Chapter 8
Conclusion

8.1. Contributions of thesis and its findings

This thesis relates systematic liquidity, market efficiency and the short-term anomalous behaviour of stock returns. Specifically, it involves three empirical chapters, each concerned with a particular issue. The first empirical chapter investigates whether systematic liquidity risk is priced in LSE. In the second empirical chapter, we explore the role of systematic liquidity risk in explaining the price anomalies following large one-day price changes. Finally, the third empirical chapter focuses on the role of the time-varying systematic risk in explaining the price anomalies following large one-day price changes. This section summarises the contributions and the findings of each of our empirical chapters.

8.1.1. Systematic liquidity risk and asset pricing: UK evidence

The first empirical chapter, Chapter 5, investigates whether systematic liquidity risk is priced in LSE. It checks whether the US evidence of Pastor and Stambaugh (2003), Amihud (2002) and Liu (2006) is a country-specific or a worldwide phenomenon. The methodology of this chapter is based on both individual stock approach and portfolio approach. The individual stock approach is based on estimating the percentage of the sample stocks with significant systematic liquidity risk coefficients. The portfolio approach starts by sorting the sample stocks according to their historical liquidity beta and assigning them to decile portfolios. The liquidity beta is the slope coefficient of the aggregate liquidity factor in a multiple regression in which the other independent variables are the three factors of Fama and French (1993) and the momentum factor of Carhart (1997). The aggregate liquidity factor is constructed following Liu (2006). Three liquidity measures are used throughout the thesis, taking into consideration the multi-dimensional nature of liquidity. These measures are the proportional quoted bid-ask spread, the Amihud (2002) illiquidity ratio and the turnover rate. The proportional quoted bid-ask spread measures the transaction cost, the illiquidity ratio measures the price impact of order flow and the turnover rate is a proxy for the trading activity. The portfolios' sort is conducted annually and the post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each decile portfolio. Furthermore, we construct a Diff(10-1) portfolio whose returns are calculated as the difference in daily returns between least liquid and most liquid portfolios. The excess returns on all portfolios are then regressed on different combinations of common risk factors. Specifically, we estimate the CAPM, the F&F, the C-F&F and the liquidity augmented versions of these models for all portfolios. If the intercept of the Diff(10-1) portfolio is statistically significant under the CAPM, the F&F and the C-F&F models and at the same time is not significantly different from zero under any of the liquidity augmented models, then we can conclude that systematic liquidity risk is priced.

This chapter contributes to the literature in several ways: first, it is the first to examine the role of the systematic liquidity risk in asset pricing in LSE, one of the major capital markets around the world. Second, it considers three different aspects of liquidity and hence sheds light on which aspect of liquidity, if any, is important in asset pricing. Third, it estimates a set of twelve asset pricing models and decides the model that best fits the return variations of the UK stocks. Finally, in addition to OLS, we employ different forms of GARCH models to account for volatility clustering, leptokurtosis and leverage effects in returns. Moreover, we adopt the GARCH models to adjust for the heteroskedastic nature of the error term generated from the OLS estimation. Conditional heteroskedasticity adjustment is recommended by many researchers, including Corhay and Rad (1996), Batchelor and Orakcioglu (2003), Gregoriou et al. (2004) and Hahn and Reyes (2004).

The empirical results of this chapter can be summarised as follows. A preliminary analysis on the individual stock level shows that approximately 50% to 90% of the sample stocks have significant liquidity betas. The systematic liquidity factor outperforms the momentum factor of Carhart (1997) in explaining the stock returns. The best model that describes the variations of stock returns is a liquidity augmented one, which consists of the three Fama and French (1993) common risk factors, the momentum factor of Carhart (1997) and a mimicking liquidity factor (regardless of which liquidity measure is used). These results are robust to different estimation methods and the distributions of regression errors. On the other hand, the portfolio approach provides evidence that systematic liquidity risk is priced exclusively when liquidity is measured by Amihud's (2002) illiquidity ratio. This is consistent with the findings of Martinaiz et al. (2005) for the Spanish stock market. The results of this chapter seem to vary across different sub-periods. Specifically, the evidence that the illiquidity ratio of Amihud (2002) is priced exists in our earliest sub-period but disappears in the two following sub-periods. This may be due to the introduction of new trading systems of the FTSEALL share index stocks, which may have improved the aggregate liquidity of the market and reduced investors' concerns with the liquidity risk.

