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Is liquidity the missing link?

Manapon Limkriangkrai[a], Robert B. Durand[b], Iain Watson[b]

[a]*Halifax Bank of Scotland Australia, Perth, 6000, Australia*
[b]*University of Western Australia, Crawley, 6009, Australia*

Abstract

Durand *et al*. (2006a) argue that the Australian market is both internationally integrated and domestically segmented. They find that the US-based three-factor model captures returns of the largest stocks in Australia (evidence of international integration), but that it is unable to account for the returns of the smallest stocks (evidence of domestic segmentation). This study resolves the puzzle left by Durand *et al*. (2006a). Incorporating a liquidity factor provides the missing link in their analysis: it results in a model that permits both the international integration of the largest stocks and the model can account for the returns of the smallest stocks. Our analysis highlights the important role of liquidity in Australian asset pricing.

Key words: Asset pricing; Three-factor model; Liquidity

JEL classification: G12

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1. Introduction

Durand *et al*. (2006a) examine the three-factor model in Australia. Using data from 1990 to 2001, they argue that the Australian three-factor model fails to adequately capture the cross-section of Australian portfolio returns: the model results in too many statistically significant alphas. If the specified independent variables are sufficient to capture cross-sectional portfolio returns, then the

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intercept terms should not be significantly different from zero for all regressions (Merton, 1973). Given that there is evidence that the Australian market is closely related to the US market, Durand *et al.* (2006a) use $R_m - R_f$, SMB and HML calculated for the US market to model the returns of Australian portfolios,[1] and find that the US three-factor model explains the returns of the largest stocks but is still unable to fully account for the returns of the smallest stocks in Australia. This, they argue, implies some extent of domestic market segmentation in Australia. The findings of Durand *et al.* (2006a) are confronting. Given the importance of models of returns, a model that only works for some stocks seems unsatisfying. Durand *et al.* (2006a) have demonstrated that the three-factor model fails for Australia and have shown that there is an important role for factors capturing Australian stocks' international exposure. They leave open the question of whether one model might adequately capture all Australian portfolio returns.

The present paper seeks to address the unanswered question of Durand *et al.* (2006a): can one model fully capture the cross-section of returns? The analysis follows the empirical tradition that has dominated the literature since Fama and French (1992), as well as other studies that have documented that liquidity is an important factor in describing stock returns.[2] We explore the possibility that a liquidity factor might provide the missing link that allows for a model to capture returns for all Australian portfolios. Our findings suggest that liquidity is the missing link: the liquidity metric, when used with both the indigenous and US-based Fama–French three-factors, enables the models to capture the entire cross-section of Australian portfolio returns. The analysis confirms the argument of Durand *et al.* (2006a) that Australian equities are internationally integrated but provides evidence against their argument that the Australian market is domestically segmented.

Similarly to studies of momentum,[3] there is a range of choices for periods over which liquidity can be examined. Section 3 of the present paper forms and examines several combinations of liquidity-based portfolios in order to construct liquidity factors. The combinations we examine include both equal- and value-weighted returns of liquidity-based portfolios held for K-months (where $K = 1$, 3 and 6). The liquidity portfolios are formed on the basis of trading activity in the month prior to the formation of the liquidity spanning portfolio using one of three liquidity metrics: trading volume (*LIQV*), dollar trading volume (*LIQD*) and share turnover (*LIQT*).[4] A long–short liquidity spanning

[1] The factors are downloaded from French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. In keeping with Durand *et al.* (2006a), the returns of these factors have not been adjusted for currency returns (i.e. they are the US dollar returns).

[2] The liquidity studies are discussed in the next section.

[3] For example, Jegadeesh and Titman (1993, 2001) and Durand *et al.* (2006b) examine 16 combinations of momentum strategies with different ranking and holding periods.

[4] Turnover is generally defined as the number of shares traded divided by the number of shares outstanding (Datar *et al.*, 1998).

portfolio is then formed using one of these three liquidity metrics for use in our analyses. We have selected the *LIQT* measure to use in the main analysis,[5] as it is consistent with approaches in the literature and also because it demonstrates the clearest illiquidity premium. The value-weighted return calculation appears to provide less difference between the illiquid and liquid stocks than the equal-weighted version.[6] Therefore, we decided to use the latter.[7]

In Section 4, we revisit the data and methodology in Durand *et al*. (2006a) and examine the monthly returns of the 25 size- and beta-sorted portfolios with a view to comparing the different effects of liquidity spanning portfolios. This study analyses the liquidity effect on the domestic and the US three-factor models. To be consistent with Durand *et al*. (2006a) we follow Gibbons *et al*. (1989) and test the hypothesis that the estimated intercept terms for each equation are jointly equal to zero. Our primary criterion for a satisfactory asset-pricing model is that there should not be any statistically significant returns left unexplained by the model; that is, there should be no significant alphas (Merton, 1973). The present paper documents that adding liquidity-based spanning portfolios to the US-based Fama–French factors allows us to satisfactorily capture the returns of all Australian portfolios: liquidity is the link between large and small stocks missing in Durand *et al*. (2006a). Therefore, the present paper presents a model that permits both the international integration of the largest Australian stocks and accounts for the returns of the smallest stocks. However, when we add our liquidity factor to the domestic three-factor model, we find that it improves the model as the model now satisfies Merton's criterion for an acceptable asset-pricing model (1973).

