+MDLI	CAPM+MILIQ+MDLI	FF	FF+MILIQ	FF+MDLI	FF+MILIQ+MDLI
CAPM		0.51	0.50	0.52	0.50	0.51	0.61	0.64
CAPM+MILIQ	1.11		0.50	0.51	0.49	0.51	0.60	0.63
CAPM+MDLI	0.66	-0.51		0.52	0.49	0.51	0.60	0.63
CAPM+MILIQ+MDLI	3.37	2.17	2.67		0.48	0.49	0.59	0.62
FF	-0.87	-2.02	-1.58	-4.27		0.52	0.61	0.64
FF+MILIQ	2.13	0.95	1.42	-1.26	2.94		0.60	0.62
FF+MDLI	18.73	17.47	18.13	15.47	19.49	16.55		0.53
FF+MILIQ+MDLI	23.55	22.27	22.99	20.38	24.30	21.41	4.92	

Table 14.D: MWW tests on the same models across low economic growth states during Jan 1971 to Dec 1998. We use leading economic indicator (lei) provided by Conference Board. We first estimate the trend in the growth of this indicator by regressing the log of the indicator on a constant and a time trend, following McQueen and Roley (1993). We then classify each sample month as being in the low (high) growth state if the indicator's growth during the month is below (above) the trend. There are in total 149 observations classified as low economic growth state.

Panel A: Using MTO as Market Liquidity Proxy

	CAPM	CAPM+MTO	CAPM+MDLI	CAPM+MTO+MDLI	FF	FF+MTO	FF+MDLI	FF+MTO+MDLI
CAPM		0.52	0.52	0.60	0.59	0.62	0.63	0.66
CAPM+MTO	3.87		0.49	0.58	0.56	0.60	0.61	0.64
CAPM+MDLI	3.05	-0.89		0.58	0.57	0.61	0.61	0.64
CAPM+MTO+MDLI	16.94	13.01	13.99		0.49	0.53	0.53	0.56
FF	15.06	11.11	12.07	-2.10		0.54	0.55	0.57
FF+MTO	21.64	17.67	18.71	4.65	6.75		0.51	0.54
FF+MDLI	22.85	18.86	19.91	5.78	7.88	1.05		0.53
FF+MTO+MDLI	27.53	23.62	24.70	10.77	12.90	6.12	5.06	

Panel B: Using MPS as Market Liquidity Proxy

	CAPM	CAPM+MPS	CAPM+MDLI	CAPM+MPS+MDLI	FF	FF+MPS	FF+MDLI	FF+MPS+MDLI
CAPM		0.52	0.52	0.54	0.59	0.60	0.63	0.66
CAPM+MPS	2.66		0.50	0.52	0.57	0.58	0.62	0.65
CAPM+MDLI	3.10	0.41		0.52	0.57	0.58	0.62	0.65
CAPM+MPS+MDLI	6.38	3.70	3.34		0.55	0.56	0.60	0.63
FF	15.11	12.35	12.12	8.70		0.51	0.55	0.58
FF+MPS	16.83	14.09	13.87	10.50	1.94		0.53	0.57
FF+MDLI	22.90	20.10	19.96	16.52	7.93	5.92		0.54
FF+MPS+MDLI	28.51	25.78	25.73	22.36	14.09	12.05	6.31	

Panel C: Using MILIQ as Market Liquidity Proxy

	CAPM	CAPM+MILIQ	CAPM+MDLI	CAPM+MILIQ+MDLI	FF	FF+MILIQ	FF+MDLI	FF+MILIQ+MDLI
CAPM		0.51	0.52	0.57	0.59	0.60	0.63	0.66
CAPM+MILIQ	2.45		0.50	0.56	0.57	0.59	0.62	0.64
CAPM+MDLI	3.05	0.52		0.56	0.57	0.59	0.61	0.64
CAPM+MILIQ+MDLI	12.64	10.06	9.66		0.51	0.53	0.56	0.59
FF	15.06	12.45	12.07	2.24		0.52	0.55	0.57
FF+MILIQ	17.83	15.21	14.86	5.06	2.83		0.53	0.56
FF+MDLI	22.85	20.18	19.91	10.07	7.88	4.96		0.53
FF+MILIQ+MDLI	27.34	24.72	24.55	14.98	12.95	10.04	5.20	

