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Liquidity Mismatch Index and Banks' Stock Returns

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Abstract:

Purpose: *This article empirically examine the relationship between Liquidity mismatch index and bank stock returns.*
Design/Methodology/Approach: *Using the panel data of 9 South African Banks from 2008 to 2019, the Augmented capital asset pricing model and Fama and French's (2015) five factor model were employed to empirically examine the nexus between Liquidity mismatch index and bank stock returns. Two liquidity measures, the bank liquidity mismatch index and the aggregate liquidity mismatch index were put into perspective.*
Findings: *The results revealed that liquidity is a significant factor when pricing banks' stock returns. Bank liquidity mismatch index was found to be positively and significantly related to bank stock returns. While, the Aggregate liquidity mismatch index was found to be negatively related to stock returns, and the relationship was significant. Therefore, liquidity can play a role in asset pricing models. Moreover, these liquidity measure effectively captured the aspect of liquidity stress test and contagion effects.*
Practical Implications: *The aggregate liquidity mismatch index provided a good macro-prudential liquidity measure which could be included in various dynamic stochastic general equilibrium (DSGE) models. Since results revealed that BLMI positively influence stock returns banks are recommended to hold significant liquidity buffers to take advantage of opportunities when they present themselves. This recommendation is in line with the BASEL III liquidity proposal.*
Originality/Value: *Investigating the impact of liquidity particularly on bank stocks provides important contribution to the body of knowledge since banks are the main drivers of liquidity creation. Empirical literature does not sufficiently articulate the linkage between bank liquidity and bank stock returns of emerging markets particularly within the context of asset-liability mismatches while accounting for liquidity spirals.*

Keywords: *Bank Liquidity, liquidity mismatch index, stock returns, LCAPM, FF5F.*

JEL codes: *E52, G11, G23.*

Paper type: *Research article.*

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1. Introduction

Undoubtedly, bank liquidity was the flagship of the global financial crisis. Acharya and Schnabl (2010) and Berger and Bouwman (2009) contend that liquidity risk was the catalyst in the events leading to 2007–2009 global financial crisis. Nevertheless, liquidity creation remains the core function of banks and is the backbone of the banks' value creation. There are two different sources of liquidity risk that banks thrive to manage and balance, the market liquidity and funding liquidity. These two are closely related and mutually reinforced, though they are determined by dissimilar fundamentals (Brunnermeier and Pedersen, 2009). The market liquidity is defined as the easy of converting a financial security into cash, therefore it is depended on company-specific factors and sector-wide factors (Chordia, Roll, and Subrahmanyam, 2001). Most of the literature focused on understanding the relationship between market liquidity and stock market returns in isolation of funding liquidity, yet these two are hand in glove (Amihud and Mendelson, 1986; 1989; Amihud, 2002; Acharya and Pedersen, 2005). The funding liquidity is argued by Brunnermeier, Krishnamurthy and Gorton (2012) as being bank or financial institution specific that is heavily dependent on the borrowing constraints of market players and the overall availability of liquidity in the market.

In times of crisis, funding liquidity and market liquidity are intertwined so much that the causality is bidirectional (Brunnermeier and Oehmke, 2013). Thus, examining the effects of market liquidity and funding liquidity in silos is improper as these measures individually fail to account for the financial sector's important feature of liquidity spirals (Bai, Krishnamurthy, and Weymuller, 2018; Berger and Bouwman, 2009). Brunnermeier *et al.* (2012) argue that, if the liquidity is meant to reflect the nexus between funding and market liquidity, then liquidity is a unique concept that have to be understood from the acuity of duality. The aim of this article is to examine the connection between bank stock returns and all-encompassing bank liquidity measure. Building on the work done by previous scholars, the study put into perspective the liquidity measures that integrate both and funding liquidity within an asset liability management framework.