2. Previous literature

Durand *et al*. (2006a) examine the competing asset-pricing models in Australia over the period 1990–2001. They argue that there is substantial evidence that the Australian market has strong links to the US market and seek to improve existing models by incorporating factors that might reflect this relationship. The paper uses the zero-intercept criterion of Merton (1973) as the major condition for a successful asset-pricing model, as a satisfactory pricing model would not leave statistically significant excess returns unexplained. Durand

[5] The results of *LIQV* and *LIQD* are reported in the supplementary information section, which can be downloaded from http://www.biz.uwa.edu.au/home/our_staff/staff_list/durand_robert.

[6] This is likely due to the fact that illiquid stocks tend to be small stocks, which receive less weight in the value-weighted return calculation.

[7] Table A (in the supplementary information section, which may be found at http://www.biz.uwa.edu.au/home/our_staff/staff_list/durand_robert) provides the descriptive statistics of the liquidity factors.

et al. (2006a) demonstrate that the capital asset pricing model (CAPM) fails to meet Merton's criterion. In addition, they document that, although the domestic three-factor model outperforms the CAPM, it still exhibits a high number of significant alphas. Durand *et al*. (2006a) then explore the proposition that Australia is part of the larger US market, and regress the portfolio returns on the US three-factor model. They find that the US three-factor model emerges as a best pricing model, as there is no significant alpha left at the 1 per cent level. The model indicates significant market and size factors for the majority of portfolios consisting of large stocks. However, it appears that the model is as yet unable to explain the smallest stocks in Australia, as there is no significant factor for the portfolios in the smallest size quintile. The results indicate that only the largest stocks in Australia are integrated with the US market and, hence, the analysis in Durand *et al*. (2006a) implies domestic market segmentation.

Given the problems of the three-factor model, it is worth looking at additional, or alternative, factors that might serve to model the cross-section of Australian returns. There is empirical evidence which finds that liquidity plays an important role in pricing assets. A number of early studies find that stock return is positively related to illiquidity, as measured by quoted bid-ask spread (see e.g. Amihud and Mendelson, 1986; Eleswarapu and Reinganum, 1993; Eleswarapu, 1997). Other studies use alternative common liquidity measures, such as share turnover (introduced by Datar *et al*., 1998), trading volume (Brennan *et al*., 1998), dollar trading volume and share turnover (Chordia *et al*., 2001; Amihud, 2002), and document a strong negative relationship between security returns and liquidity. Lee and Swaminathan (2000) provide further evidence that the well-documented momentum effect is strongly related to turnover. Other studies also find that stock returns are affected by order imbalance (Chordia *et al*., 2002; Chordia and Subrahmanyam, 2004).

Sadka (2006) estimates the variable and fixed price effects of firm-level liquidity using intraday data, and examines how these components explain asset-pricing anomalies. He finds that the unexpected variations of the variable liquidity component explain the momentums and post-earnings announcement drift. Examining liquidity in the context of asset-pricing model, Acharya and Pedersen (2005) derive a liquidity-adjusted CAPM, finding that security returns are affected by their expected liquidity. Using an innovative metric to calculate liquidity, Liu (2006) argues that a two-factor model incorporating the market and liquidity outperforms Fama and French's three-factor model.

In Australia, Beedles *et al*. (1988) examine the role of liquidity on stock returns over the period 1974–1984. They document that illiquidity is partly related to the small firm premium effect, as the small firms that provide high returns are relatively illiquid. Anderson *et al*. (1997) investigate the effects of information and liquidity risks on Australian security returns over the period 1982–1989. Although their results indicate that abnormal returns and information risk are strongly correlated, they show no significant relationship between returns and liquidity, as proxied by the average monthly dollar trading value.

Marshall and Young (2003) use three liquidity proxies (namely, the bid-ask spread, amortized spread and turnover) and find a small liquidity premium in the Australian market over the period 1994–1998. Chan and Faff (2003) examine the role of liquidity on cross-sectional monthly stock returns in Australia over the 1990s. They find that the liquidity factor, as proxied by turnover, is negatively related to stock returns. Furthermore, they document that this effect is robust to the inclusion of beta, size, book-to-market, momentum factors, seasonality and non-linearities. Chan and Faff (2005) provide additional evidence for the effect of the liquidity factor in the Australian stock market over the period 1990–1998. Using the generalized method of moments (GMM) to test the liquidity-augmented Fama–French model, they find that the GMM test statistic supports the model, with the market, size and the liquidity factors being statistically significant.

Given that the US-based three-factor model emerges as the candidate for the 'preferred' asset-pricing model in Australia (Durand *et al.*, 2006a), although still incomplete, and that there is potentially a role for the liquidity factor as a pricing factor in Australia in the cross-sectional framework, the aim of this paper is to examine the liquidity factor, as measured by *LIQT*, in explaining Australian stock returns.[8] Following the methodology of Fama and French (1992, 1993), we analyse the effects of the liquidity factor with the models previously examined in Durand *et al.* (2006a); namely, the Australian and the US three-factor models.

3. Capturing liquidity

To be consistent with the long–short variables used in the three-factor model, the present study first needs to establish if the returns of illiquid stocks are different from those of liquid stocks, and then this study needs to create an appropriate long–short portfolio. To determine this, it requires that there be a statistically significant difference between the returns of the components of long–short portfolio. Formally, the null hypothesis that the returns of portfolios of illiquid stocks equal those of liquid stocks is tested. Each liquidity factor is defined as the return to an equal-weighted portfolio of the 30 per cent of the most illiquid stocks, minus the return to an equal-weighted portfolio of the 30 per cent of the most liquid stocks, rebalanced on the last trading day of the month.