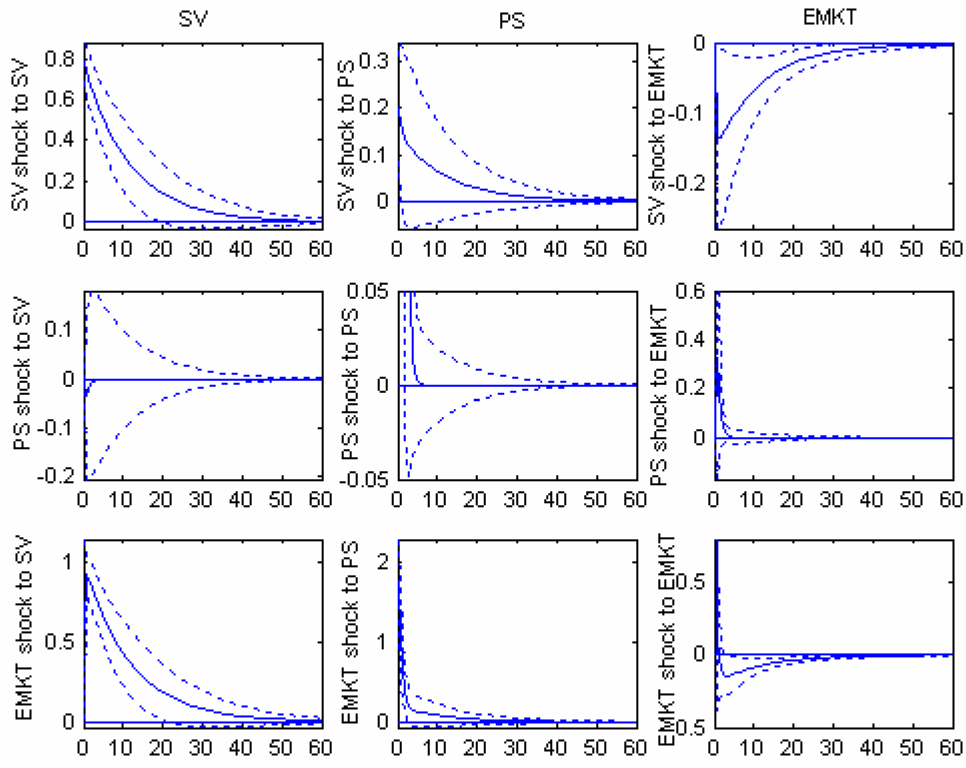

Figure 1.A **Orthogonalized Impulse Responses of** SV **,** PS **and** $EMKT$. This figure shows impulse responses of market default risk SV , market liquidity PS and market return $EMKT$ to a Cholesky one-standard-deviation innovation to VAR variables. The VAR lag length is chosen by the Schwartz Information Criterion. The left-most column gives the impulse responses of SV . The middle column reports the impulse responses of PS . The right-most column documents the impulse responses of $EMKT$. Dashed lines represent two-standard error bands. The sample period is from Jan 1971 to Dec 1998.