Despite the significance of liquidity in asset pricing, most asset pricing models were built on the assumption that markets are free from any constraints. Therefore, liquidity and the banking sector plays no role in Dynamic stochastic general equilibrium (DSGE) modeling and asset pricing models. However, there are very few financial economics models that tried to account for financial frictions, see for example Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999), and Geanakoplos (2003), and Marozva (2019). The focus of their research was mainly in times of crisis, where a small shock in the market was overblown into tenacious instabilities in the greater economy through the financial accelerator. Goyenko (2013) and Makina and Marozva (2020) assert that, despite this literature forming the foundation of liquidity spirals, systemic and endogenous risk banks are up to this moment not part of the most financial models.

The commonly and widely accepted Capital asset pricing model (CAPM), for instance, operates in a frictionless world where markets are presumed to be complete, where there are no transaction costs, and market players face no liquidity and or leverage constraints. The reality shows otherwise, Black (1972) pointed out that investors in the real-world face borrowing constraints, though the CAPM assumes otherwise. In practice, most of these risks, such as the possibility of a liquidity or systemic crisis, are outside of conventional risk measurement practices. A proper model that is concerned with risk and uncertainty, should focus on how an interruption on the banking sector disrupts liquidity and, eventually, market efficiency (Bai *et al.,* 2018). Improperly constructed stock models result in market anomalies. The market anomalies have attracted questions over the applicability of CAPM and the Fama and French (1992) three-factor model amongst other general equilibrium models in their ability to effectively forecast stock market returns (Fama and French, 2015; Avramov and Chordia, 2006). The aim of this article is not to put different models into perspective, but it complements the growing literature on financial constraints of intermediaries and their effect on asset prices.

In general, modern asset friction modeling is worried about the effects of liquidity on financial stability than being concerned with asset pricing. In this article, bank liquidity is interrogated by examining the relationship between bank liquidity and bank stock returns. Other scholars like Xu, Lu and Xiao (2020) examined the effects of financial intermediaries using leverage as a proxy for intermediary. However, leverage alone is not an accurate measure of liquidity as it is uncorrelated with shocks to market liquidity and this opposes the Brunnermeier and Pedersen's (2009) proposal that market and funding liquidity are mutually reinforcing.

Despite different meanings and measures of liquidity, liquidity remains critically important to investors. Therefore, it is crucial to investigate a more precise measure of liquidity when exploring how liquidity affects asset pricing. Measurement is the crux of science as it forms the basis of macro-prudential regulation. The accurate measure of liquidity risk in banks should assist to superintend the build-up of systemic or contagion risk (He and Krishnamurthy, 2019; Meuleman, Vander, and Vennet, 2020). An example of a properly constructed measure is Brunnermeier *et al.* (2012) liquidity mismatch index (LMI). This measure integrates market and funding liquidity in an asset liability management framework. Moreover, it takes into account liquidity spirals and systemic risk.

This article is an extension of Brunnermeier *et al.* (2012) and Bai *et al.* (2018)'s work, they developed system-wide LMI. The modified LMI inform of the Bank liquidity mismatch index (BLMI) and the Aggregate liquidity mismatch index (ALMI) were constructed and empirically tested. BLMI and ALMI were constructed to estimate liquidity associated with a particular bank and the market-wide liquidity in that order (Marozva and Makina, 2020; Marozva, 2017). Therefore, these liquidity measures capture the aspect of liquidity stress test and contagion effects. Arguably, an accurate measure of bank liquidity should account for bank's cross-section

liquidity risk in doing so it should capture the level of liquidity risk in a particular financial institution. Therefore, if market-wide liquidity conditions worsens, the bank with the worst liquidity position should be adversely affected. Bai *et al.* (2018) argue that, the liquidity condition of a bank is manifest in form poor stock performance and poor profitability.

The study is motivated by the recent events resulting from the COVID-19 pandemic. The recent health crisis shook a number of global financial markets. Though the root cause of current situation is different from the 2007/9 financial crisis, asset liquidity risk has again taken the center stage as the most dreaded financial risk of all times. Bank liquidity is again put into perspective as Acharya and Steffen (2020) shows that, despite banks being better capitalized and having better liquidity positions relative to pre-2007/9 financial crisis, the financial intermediaries in advanced markets, for example in America the bank stock prices tumbled by approximately 40-50%. This is comparable to what transpired during the global financial crisis. According to Sornette (2017) the equity market was severely affected, losing over $30 trillion worldwide, where on average major stock markets lost between 40% and 60% during the period from September 2008 to March 2009.