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[8] We do not consider momentum as a potential factor in this study. Durand *et al.* (2006b), who replicate the seminal methodology in Jegadeesh and Titman (1993, 2001), do not find evidence for momentum in Australia over the period 1980–2001 (a period partially contemporaneous with that in this study). Rather, they find evidence that there is a contrarian effect confounded in January and July; we control for those seasonal effects in this study. The findings of Durand *et al.* are consistent with Gaunt and Gray (2003), who document large and negative autocorrelation in stock returns. Durand *et al.* also demonstrate that the evidence of Demir *et al.* (2004) for momentum, obtained using daily data, does not 'scale up' to monthly observations over the longer period of 1980–2001 studied in their paper.

The results of the liquidity factor analyses are presented in Table 1. Using data from the month preceding the formation of the portfolios, we examine a 1 month formation period and three possible holding periods – namely, 1, 3 and 6 month periods (i.e. M1, M3 and M6) – over which liquidity portfolio return is assessed. As stated, we also consider three different liquidity measures; namely, *LIQV*, *LIQD* and *LIQT*. The results for equal- and value-weighted portfolios are presented in Panels A and B, respectively. The results for two of the three metrics – M1 and M3 – reported in Panel A are surprising: the returns of the most liquid portfolios (denoted 'T' for Top) are greater than the returns of the least liquid portfolios (denoted 'B' for Bottom). This would indicate a liquidity premium, rather than an illiquidity premium. At the longer horizon (M6) we note that, for *LIQV* and *LIQD*, the returns of illiquid stocks outperform liquid stocks, although this is still not the case for *LIQT*. Therefore, it would appear that the liquidity premium observed in the literature might be found only

Table 1
Liquidity factors – descriptive statistics and paired *t*-tests

		Descriptive statistics					
		M1		M3		M6	
		B	T	B	T	B	T
Panel A: Equal weighted							
LIQV	Mean	1.0149	1.0485	1.0235	1.0379	1.0248	1.0001
	Standard deviation	0.0376	0.0907	0.0427	0.0857	0.0428	0.0131
LIQD	Mean	1.0310	1.0323	1.0441	1.0208	1.0470	1.0183
	Standard deviation	0.0554	0.0658	0.0621	0.0603	0.0645	0.0585
LIQT	Mean	1.0092	1.0700	1.0115	1.0669	1.0120	1.0658
	Standard deviation	0.0283	0.1210	0.0316	0.1168	0.0324	0.1144
Panel B: Value weighted							
LIQV	Mean	1.0019	1.0090	1.0033	1.0087	1.0044	1.0084
	Standard deviation	0.0279	0.0426	0.0316	0.0427	0.0333	0.0426
LIQD	Mean	1.0034	1.0092	1.0095	1.0087	1.0132	1.0083
	Standard deviation	0.0364	0.0406	0.0420	0.0428	0.0433	0.0404
LIQT	Mean	1.0104	1.0184	1.0100	1.0241	1.0090	1.0239
	Standard deviation	0.0401	0.1042	0.0392	0.0912	0.0395	0.0939

	Paired *t*-tests		
	M1	M3	M6
Panel C: Equal weighted – all months			
LIQV	–5.241**	–2.314*	6.526**
LIQD	–0.277	4.717**	5.957**
LIQT	–6.643**	–6.353**	–6.422**

Table 1 (continued)

	Paired *t*-tests		
	M1	M3	M6
Panel D: Value weighted – all months			
LIQV	–2.212*	–1.507	–1.151
LIQD	–1.487	0.159	1.184
LIQT	–1.01	–1.794	–2.151*
Panel E: Equal weighted – seasonalities			
	January		
LIQV	–3.625**	–3.625**	3.397**
LIQD	–1.478	–1.478	–1.478
LIQT	–3.786**	–3.786**	–3.786**
	July		
LIQV	–4.482**	–4.482**	4.829**
LIQD	0.778	0.778	0.778
LIQT	–5.205**	–5.205**	–5.205**
	Other months		
LIQV	–4.704**	–1.663	5.768**
LIQD	–0.962	4.249**	5.512**
LIQT	–5.873**	–5.572**	–5.659**
Panel F: Value weighted – seasonalities			
	January		
LIQV	–2.713	–2.713	1.787
LIQD	–0.853	–1.279	–0.853
LIQT	–4.809**	–4.245**	–4.809**
	July		
LIQV	–2.781*	–2.781*	1.191
LIQD	0.149	0.428	0.149
LIQT	–3.687**	–2.017	–3.687**
	Other months		
LIQV	–3.56**	–2.851**	–0.569
LIQD	–2.551*	0.598	0.279
LIQT	–1.108	–2.667**	–2.225*

Stocks are sorted into the bottom 30 per cent and top 30 per cent based on their liquidity over the period 1990–2001. Three different measures of liquidity (namely, trading volume (*LIQV*), dollar trading volume (*LIQD*) and share turnover (*LIQT*)) are examined. Both equal- and value-weighted returns of each portfolio are then calculated. Panels A and B show the descriptive statistics of the returns of the bottom (B) portfolio consisting of the most illiquid stocks and top (T) portfolio consisting of the most liquid stocks. Panels C, D, E and F show the paired *t*-tests examining the null hypothesis that the factor returns of the bottom (B) portfolio are equal to those of the top (T) portfolio
** and * denote significance at 1 and 5 per cent levels, respectively.

over longer time frames in Australia, and might also depend on the way liquidity is proxied.[9] The analysis of value-weighted stocks is generally consistent with the analysis for equal-weighted portfolios, although an illiquidity premium is observed in M6 only for *LIQV* and *LIQD*.