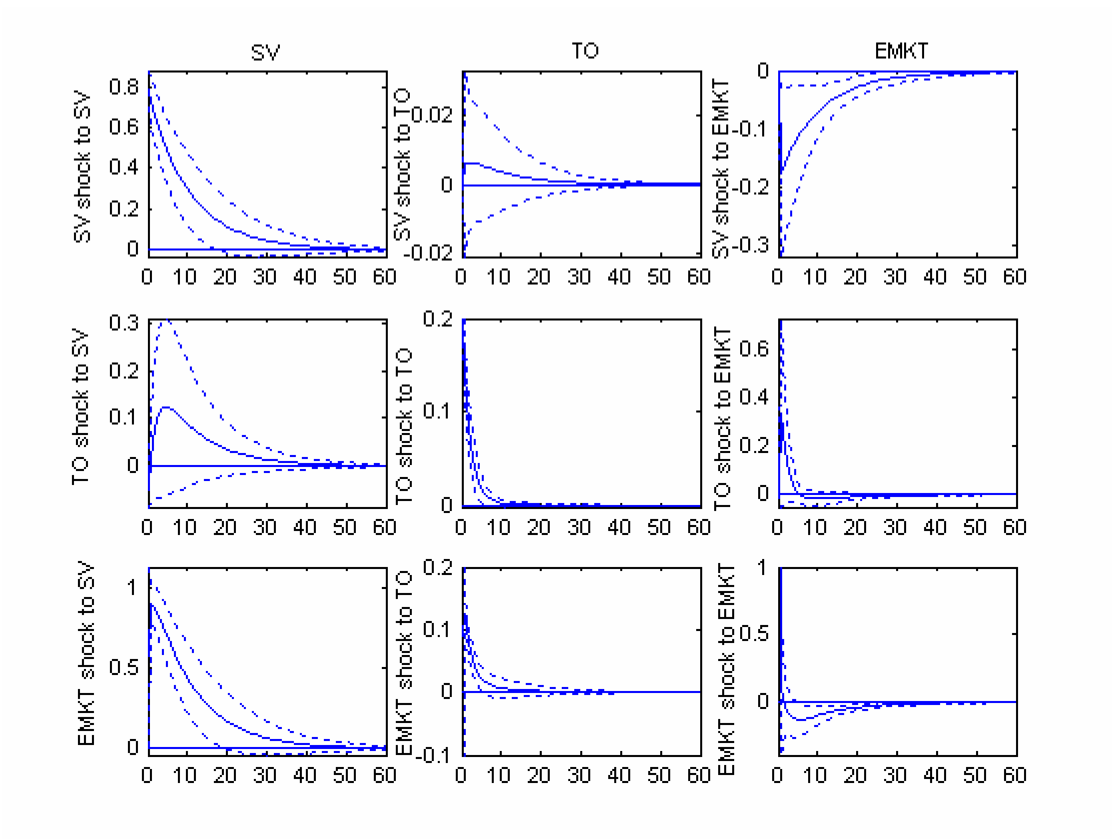

Figure 1.B **Orthogonalized Impulse Responses of SV, TO and $EMKT$**. This figure shows impulse responses of market default risk SV, market liquidity TO and market return $EMKT$ to a Cholesky one-standard-deviation innovation to VAR variables. The VAR lag length is chosen by the Schwartz Information Criterion. The left-most column gives the impulse responses of SV. The middle column reports the impulse responses of TO. The right-most column documents the impulse responses of $EMKT$. Dashed lines represent two-standard error bands. The sample period is from Jan 1971 to Dec 1998.

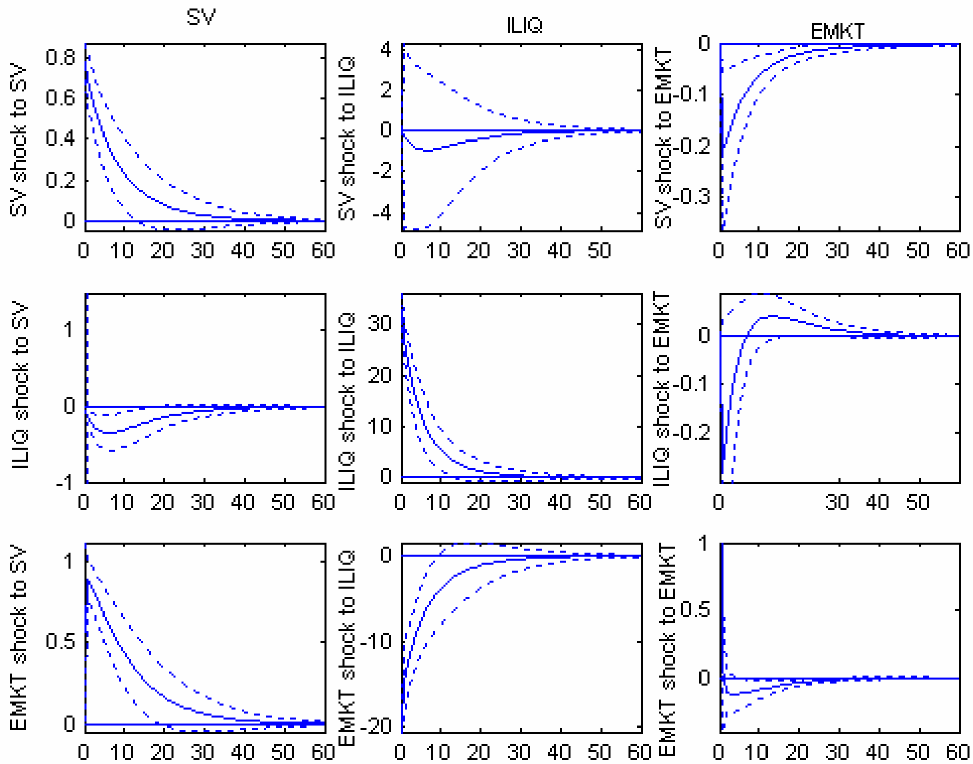

Figure 1.C **Orthogonalized Impulse Responses of** SV **,** $ILIQ$ **and** $EMKT$. This figure shows impulse responses of market default risk SV , market liquidity $ILIQ$ and market return $EMKT$ to a Cholesky one-standard-deviation innovation to VAR variables. The VAR lag length is chosen by the Schwartz Information Criterion. The left-most column gives the impulse responses of SV . The middle column reports the impulse responses of $ILIQ$. The right-most column documents the impulse responses of $EMKT$. Dashed lines represent two-standard error bands. The sample period is from Jan 1971 to Dec 1998.