During crisis the liquidity situation is intensified as most banks and institutional investors re-allocate their portfolios from long term illiquid loans towards safe haven of more liquid assets. Safe haven and more liquid assets are naturally less profitable thereby negatively affecting the earning capabilities and forecasts of the financial sector. Moreover, the movement from illiquid profitable assets towards the safe havens involves a costly liquidation of illiquid assets in a low-liquidity environment there by further eroding bank portfolios. This consequently results in a short-term market crash. It is these bank liquidity developments that motivated the researcher to further interogate the role of liquidity in financial markets, precisely the relationship between bank liquidity and bank stock returns.

Investigating the impact of liquidity particularly on bank stocks provides important contribution to the body of knowledge since banks are the main drivers of liquidity creation. In this article, a panel data regression approach is adopted to investigate the relationship between liquidity mismatch indices and the stock returns of South Africa locally registered banks listed on the Johannesburg stock Exchange (JSE). Empirical literature does not sufficiently articulate the linkage between bank liquidity and bank stock returns of emerging markets, the only study that scantly test this relationship is that of Bai *et al.* (2018). Unlike Bai *et al.* (2018), the augmented CAPM and the Fama and French (2015) five-factor model (FF5F) were employed in this study. These models are more appropriate because liquidity is interrogated together with other relevant determinants of stock returns, which include the security beta, size, and spread between value stocks and growth stocks.

The results revealed that bank liquidity is an significant factor in pricing stock returns of bank stocks registered in South Africa and listed on the Johannesburg stock

exchange. The bank liquidity mismatch index was found to be positively and significantly related with bank stock returns. While, the aggregate liquidity mismatch index was found to be negatively related with stock returns, and the relationship was significant.

This article contributes to literature in two ways: Firstly, the investigation relates to whether liquidity is an important determinant in the prediction of bank stock returns. Altay and Çalgıcı (2019) argue the liquidity risk one of the most important determinants of asset pricing as stock returns dependent on investors' preferences as well as the extent of the liquidity level in the market. Unlike other researchers, this research examined the effects of liquidity measures that incorporates three important aspects of liquidity, the funding side, asset side and the liquidity spirals (liquidity systemic risk). Academic research distinguishes between two different sources of liquidity risk: market liquidity and funding liquidity. While both are correlated and mutually reinforcing, they are driven by different mechanisms (Brunnermeier and Pedersen, 2009). Therefore, BLMI and ALMI have a strong footing in literature.

Secondly, the liquidity indices developed and empirically tested were motivated by the fact that banks are unique in the manner they do their business and are central in the creation of liquidity. According to Acharya and Steffen (2020), there are incidents when market crashes are caused by both funding liquidity and market liquidity. Consequently, it is vital to assess how market and funding liquidity in the presence of markets spirals affects banks stock returns. Brunnermeier and Pedersen (2009) assert that under certain conditions margins are destabilizing and market and funding liquidity are mutually reinforcing, leading to liquidity spirals. Moreover, the study was carried out using South Africa an emerging market as the unit of analysis. Structurally, emerging markets are highly illiquid, and they constitute highly inefficient markets. Thus, an analysis of banks in such markets provided some important insights as revealed by the results.

The paper proceeds as follows. Section 2 describes the data and liquidity indices tested in the analysis. Section 3 presents the models used in the estimation of the results. Section 4 reports the results analysis and discussion. Section 5 concludes.

2. Methodology and Data

2.1 Data and Definition of Variables

The monthly time series data for the period between 2008 and 2019 was utilised. The article focuses on this period as it is current, long enough to capture important event that had huge impact on asset liquidity, the 2007-2009 global financial crisis. The data set used in this study covers all listed locally registered banks on Johannesburg stock exchange (JSE) from January 1, 2008 through December 2019. Including all banks and not just those active as of December 2019 reduced the bias of survivorship. The data selection process was as following: all bank stocks which

had information to calculate annual returns. The variables under examination for these banks are presented in Table 1.