The present paper uses paired *t*-tests to test the null hypotheses that the returns of the illiquid stocks are equal to those of the liquid.[10] These results are reported in Panels C and D of Table 1. A comparison reveals that the null hypothesis is rejected in most instances for the analysis of returns for the equal-weighted portfolios (save for LIQD (M1)), but is rejected in only two instances for the value-weighted portfolios (LIQV (M1) and LIQT (M6)). Therefore, the liquidity premium appears to be associated with size. Further analysis of seasonality, reported in Panels E and F, indicates that the differences are not caused by the seasonal effects. It is instructive to compare these results with those of Durand *et al.* (2006b): in contrast to the strong seasonality effects found by Durand *et al.* (2006a), the liquidity premium we examine is not confounded with either January or July effects. Therefore, it seems that the liquidity premium is robust and is, indeed, a candidate for consideration as a priced factor in a model of the cross-section of returns.

4. Durand *et al.* (2006a) revisited

In this section, we revisit Durand *et al.* (2006a) by analysing their data and the same dependent variables (25 size- and beta-sorted portfolios), and using the methodology in their paper, but with the addition of the liquidity metric adopted on the basis of the analysis reported in Section 3. In keeping with Durand *et al.* (2006a), this study estimates five groups of equations using the full information maximum likelihood (FIML) estimation. The Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC) are applied to measure the ability of a specified regression system in explaining portfolio returns as they capture the trade-off between a model's parsimony and its ability to explain the data.[11] Systems that have lower AIC and SBC scores are therefore preferable to those with higher scores. To be consistent with Durand *et al.* (2006a) we use the GRS test (Gibbons *et al.*, 1989) to examine the 'success' of the model; examination

[9] While a liquidity premium, rather than an illiquidity premium, might be at odds with much literature, Durand *et al.* (2007) argue that higher returns are associated with stocks about which investors are emotionally aroused and that this arousal is associated with increased liquidity.

[10] In an unreported result, the Kolmogorov–Smirnov test of the null hypothesis of normality indicates that it cannot be rejected for any of the liquidity portfolio returns we consider, suggesting that they are normally distributed and that a parametric test is appropriate.

[11] To be consistent with Durand *et al.* (2006a), we also report estimates of adjusted R^2 but, noting the discussion in footnote 2 (p. 578) of their article, we acknowledge the limitations of this measure and do not discuss inferences based on it in this paper.

of the data indicates that the assumptions of multivariate normality underpinning the valid application of this test were not violated. If the specified independent variables adequately capture cross-sectional portfolio returns, then the intercept terms should not be significantly different from zero for all regressions (Merton, 1973).[12]

The results of the Australian three-factor model with the liquidity factor are presented in Table 2. The general results indicate that the market excess return and SMB factor are statistically significant, which is as expected given the findings in Durand *et al.* (2006a).[13] No role is found for HML; indeed, it is statistically significant in only one instance. However, in contrast to our expectations, the liquidity factor does not appear to be as prominent in asset pricing when added to the domestic three-factor model, as we document only seven significant values for *LIQT* in Table 2. Additionally, the GRS tests reported in Table 2 are insignificant. Therefore, this model satisfies Merton's criterion for a good model, as we have already noted, as the *LIQT* measure is significant in only 7 of the 25 portfolios. HML is significant in only 1 of the 25 portfolios. Therefore, it seems that the inclusion of *LIQT* saves the model using Australian factors. Likelihood ratio tests reported in table A (in the supplementary information section that may be downloaded from our website) also indicate that the inclusion of *LIQT* adds explanatory power to the Australian three-factor model. Therefore, the evidence suggests that the inclusion of liquidity, as measured by *LIQT*, is an improvement on the domestic three-factor model, which satisfies Merton's (1973) no-significant-alpha criterion.

The results of the US three-factor model and the model with the liquidity factor are presented in Table 3. We find that, when a liquidity spanning portfolio is added to the US three-factor model, the explanatory power of the models improves and the model now appears to explain the portfolio returns in Australia. Table 3 indicates that *LIQT* is statistically significant for the majority of the portfolios. The US market excess return and US SMB factors have significant explanatory power for the 22 of the 25 of portfolios comprising larger stocks, while the US HML factor shows weaker effect, which is consistent with

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[12] We note (as do Durand *et al.*, 2006a, in footnote 18 (p. 585) of their article) that alternate techniques might also be utilized to test the proposition that the alphas are jointly equal to zero. The findings in this paper, as well as those in Durand *et al.*, might be driven by the experimental design followed in both papers. For example, a useful future examination of the robustness of the findings in this paper might be conducted following the GMM methodology used by Faff (2001, 2004).

[13] We differ from Durand *et al.* (2006a) in that we use the value-weighted market index, rather than the equal-weighted index, as the market return. As the analysis in this paper shows, the findings in Durand *et al.* (2006a) are robust to whichever index is used. However, we note that the effect of the SMB factor has become slightly more pronounced for the Australian three-factor model with the value-weighted market index (as might be expected given the value-weighted index will give less weight to the returns of smaller stocks).