8.1.2. Systematic liquidity risk and stock price reaction to large one-day price changes

The second empirical chapter of this thesis, Chapter 6, investigates whether systematic liquidity risk explains the stock price reaction to large one-day price changes in LSE. The contribution of this chapter lies in proposing a new potential rationalisation of the price anomalies following large one-day price changes. The literature used market microstructure, behavioural finance and size effect as possible explanations of the observed anomaly. Zarowin (1990) argues that the price reversal anomaly is a demonstration of the size anomaly. Chan (1988), Ball and Kothari (1989), Wu (2002) and Wang (2003) argue that markets are efficient and the observed abnormal returns are a result of the failure to adjust for time-varying risk. Atkins and Dyi (1990), Cox and Peterson (1994) and Li et al. (2008) document that the abnormal returns are not adequate to cover the transaction cost of trading. Moskowitz and Grinblatt (1999) point out that industry momentum explains the individual stock momentum. Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) use concepts from behavioural finance and psychology, such as overconfidence, biased self-attribution, conservatism and representativeness to explain investors' behaviour around shocks. This chapter proposes systematic liquidity risk as another possible explanation for the price anomalies observed following large one-day price changes.

We argue that the variations in systematic liquidity risk between stocks may explain their different price reactions to large one-day price changes. Specifically, we expect stocks with high sensitivity to the fluctuations in aggregate market liquidity to be more affected by price shocks. Several factors have motivated us to propose systematic liquidity risk as an explanation for the abnormal returns following price shocks. First, the recent evidence of the important role of systematic liquidity risk in asset pricing (see, for example, Pastor and Stambaugh, 2003; Liu, 2006). Second, the findings of Lasfer et al. (2003) that price anomalies are more pronounced in less liquid markets. Third, the conclusion of Sadka (2006) that the systematic variations in the variable component of liquidity risk, when liquidity is measured by the price impact of trade, can explain a substantial part of the momentum strategies profits. Finally, Spyrou et al. (2007) and Mazouz et al. (2009) find that large capitalisation stocks react efficiently to large one-day price changes.

This chapter compares the reaction of stocks with high and low systematic liquidity risk to shocks. Specifically, we sort our sample stocks according to their historical liquidity betas and we assign them to decile portfolios. Then, we estimate the CAARs following large one-day price changes for each decile portfolio. The chapter examines the stock reaction to the price shocks of 5%, 10% and 20% or more and the price shocks of -5%, -10% and -20% or less. The abnormal returns are calculated as the residuals of the four-factor model consisting of the three Fama and French (1993) common risk factors and the momentum factor of Carhart (1997).

The empirical results of the chapter show that the reaction of the sample stocks to large one-day price changes follows the uncertain information hypothesis of Brown et al. (1988). Particularly, there is a significant underreaction (return continuation) that extends up to several days following shocks of 5%, 10% and 20% or more. On the other hand, there is evidence of a delayed overreaction (price reversal) following shocks of -5%, -10% and -20% or less. The underreaction lasts up to 10 days after the shock. Our findings contrast with Lasfer et al. (2003) and Spyrou et al. (2007) who document significant return continuation following both positive and negative shocks. The role of the systematic liquidity risk in explaining the price reaction to large shocks is apparent. While the stocks with the highest systematic liquidity beta, the least liquid stocks, show anomalous behaviour following large one-day shocks, the most liquid stocks, in most cases, react efficiently to shocks. The evidence is stronger when the proportional bid-ask spread and Amihud's (2002) illiquidity ratio are used as liquidity measures. However, a liquidity augmented model of the three factors of Fama and French (1993), the momentum factor of Carhart (1997) and a systematic liquidity risk factor does not explain the abnormal returns following the large one-day shocks. We argue that the way we account for the systematic liquidity risk may not be appropriate. Specifically, we expect that the abnormal returns may result from the potential biases arising from the use of the static versions of the asset pricing models. Thus, using a conditional version of the liquidity augmented C-F&F may account for the observed anomalies. We examine this issue in more detail in Chapter 7.

The sub-period analysis shows that the results of this chapter vary over time. This is expected because market liquidity tends to improve over time as a result of developing new trading systems and increasing the numbers of companies and investors.[1] However, the most liquid stocks react differently from the least liquid to large one-day price changes in most of the sub-periods, suggesting that liquidity explains, at least partially, the observed price anomalies following these shocks.

8.1.3. Time-varying risk and stock price reaction to large one-day price changes

The third empirical chapter of this thesis, Chapter 7, investigates whether time-varying risks can explain the price anomalies following large one-day price changes. Fabozzi and Francis (1978), Bollerslev et al. (1988), Wang (2003), Ferson et al. (2006) and Ammann and Verhofen (2008) are among the studies which find that risk and return are time-varying. Chan (1988), Ball and Kothari (1989) and Chordia and Shivakumar (2002) are examples of the authors who suggest time-varying risk as one of the explanations of both the long-term price reversal of DeBondt and Thaler (1985) and the medium-term momentum of Jegadeesh and Titman (1993). They argue that the momentum and contrarian profits are nothing other than pricing errors resulting from the poor performance of the static asset pricing models that have been used. More importantly, Brown et al. (1988) argue that major informational surprises increase both the risk and the expected return of stocks in a systematic manner. Motivated by these studies, this chapter is the first to propose time-varying risk as an explanation for the price anomalies following large one-day price changes. In a dynamic world, we expect that static asset pricing models may result in pricing