Table 1. *Variables and expected signs with the bank stock returns at time t (R_{it})*

VARIABLE	MEASURE	EXPECTED SIGN	DATA SOURCES
Rf_{it}	Risk-free asset return at time t	+	The South African Reserve Bank
Rm_{it}	Market portfolio return at time t,	+	Johannesburg stock exchange
SMB_{it}	SMB portfolio return at time t,	+	Johannesburg stock exchange
HML_{it}	HML portfolio return at time t,	+	Johannesburg stock exchange
$BLMI_{it}$	Bank liquidity mismatch index for bank i at time t,	+/-	Johannesburg stock exchange
$ALMI_t$	Aggregate liquidity mismatch index at time t,	+/-	Johannesburg stock exchange

Source: *Author's compilation*

The liquidity measures i.e. the BLMI and the ALMI that are put into perspective in this article are measured as following; through integrating the asset liquidity and funding liquidity of banks. The liquidity mismatch indices are computed to capture the systemic risk/ liquidity spirals. The formulas are presented in table 2.2 and discussed thereafter.

Table 2. *Liquidity measures*

VARIABLE	*MEASURE*	*DATA SOURCES*
LIQUIDITY MISMATCH INDEX		
$BLMI_t^i$	$\sum_k \lambda_t A_k, x_t^i A_k + \sum_{k'} \lambda_t L_{k'}, x_t^i L_{k'}$	South African Reserve Bank (SARB)
$ALMI_t$	$\frac{\sum_i \sum_k x_t^i, A_k (1 - \frac{1}{LIX_{K,t}}) + \sum_i \sum_{k'} x_t^i, L_{k'} \left(\bar{\lambda}_{L_K} + (1 + \bar{\lambda}_{L_K}) \beta_{L_K} (1 - \alpha) STBS_t \right)}{1 - \sum_i \sum_{K'} x_t^i, L_{K'} (1 + \bar{\lambda}_{L_K}) \beta_{L_K}}$	*i*ress database

Source: *Adapted from Makina and Marozva (2020).*

2.2 Liquidity Mismatch Index (LMI)

The LMI measures the difference between the asset liquidity and the liabilities' liquidity i.e. funding liquidity (Bai *et al.,* 2018). Thus, the BLMI for bank *i* at a point in time is computed as (equation 1):

$$\sum_{k} \lambda_t A_k, x_t^i A_k + \sum_{k'} \lambda_t L_{k'}, x_t^i L_{k'}, \quad (1)$$

where assets ($x_t^i A_k$) and liabilities ($x_t^i L_{k'}$) are from the bank's statement of financial position and they fluctuate over time. The variation in these balance sheet iterms is dependent on the specific class of asset (k) or class of liability (k'). Liquidity weights, $\lambda_t A_k > 0$ and $\lambda_t L_{k'} < 0$ are important constituent of the equation that are calculated. The asset liquidity weights assigned ranges from 0 to 1.

Using the data from the banks' statement of financial position, the asset weight were set at $\lambda_t A_k = 1$ for cash and cash equivalent and $\lambda_t A_k = 0$ to represent mainly the non-current goodwill and intangible assets. Other assets which had intermediate liquidity were assigned weights greater than zero but less than one. Deviating from Bai et al. (2018) the weights were computed using Danyliv, Bland and Nicholass's (2014) liquidity index (LIX). The asset liquidity weights were computed as follows:

$$m = \left[1 - \frac{1}{LIX_t}\right]\pi \quad (2)$$

The calculated liquidity weight was scaled by π , a factor that was set for assets and these varied with the asset's level of liquidity. Since asset weights were assigned weights between 0 and 1, this meant that assets liquidity weights were computed and the outcome was confined to $0 < \lambda_t A_k < 1$.