Table 2
Australian three-factor model with *LIQT* (M6) regressions

Panel A: Coefficient estimates and p-*values*

Size/beta	Low	2	3	4	High	Low	2	3	4	High
	a					p(a)				
Small	0.2842	0.3674	0.1108	0.0869	0.1648	0.7555	0.6095	0.8503	0.9115	0.7490
2	–0.4679	–0.1778	–0.2424	–0.2180	0.1360	0.1879	0.6077	0.5810	0.6027	0.7808
3	–0.0897	–0.2303	–0.2113	–0.3322	–0.0154	0.7522	0.3594	0.5699	0.4766	0.9729
4	0.2162	–0.0232	–0.2688	–0.2108	–0.6741	0.2424	0.8908	0.2269	0.3679	0.1210
Big	0.3335	0.0128	–0.1404	–0.4286	–0.5043	0.0020**	0.9250	0.2857	0.0213*	0.1167
	b					p(b)				
Small	0.5802	0.6925	0.7629	1.0490	0.8995	0.2902	0.0572	0.0397*	0.0043**	0.0002**
2	0.9217	0.8407	0.8349	1.0766	1.0116	0.0000**	0.0000**	0.0002**	0.0000**	0.0002**
3	0.7322	0.7955	0.9098	1.1723	1.1114	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**
4	0.5483	0.6925	0.9352	1.0634	1.3867	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**
Big	0.7090	0.8689	0.9597	1.1615	1.2858	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**
	s					p(s)				
Small	0.5651	0.2927	0.6679	0.7120	0.7367	0.1275	0.2400	0.0001**	0.0085**	0.0001**
2	0.4650	0.4779	0.5971	0.6190	0.5558	0.0001**	0.0000**	0.0003**	0.0000**	0.0007**
3	0.2133	0.3545	0.3206	0.5248	0.4124	0.0482*	0.0006**	0.0021**	0.0025**	0.0147*
4	0.1539	0.2450	0.2369	0.2445	0.4224	0.0281*	0.0000**	0.0058**	0.0127*	0.0150*
Big	0.0063	0.0466	0.0575	0.1082	0.1466	0.9002	0.3117	0.2723	0.1579	0.1865
	h					p(h)				
Small	–0.3385	0.4024	0.0500	–0.1143	–0.1119	0.3969	0.0481*	0.8194	0.6586	0.4962
2	0.0865	–0.0219	–0.0165	–0.0823	–0.1977	0.5244	0.8725	0.9139	0.6214	0.3038
3	0.0957	0.0629	0.0919	–0.1666	–0.0903	0.3608	0.5153	0.4255	0.2568	0.5489
4	0.0480	0.0315	0.0000	0.0126	0.0093	0.3861	0.6282	0.9999	0.8890	0.9499
Big	–0.0551	0.0415	0.0871	0.1073	0.2053	0.1558	0.3273	0.0855	0.1231	0.0526
	l					p(l)				
Small	–0.0787	–0.7621	–0.5977	–0.7487	–0.7151	0.8024	0.0000**	0.0000**	0.0009**	0.0000**
2	–0.0118	–0.1397	–0.1917	–0.4322	–0.5494	0.9023	0.2424	0.1374	0.0001**	0.0001**
3	0.0466	0.0071	–0.1307	–0.2332	–0.4706	0.6190	0.9336	0.2334	0.1098	0.0026*
4	0.0296	0.0498	0.0937	–0.1349	–0.1825	0.6079	0.3481	0.1463	0.0693	0.1493
Big	0.0082	0.0310	0.0320	0.0464	–0.1610	0.8181	0.4958	0.5077	0.4687	0.1478

	j					p(j)				
Small	–0.0073	–0.0091	0.0010	0.0291	0.0504	0.9064	0.8735	0.9811	0.4423	0.3107
2	–0.0246	0.0210	–0.0290	0.0038	0.0178	0.2270	0.4909	0.5476	0.8873	0.5464
3	–0.0151	–0.0260	–0.0046	–0.0067	0.0183	0.4007	0.2170	0.8208	0.8622	0.5457
4	–0.0040	–0.0111	0.0016	0.0000	0.0171	0.7639	0.2958	0.9062	0.9990	0.4651
Big	–0.0020	0.0019	0.0045	–0.0051	–0.0022	0.7573	0.8782	0.8741	0.7542	0.9019
	k					p(k)				
Small	0.0055	0.0334	–0.0247	0.0058	0.0048	0.9551	0.3708	0.6201	0.8966	0.9365
2	–0.0154	0.0271	0.0063	0.0040	0.0040	0.5009	0.2286	0.8489	0.8978	0.9063
3	0.0069	–0.0048	–0.0088	–0.0147	0.0064	0.7341	0.7577	0.6918	0.7157	0.8429
4	0.0010	0.0048	0.0168	–0.0013	–0.0235	0.9358	0.7202	0.1573	0.9513	0.3564
Big	0.0064	0.0043	0.0025	–0.0068	–0.0201	0.3380	0.5885	0.8161	0.7610	0.3019

		Panel C: AIC and SBC						
	Panel B: GRS	AIC	SBC	*Panel D: Adjusted* R^2				
System 1	1.8685	–19.2865	–19.2788	0.2205	0.5800	0.5829	0.6903	0.7297
System 2	0.2437	–18.6748	–18.6671	0.5134	0.5825	0.5865	0.7749	0.7347
System 3	0.3533	–17.7222	–17.7145	0.4223	0.5325	0.5882	0.6249	0.7200
System 4	0.9787	–16.5424	–16.5347	0.4738	0.5721	0.5921	0.6498	0.6248
System 5	0.8733	–15.0446	–15.0369	0.6677	0.7265	0.7004	0.6725	0.6408

$$R_{p,t} - R_{f,t} = a_p + b_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + l_p LIQT_t + j_p JAN_t + k_p JULY_t + e_{p,t}.$$

At the end of December each year from 1990 to 2001, all of the stocks publicly listed on the Australian Stock Exchange, with the exception of those in banking, finance, insurance, investment and financial services, and property trusts, are used to form 25 portfolios based on their size and beta values. Individual firms' betas are estimated using past monthly returns over the period 24–60 months (i.e. $t-2$ to $t-5$ years) prior to formation. Stocks are first sorted into size quintiles based on their market values (at $t-1$) and subsequently into beta quintiles based on their pre-estimated beta values, in order to form the 25 portfolios. These portfolios are then divided into five systems, with each individual system representing each beta quintile. Therefore, System 1 contains the five portfolios in the lowest beta quintile, while System 5 contains the five portfolios in the highest beta quintile. The full information maximum likelihood is then used to estimate the regression coefficients in each system. This table reports the Australian three-factor model with *LIQT* regression coefficient estimates and their *p*-values in Panel A, the GRS test statistics in Panel B, and the AIC and SBC test statistics in Panel C. ** and * denote significance at the 1 and 5 per cent levels, respectively. Panel D reports the value of adjusted R^2 for each equation in the system.