[1] During 1986-1997, the trading of FTSEALL share index stocks was happening through SEAQ (stock exchange automated quotation system), that is a dealership market. On 20th October 1997, the trading mechanism of FTSEALL share index stocks had been changed to an order-driven market where SETS (Stock Exchange Trading System) had been introduced. Since 4th November 2003, a hybrid market prevails, thus a new trading system has been introduced, which is SETSmm (Stock Exchange Trading System with Market Makers).

errors emphasising the abnormal returns following large one-day price shocks. This chapter analyses the relative importance of time-varying risk and systematic liquidity in explaining the anomalous short-term behaviour of the sample stocks following large one-day price shocks.

The methodology of this chapter is based on the simplified GARCH (S-GARCH) of Harris et al. (2007). This approach is easy to use, simple, flexible and equivalent in its efficiency to other complicated time-varying risk estimates. The Kalman filter and the multi-variate GARCH models are examples of the most widely used approaches in the literature. However, these two approaches are complicated, difficult to use and problematic in some cases[1]. The S-GARCH is based on the estimation of only univariate GARCH models, both for the individual return series and for the sum and difference of each pair of series. The covariance between each pair of return series is then imputed from these variance estimates. The chapter analyses the S-GARCH-based cumulative returns of the sample stocks following positive and negative price shocks of different magnitudes. Thereafter, the chapter compares the S-GARCH-based cumulative returns between the stocks of historical liquidity beta sorted decile portfolios. We do so in order to estimate the relative importance of time-varying risk and systematic liquidity risk in explaining the price reaction to large one-day price changes.

The findings of this chapter can be summarised as follows. The evidence of stock price reaction to large one-day price shocks reported in Chapter 6 changes significantly after conducting the time-varying risk adjustment. In particular, the

[1] More discussions on the disadvantages of these two approaches are available in Gencay et al. (2002), Harris et al. (2007) and Palandri (2009).

sample stocks react in an efficient manner to shocks of 10% and 20% or more and to shocks of -5%, -10% and -20% or less. Only one day price reversal is found following shocks of 5% or more. Hence, time-varying risk plays a vital role in explaining the documented overreaction and underreaction following large one-day price shocks. Indeed, it explains most of these anomalies. Time-varying risk is more important than systematic liquidity risk in explaining the price reaction of the stocks of different liquidity portfolios. Regardless of the liquidity measure, the S-GARCH-based CAARs, following both positive and negative shocks, associated with most of stocks in both liquid and illiquid portfolios, are not significantly different from zero. Only some portfolios exhibit significant overreaction following positive shocks. The smallest liquidity beta stocks underreact to the negative, large one-day shocks. Overall, the conditional four-factor model of Carhart (1997) and the conditional version of the same model augmented with the systematic liquidity risk are superior to their static versions in explaining the return variations of FTSEALL stocks. These finding are robust to different sub-periods and different versions of GARCH models.

8.2. Results implications, limitations and future research

The empirical results of this thesis have several important implications for both academics and practitioners in the fields of liquidity, market efficiency and asset pricing. First, we shed light on the importance of the aggregate market liquidity as a source of systematic risk. Second, we confirm the time-varying nature of both risk and return, indicating that any future work should depend on dynamic rather than static asset pricing models. Third, we support the efficient market hypothesis which has been challenged in the last two decades or so. Finally, we explain two important price anomalies following large one-day price changes (i.e., price reversal and return continuation).

On the limitations' side, the sample of this thesis may suffer from survivorship bias. The reason is that it uses the constituents of FTSEALL share index according to the list of February 2008. Indeed, the financial constraints restricted us from using the actual lists. However, we do not believe that this would be a problem to our research. Thus, this sort of bias most probably causes serious effects on long run horizons. In our case, the analysis is mainly based on a 10-day window. Therefore, we expect that the survivorship bias has minimum and most likely insignificant effects on our results.

Despite the fact that our results show that time-varying risk can explain most of the documented price anomalies following large one-day price shocks, there is still no single factor that can fully explain all these anomalies. Finding this factor is left for future research. Our results also left at least three interesting issues for future research. First, one dimension of liquidity is still ignored, resiliency. The difficulty in finding a proxy that measures this dimension limits the ability to examine it. By definition, resiliency is about how quickly the prices absorb shocks. Accounting for this factor may explain the different price behaviour of different stocks. Second, researchers suggest various explanations for the anomalous price behaviour. Thus, literature has used market microstructure, risk, behavioural finance and size effect as possible explanations of the observed anomaly. One possible direction of future research is to consider simultaneously all the possible explanations. Finally, other techniques may be used to model the time-varying risk and then examine the short-term price reaction. Overall, the critical question is still open for future research, to what extent are markets efficient?