The Liability-side liquidity captured the funding liquidity risk. According to Drehmann and Nikolaou (2013) funding liquidity risk is the failure by a bank to fund its liabilities as they mature. Liability-side liquidity weights were calculated in line with Brunnermeier *et al.'s* (2012) computations. The model access to liquidity is argued to follow a Poisson distribution process. Where probability θ captures the ability of the bank to get funding at a point in time. Thus, BLMI is computed based on anticipated bank cash out-flows in subsequent periods. As a result the following equation is derived: $f(s,\theta) \in [0,1]$. The function measures the probability of the bank failing to raise capital by time s, where s represent the number of days. Thus, the probability in *s* reduces at a decay rate governed by the parameter θ. The asymptotic liquidity weight is modulated by altering the funding liquidity weight that factors in the variation in θ, leading to the following equation 3:

$$\lambda_t, L_{k'} = \bar{\lambda}_{L_{k'}} - (1 + \bar{\lambda}_{L_{k'}})(1 - \ell^{\beta_{L_{k'}}.FL_t}) \tag{3}$$

where $\bar{\lambda}_{L_{k'}}$ is the asymptotic liquidity weight and FL_t is the state-dependent funding factor and $\beta_{L_{k'}}$ regulates the exposure of the bank. To account for the feedback between BLMI and liquidity stress, the endogenous funding liquidity factor is computed as follows (equation 4):

$$FL_t = (1-\alpha)TOIS_t + \alpha(\upsilon LMI_t) \tag{4}$$

where υ represent a weighting parameter that weighs down the scale of aggregate BLMI to a similar level of spread between the treasury bills rate and the South African benchmark overnight rate (SABOR). Nagel (2014) argues that SABOR correctly represents the time varying value of money market securities. Therefore, the liability weights were computed through the adjustment of the state-dependent funding factor, resulting in equation 5:

$$FL_t = [1 - STBS_t]\pi' \tag{5}$$

where π' is the factor allocated to the liability depending on liquidity level.

By aggregating BLMI and then linearizing the exponential term, the closed-form solution for the market wide liquidity i.e. ALMI was as follows:

$$\frac{\sum_i \sum_k x_t^i, \mathrm{A}_k\left(1 - \frac{1}{LIX_{K,t}}\right) + \sum_i \sum_{k'} x_t^i, L_{k'}\left(\bar{\lambda}_{L_K'} + (1 + \bar{\lambda}_{L_K'})\beta_{L_K'}(1-\alpha)STBS_t\right)}{1 - \sum_i \sum_{K'} x_t^i, L_{K'}(1 + \bar{\lambda}_{L_K'})\beta_{L_K'}} \tag{6}$$

The ALMI can be used as a barometer for market wide liquidity condition and this measure satisfies all the conditions that are required for a good measure of market wide liquidity.

3. Model Specification and Estimation Techniques

The aim of the article was to examine the linkage between the expected bank stock returns and the two liquidity indices, the BLMI and the ALMI. The indices were evaluated previously using the determinants of liquidity (Marozva, 2017; Makina and Marozva 2020). In this article, another benchmark was used to evaluate the two indices in question. Since BLMI arguably captures that bank liquidity therefore, adverse movement in market-wide liquidity was hypothesized to influence bank

stock returns in varied ways depending on the bank's LMI. That is, as market-wide liquidity situation worsens, a bank with an inferior liquidity position (i.e. a lower BLMI) should be associated with lower stock return. Amihud and Mendelson (1986), and Brennan and Subrahmanyam (1996) argue for a direct and linear linkage between liquidity and stock returns. However, the is contradicting evidence on how stock returns are related with liquidity. Nevertheless, liquidity has proven to be an vital variable that affects stock returns and require further research (Marozva, 2019).

This article modified and employed the two-factor Liquidity-Augmented CAPM of Liu (2006) on the selected publicly traded locally registered banks over the period 2008 – 2019. Also, the Fama and French (2015) five-factor model was adopted and modified to include the two liquidity measures, the BLMI and ALMI. Risk factors considered here are those of the Fama and French (1992) three factor model.