Table 3
US three-factor model with *LIQT* (M6) regressions

Panel A: Coefficient estimates and p*-values*

Size/beta	Low	2	3	4	High	Low	2	3	4	High
	a					p(a)				
Small	1.2373	1.1787	2.1030	1.9939	1.6897	0.2075	0.1889	0.0601	0.0424*	0.0099**
2	0.6321	0.5299	1.1536	1.2291	1.5096	0.0751	0.1872	0.0169*	0.0286*	0.0169*
3	0.4732	0.5569	0.7029	0.6585	1.0997	0.2570	0.3083	0.0659	0.3992	0.0607
4	0.4047	0.4854	0.3831	0.4148	0.4077	0.0239*	0.0888	0.1275	0.3097	0.5190
Big	0.5911	0.0926	0.2314	0.1576	0.1259	0.0017**	0.6983	0.3383	0.6058	0.8030
	b					p(b)				
Small	0.0520	0.4567	0.0943	0.0942	0.0632	0.9036	0.1948	0.7686	0.7947	0.8150
2	0.1374	0.2574	0.1034	0.2838	0.1893	0.4399	0.1588	0.6062	0.1603	0.4285
3	0.2353	0.2873	0.2413	0.3198	0.3827	0.1546	0.1263	0.1290	0.3181	0.1165
4	0.2494	0.2863	0.3098	0.3763	0.4208	0.0023**	0.0048**	0.0053**	0.0231*	0.0942
Big	0.2951	0.4643	0.3946	0.4125	0.5140	0.0004**	0.0000**	0.0000**	0.0011**	0.0088**
	s					p(s)				
Small	0.3405	0.2366	0.0601	0.3512	0.3249	0.5518	0.5522	0.8953	0.3874	0.3417
2	0.4105	0.4639	0.3737	0.3454	0.4280	0.0951	0.0622	0.1311	0.2542	0.1156
3	0.2007	0.2625	0.3602	0.4213	0.2901	0.3047	0.1415	0.0527	0.1594	0.2509
4	0.2258	0.2141	0.2697	0.3894	0.5887	0.0158*	0.0783	0.0747	0.0323*	0.0189*
Big	0.0717	0.2340	0.2431	0.3189	0.4520	0.4573	0.0145*	0.0602	0.0442*	0.0439*
	h					p(h)				
Small	–0.1617	0.1216	–0.1658	–0.1729	0.1623	0.7148	0.7376	0.7644	0.6587	0.6286
2	0.2057	0.2290	–0.0121	0.0057	–0.2122	0.1994	0.2222	0.9644	0.9826	0.3863
3	0.2443	0.1627	0.0806	0.2144	–0.0224	0.1989	0.5253	0.5957	0.5835	0.9245
4	0.2235	0.1657	0.1609	0.1564	0.0863	0.0049**	0.1609	0.1732	0.3256	0.7401
Big	0.0885	0.2646	0.2022	0.2188	0.2290	0.2845	0.0060**	0.0489*	0.0674	0.3260
	l					p(l)				
Small	–0.4557	–0.9999	–1.0960	–1.2806	–1.2648	0.0128*	0.0000**	0.0000**	0.0000**	0.0000**
2	–0.3912	–0.5009	–0.6359	–0.9010	–0.9589	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**
3	–0.1559	–0.2798	–0.4049	–0.6502	–0.8044	0.0077**	0.0000**	0.0000**	0.0000**	0.0000**
4	–0.1084	–0.1568	–0.1281	–0.3640	–0.5433	0.0014**	0.0001**	0.0030**	0.0000**	0.0000**
Big	–0.0472	–0.0576	–0.0778	–0.1154	–0.3505	0.1663	0.1359	0.0892	0.0163*	0.0000**

	j					p(j)				
Small	–0.0133	–0.0098	0.0026	0.0243	0.0397	0.8703	0.8862	0.9707	0.6030	0.5458
2	–0.0349	0.0091	–0.0352	–0.0036	0.0120	0.1238	0.7844	0.3739	0.9111	0.7182
3	–0.0230	–0.0331	–0.0115	–0.0208	0.0117	0.2769	0.0906	0.5838	0.6331	0.7853
4	–0.0116	–0.0179	–0.0071	–0.0102	0.0051	0.4086	0.1757	0.7554	0.7114	0.8586
Big	–0.0072	–0.0075	–0.0038	–0.0151	–0.0128	0.4830	0.5141	0.8584	0.4731	0.6555
	k					p(k)				
Small	0.0219	0.0474	–0.0107	0.0248	0.0193	0.8362	0.4083	0.8910	0.6105	0.7570
2	–0.0031	0.0418	0.0228	0.0212	0.0232	0.9205	0.0940	0.5407	0.5155	0.4474
3	0.0118	0.0056	0.0030	–0.0011	0.0202	0.6353	0.8666	0.9228	0.9741	0.5346
4	0.0064	0.0123	0.0243	0.0093	–0.0053	0.6416	0.6624	0.4085	0.6607	0.8424
Big	0.0072	0.0087	0.0071	–0.0006	–0.0092	0.6485	0.6781	0.8115	0.9806	0.6897