The modified liquidity mismatch indices were analysed as a second and third factors in the augmented liquidity CAPM model. The same indices were examined as fourth and fifth factors in the standard Fama-French (2015) five factor analysis. This was done to determine the relationship between returns of banks stocks and liquidity, and is expressed in equation 2. Having BLMI and ALMI as part of the regression equation, assists in determining the direct influence of bank liquidity on stock return

$$R_{it} = \alpha i + \beta_{it}^{BLMI} * R_{it}^{BLMI} + \beta_{it}^{ALMI} * R_{it}^{ALMI} + \beta_{it}^{m} Rm_{it} + \mathrm{Dummy_{it}} + \varepsilon_{it} \quad (7)$$

$$R_{it} - R_t^f = \beta_{it}^{m}\left(Rm_t - R_t^f\right) + \beta_{it}^{HML} * R_{it}^{HML} + \beta_{it}^{SMB} * R_{it}^{SMB} + \beta_{it}^{BLMI} * R_{it}^{BLMI} + \beta_{it}^{ALMI} * R_{it}^{ALMI} + \varepsilon_{it} \quad (8)$$

Where $\mathbf{R_{it}}$ is the stock return for bank i in time t, $\mathrm{R_t^f}$ is the risk-free rate of return in time t, $\boldsymbol{\beta_{it}}$ is the time varying beta for bank i in time t, $\mathrm{Rm_t}$ is the market rate of return in time t, $\mathrm{R_t^{HML}}$ is the return difference between stocks with high book to market ratios (value stocks) and low book to market ratio (growth stocks) in time t, $\mathrm{R_t^{SMB}}$ is the return that captures the difference between the small cap stock and big cap stock returns in time t, $\mathrm{RB_{it}^{LMI}}$ is the return that captures the effects of liquidity as measured by the BLMI in time t for bank i, ε_{it} is the error term. $\mathbf{Dummy_{it}}$ is the dummy variable that captures the presence of the 2007-2009 global financial crisis

Moreover, in a financial crisis, it is expected that banks with worse ex-ante liquidity mismatch index would perform worse than banks with better liquidity positions. The analysis and discussion of the results begin with descriptive statistics, followed by a presentation and discussion of cross-correlations and finally the estimation results are presented and analysed.

4. Descriptive Statistics, Cross Correlation, Results Presentation and Discussion

4.1 Descriptive Statistics

This section presents the descriptive statistics of both independent and dependent variables used in the estimations. The summary statistics are for the panel of selected banks from 2008 to 2019 (Table 3).

Table 3. *Descriptive Statistics*

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Jarque-Bera
ALMI	11.82	11.73	12.25	11.55	0.24	14.81***
BLMI	(0.20)	0.16	0.85	(39.61)	3.83	49307.08***
HML	(0.03)	(0.06)	0.21	(0.32)	0.14	1.27
RETURN	20.20	0.09	139.90	(0.99)	42.14	63.45***
RM	0.10	0.12	0.29	(0.11)	0.11	3.21***
SMB	(0.02)	0.00	0.18	(0.42)	0.18	9.00**

Note: ** p < 0.05, ** p < 0.01, *** p < 0.001*
Source: *Authors' computation.*

As can be derived from the summary of descriptive statistics in Table 3, the pooled results for all the banks in this study cover the period 2008-2019. The descriptive statistics reflect that the bank's annual stock returns over the period of analysis were significantly high. The mean of bank's annual stock return over the period under review was 20.20%, with a standard deviation of 42.14. The minimum return was -0.99%, while the maximum was 139.9%.

Regarding normalized ALMI, the average was 11.82, with a very tight standard deviation of 0.24. The minimum of ALMI was 11.55, while the maximum was 12.25%. The BLMI had a negative normalized mean of 0.20. The minimum of BLMI was -39.61 while the maximum was 0.85. In line with a wider range, the standard deviation for BLMI was 3.83.

The market returns (RM) as calculated from JSE all share index were relatively depressed over the period of review. The average market returns were 0.10, with a minimum of -0.11 and maximum of 0.39. The South African stock market did not perform as its peers because the GDP growth for the past decade was fluctuating around zero percent. The standard deviation of RM was 0.11. Results also revealed that mean spread between growth stocks and value stocks was -0.03, with a

minimum of -0.32 and a maximum of 0.2. The standard deviation of HML was 0.14. Finally, the mean spread between the large cap stock returns and small cap stock returns was 0.02, with a minimum of -0.42 and a maximum of 0.18. The standard deviation for SMB was 0.18.

4.2 Cross Correlations

This section presents the cross-correlation analysis of the variables used in the estimations for the entire sample of the selected banks over the period of 2008 to 2019.

Table 4. *Cross correlations*

Variables	ALMI	BLMI	HML	RETURN	RM	SMB
ALMI	1					
BLMI	0.1196	1				
HML	0.1111	0.0548	1			
RETURN	-0.0811	0.0416	0.18*	1		
RM	-0.39***	0.0235	-0.0704	-0.0662	1	
SMB	-0.32***	-0.0495	0.38***	0.0278	0.27***	1

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Source: *Authors' computation.*

Bank returns and the spread between the value stocks and growth stocks were positively correlated and significant at 10% significance level. This confirms the *a priori* expectations that value stocks perform better than growth stock. The ALMI and returns of the market are inversely related and the relationship is significant at 1% significance level. Similarly, results revealed a negative and significant relationship between ALMI and SMB. Therefore, the *a-priori* expectation was that, the market wide liquidity as measured by ALMI negatively affects stock returns in general. There is a positive relationship between HML and SMB, same applies for RM and SMB, these relationships were significant at 1% significance level. The following section discusses the linkage between banks' stock returns and liquidity using a modified liquidity augmented CAPM and the Random effects (RE) as the primary estimation technique.

4.3 Estimation Results, Analysis and Discussion

This section presents the estimation results, the analysis and discussion on the linkage between the constructed liquidity indices and bank stock returns. Initially, the results from augmented CAPM are presented, analysed and discussed. This is followed by the presentation, analysis and discussion of results from the Fama and French (2015) modified five factor model.

Table 5 details the estimation results for the augmented CAPM pooled OLS model, the Fixed effects model, the Random effects model, and the Generalized least square

model. The Hausman statistic had a probability of 0.70, well above the threshold of 5% implying that the Random effects was more efficient. The results from Random effects model were discussed in this article while the results of other estimation models were presented for robustness.

Table 5. *Empirical results for Augmented capital asset pricing model*

	Pooled Effects	Fixed Effects	Random Effects	GLS
	Return	**Return**	**Return**	**Return**
BLMI	0.603*	0.842**	0.603*	0.547
	(0.242)	(0.187)	(0.242)	(1.048)
ALMI	-4.889	-5.864	-4.889	-4.662
	(21.65)	(21.45)	(21.65)	(22.37)
RM	-1.093*	-1.070	-1.093*	-1.093
	(0.541)	(0.534)	(0.541)	(0.666)
Dummy	-35.72***	-35.62**	-35.72***	-35.75*
	(10.39)	(10.34)	(10.39)	(15.26)
_cons	134.1	144.8	134.1	131.5
	(241.3)	(237.7)	(241.3)	(247.7)
N	108	108	108	108
R^2	0.270	0.266	0.270	
Pesaran		1.747	1.704	
Frees		0.778	0.781	
Hausman		0.72	0.72	

Note: *Standard errors in parentheses,* * *p < 0.05,* ** *p < 0.01,* *** *p < 0.001.*
Source: *Authors' computation.*

The coefficient of BLMI is positive and statistically significant at 5% significance level. This indicates that banks with high liquidity buffers perform better that those in a worse position, which is the case especially during non-crisis periods. The results confirm Bai *et al.* (2018) findings of a positive and significant linkage between bank liquidity and bank stock returns. Their findings reveal that in the cross section, the banks with high LMI over the period of their analysis were faced with significant negative stock returns during in times of turmoil, but these banks exhibited positive returns during normal periods. However, there is a negative relationship between bank stock returns and the broad market liquidity as measured by ALMI and the relationship is not significant.