			Panel C: AIC and SBC							
	Panel B: GRS		AIC	SBC		*Panel D: Adjusted* R^2				
System 1	2.0986		–18.0507	–18.0430		0.1787	0.5576	0.5406	0.6492	0.6814
System 2	1.2475		–17.4361	–17.4284		0.3456	0.5077	0.4998	0.6976	0.6957
System 3	1.3537		–16.4219	–16.4142		0.2007	0.3625	0.4521	0.5044	0.6536
System 4	1.3039		–15.4118	–15.4041		0.3030	0.3465	0.2496	0.4751	0.4911
System 5	1.3487		–14.3895	–14.3818		0.1772	0.3614	0.2354	0.2120	0.4072

$$R_{p,t} - R_{f,t} = a_p + b_{pus}(USR_{m,t} - USR_{f,t}) + s_{pus}USSMB_t + h_{pus}USHML_t + i_pLIQT_t + j_pJAN_t + k_pJULY_t + e_{p,t}.$$

At the end of December each year from 1990 to 2001, all of the stocks publicly listed on the Australian Stock Exchange, with the exception of those in banking, finance, insurance, investment and financial services, and property trusts, are used to form 25 portfolios based on their size and beta values. Individual firms' betas are estimated using past monthly returns over the period 24–60 months (i.e. $t-2$ to $t-5$ years) prior to formation. Stocks are first sorted into size quintiles based on their market values (at $t-1$) and subsequently into beta quintiles based on their pre-estimated beta values, in order to form the 25 portfolios. These portfolios are then divided into five systems, with each individual system representing each beta quintile. Therefore, System 1 contains the five portfolios in the lowest beta quintile, while System 5 contains the five portfolios in the highest beta quintile. The full information maximum likelihood is then used to estimate the regression coefficients in each system. This table reports the US three-factor model with *LIQT* regression coefficient estimates and their *p*-values in Panel A, the GRS test statistics in Panel B, and the AIC and SBC test statistics in Panel C. ** and * denotes significance at 1 and 5 per cent levels, respectively. Panel D reports the value of adjusted R^2 for each equation in the system.

the results of Durand *et al.* (2006a). Our findings for the US SMB factor throw the findings of Liu (2006) into sharp relief. Liu argues that, for the USA, a model incorporating the market and liquidity factor outperforms the three-factor model. We find that, for the Australian market (which Durand *et al.* (2006a) regard as an offshore subset of the US market), liquidity augments the model but does not subsume the effect of size.[14]

In replicating and extending the analysis in Durand *et al.* (2006a), we have thus far constrained ourselves to using the data used in that paper. However, our analysis and that of Durand *et al.* (2006a) follow the empirically driven methodology established by Fama and French (1993), who establish their model atheoretically. Although Durand *et al.* argue that there is a good reason for Australian returns to be linked to US returns, and although we argue that there is a considerable body of literature pointing to an important role for liquidity, it still might be the case that the findings that have been presented might simply be serendipitous. We examined if the findings reported in Tables 2 and 3 were robust out-of-sample by extending the sample to the end of 2004 (the data available to us at the time of writing). Using a dummy variable taking the value of 1 if the data were from the period following that examined by Durand *et al.* (2006a) to examine if the alphas vary out-of-sample, and interacting the dummy with the coefficients, we found that our estimates were stable (i.e. we could not reject the null hypothesis that the dummy and the interaction terms were significantly different from zero).[15] In addition, as the seasonal dummy variables appear to be statistically insignificant, we also conducted the regression analyses without them. However, for the US model with *LIQT* (but without January and July dummies), the results show a slight increase in GRS test statistics, which are now statistically significant. We also examine a 'parsimonious' model test that excludes seemingly irrelevant variables (i.e. US HML, January and July dummies), and find that the exclusion of such variables does not affect the significance of the liquidity factor. These results are reported in the supplementary information section, which can be downloaded from http://www.biz.uwa.edu.au/home/our_staff/staff_list/durand_robert.

Summarizing the findings in this section, our replication and extension of Durand *et al.* (2006a) has allowed us to address their unanswered question; that is, can one model fully capture the cross-section of returns? We find that adding liquidity-based spanning portfolios to the US-based Fama–French factors allows us to satisfactorily capture the returns of all Australian stocks – both large and small. In this way, liquidity, in its various forms, provides the link between large and small stocks – the link that is missing in Durand *et al.* (2006a). The inclusion

[14] This finding of independent effects of size and liquidity is in keeping with the findings of Gaunt *et al.* (2000), who also find independent size and share price effects on Australian portfolio returns.

[15] However, the tests might lack power due to the size of the sample available to us. We look forward to further research testing the applicability of our findings in the future.

of liquidity factors results in a model that permits both the international integration of the largest Australian stocks with a model that can account for the returns of the smallest stocks.

6. Summary and conclusion

The present research is motivated by Durand *et al*. (2006a), who find that the US three-factor model unexpectedly outperforms the domestic three-factor model, but that it is still not able to capture the returns of the smallest stocks in Australia. Durand *et al*. left open the question as to whether one model might adequately capture the returns of the portfolios of the Australian stocks studied in that paper. The analysis in this study has addressed that unanswered question. The inclusion of a liquidity metric (*LIQT*) results in a model that adequately captures the returns of these portfolios when added to the US factors studied in Durand *et al*. (2006a). The major analysis has focused on the dataset of Durand *et al*. (2006a) to ensure that our results are comparable with their findings. We further utilize out-of-sample data, and document that the model holds well in the recent period.

The present study supports the finding that the US model augmented with an Australian liquidity factor can capture the cross-section of returns of Australian stocks. In examining this proposition, we also find that the addition of the liquidity factor to the Australian three-factor model also improves that model. The question as to why the liquidity factor performs this important role in explaining Australian equity returns is still to be determined. We do not know if the spanning portfolio captures liquidity risk, if it proxies for exposure to systematic macroeconomic factors or is a function of investors' behavioural biases. We do not know if the liquidity factor simply captures a characteristic of the firms in the portfolio or whether the spanning portfolio captures a fundamental dimension of priced risk in the Australian market.[16]

Confirming Durand *et al*. (2006a), the present study highlights the importance of critically evaluating overseas findings when examining asset-pricing models. Our work also highlights the need for further research on asset pricing in Australia; given the potentially high costs for academia and practitioners of using a wrong model, the rejection of incorrect models must be a research priority.

References

Acharya, V. V., and L. H. Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375–410.

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

Amihud, Y., and H. Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223–249.

[16] Daniel and Titman (1997) discuss this issue with reference to the HML factor.

Anderson, D., P. Clarkson, and S. Moran, 1997, The association between information, liquidity and two stock market anomalies: the size effect and seasonalities in equity returns, *Accounting Research Journal* 10, 6–19.

Beedles, W., P. Dodd, and R. Officer, 1988, Regularities in Australian share returns, *Australian Journal of Management* 13, 1–29.

Brennan, M. J., T. Chordia, and A. Subrahmanyam, 1998, Alternative factor specifications, security characteristics and the cross-section of expected stock returns, *Journal of Financial Economics* 49, 345–373.

Chan, H. W., and R. W. Faff, 2003, An investigation into the role of liquidity in asset pricing: Australian evidence, *Pacific-Basin Finance Journal* 11, 555–572.

Chan, H. W., and R. W. Faff, 2005, Asset pricing and the illiquidity premium, *Financial Review* 40, 429–458.

Chordia, T., R. Roll, and A. Subrahmanyam, 2002, Order imbalance, liquidity, and market returns, *Journal of Financial Economics* 65, 111–130.

Chordia, T., and A. Subrahmanyam, 2004, Order imbalance and individual stock returns: theory and evidence, *Journal of Financial Economics* 72, 485–518.

Chordia, T., A. Subrahmanyam, and V. R. Anshuman, 2001, Trading activity and expected stock returns, *Journal of Financial Economics* 59, 3–32.

Daniel, K., and S. Titman, 1997, Evidence on the characteristics of cross-sectional variation in stock returns, *Journal of Finance* 52, 1–33.

Datar, V. T., N. Y. Naik, and R. Radcliffe, 1998, Liquidity and stock returns: an alternative test, *Journal of Financial Markets* 1, 203–219.

Demir, I., J. Muthuswamy, and T. Walter, 2004, Momentum returns in Australian equities: the influences of size, risk, liquidity and return computation, *Pacific-Basin Finance Journal* 12, 143–158.

Durand, R. B., A. Juricev, and G. Smith, 2007, SMB – arousal, disproportionate reactions and the size-premium, *Pacific-Basin Finance Journal* 15, 315–328.

Durand, R. B., M. Limkriangkrai, and G. Smith, 2006a, In America's thrall. The effect of the US market and US security characteristics on Australian stock returns, *Accounting and Finance* 46, 577–604.

Durand, R. B., M. Limkriangkrai, and G. Smith, 2006b, Momentum in Australia – a note, *Australian Journal of Management* 31, 355–364.

Eleswarapu, V. R., 1997, Cost of transacting and expected returns in the NASDAQ market, *Journal of Finance* 52, 2113–2127.

Eleswarapu, V. R., and M. R. Reinganum, 1993, The seasonal behavior of the liquidity premium in asset pricing, *Journal of Financial Economics* 34, 373–386.

Faff, R., 2001, An examination of the Fama and French three-factor model using commercially available factors, *Australian Journal of Management* 26, 1–17.

Faff, R., 2004, A simple test of the Fama and French model using daily data: Australian evidence, *Applied Financial Economics* 14, 83–92.

Fama, E., and K. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

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

Gaunt, C., and P. Gray, 2003, Short-term autocorrelation in Australian equities, *Australian Journal of Management* 28, 97–117.

Gaunt, C., P. Gray, and J. McIvor, 2000, The impact of share price on seasonality and size anomalies in Australian equity returns, *Accounting and Finance* 40, 33–50.

Gibbons, M. R., A. Ross, and J. Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121–1152.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jegadeesh, N., and S. Titman, 2001, Profitability of momentum strategies: an evaluation of alternative explanations, *Journal of Finance* 56, 699–720.

Lee, C., and B. Swaminathan, 2000, Price momentum and trading volume, *Journal of Finance* 55, 2017–2069.

Liu, W., 2006, A liquidity-augmented capital asset pricing model, *Journal of Financial Economics* 82, 631–671.

Marshall, B. R., and M. Young, 2003, Liquidity and stock returns in pure order-driven markets: evidence from the Australian stock market, *International Review of Financial Analysis* 12, 173–188.

Merton, R., 1973, An intertemporal capital asset pricing model, *Econometrica* 41, 867–887.

Sadka, R., 2006, Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk, *Journal of Financial Economics* 80, 309–349.