The results showed a significant linkage between the bank stock returns and the general market return as measured by the returns on JSE All-Share index. This implies that banks in general perform better when the overall market is not performing. Therefore, bank stocks can be used as a hedging mechanism within a well-diversified portfolio in an emerging market like South Africa. The dummy variable was found to be significant, meaning that the global financial crisis of 2007-

2009 had significant influence on bank stock returns. This was expected as the crisis was triggered and perpetuated by banks through magnified systemic/ contagion risk. The model explained about 27% variation in the banks' stock returns. Given that there are other factors that cannot explain stock returns, the FF5F model was adopted and modified to include the two liquidity measures, the BLMI and the ALMI and the estimation results are presented in Table 6.

Table 6. *Empirical results from the FF5F model*

	Pooled Effects	Fixed Effects	Random Effects	GLS
	Return	**Return**	**Return**	**Return**
BLMI	1.011**	1.254**	1.011**	0.923
	(0.317)	(0.256)	(0.317)	(0.996)
ALMI	-91.97*	-93.64*	-91.97*	-91.36**
	(35.96)	(35.88)	(35.96)	(33.39)
RM	0.788	0.821	0.788	0.776
	(0.661)	(0.655)	(0.661)	(0.826)
HML	169.5**	170.7*	169.5**	169.1***
	(51.54)	(51.70)	(51.54)	(46.80)
SMB	-82.64***	-83.41**	-82.64***	-82.36*
	(24.41)	(24.35)	(24.41)	(32.06)
Dummy	-30.96**	-30.83*	-30.96**	-31.01*
	(9.567)	(9.497)	(9.567)	(14.48)
_cons	1084.8**	1103.1*	1084.8**	1078.1**
	(406.0)	(402.1)	(406.0)	(367.2)
N	108	108	108	108
R^2	0.460	0.479	0.463	
Pesaran		0.898	0.893	
Frees		0.526	0.546	
Hausman		0.830	0.830	

Note: *Standard errors in parentheses,* * *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*
Source: *Authors' computation.*

Results from Hausman test revealed that the Random effects model was the most efficient model as the probability was 0.93. This meant that the null hypothesis could not be rejected at 5% significance level. Again, the other models were presented for robustness. The results in line with those in Table 6, showed evidence of a positive and significant relationship between bank stock returns and BLMI. A confirmation that banks that hold significant liquidity as measured by BLMI. Table 4 revealed that aggregate liquidity mismatch index is negatively related with bank stock returns. As the market is highly liquid banks lose the ability to price loans and advances at high

rates. In low interest rate regimes, naturally margins tighten. All other things being equal net interest income shrinks because of low interest rates emanating from high liquidity in the market.

Other results revealed that bank stock returns are positively and significantly related to HML. This means that as the spread between value stocks and growth stocks increase, the banks stocks perform better. On the contrary, the banks' stock returns are negatively and significantly related with SMB. This implies that, as the spread between large cap and small cap stocks increased, bank stock returns deteriorated.

The most captivating results are that the coefficient of determination increased significantly from 27% to 46.3% as the results were estimated using FF5F model. This implies that FF5F can predict bank stock return better than an augmented CAPM.

5. Conclusion

Given that market crashes are a consequence of both funding liquidity and market liquidity, it was imperative to empirically test how market and funding liquidity in the presence of markets spirals affect banks' stock returns. Specifically, the aim of this article was to empirically test the effects of the Bank liquidity mismatch index and Aggregate liquidity mismatch index on banks' stock returns. The Augmented capital asset pricing model and the Fama and French's (2015) five factor model were adopted and modified to examine the nexus between the variables. A panel data methodology was employed, and a couple of results were revealed.

The results revealed that BLMI had a positive and significant effect on stock returns. Contrary to liquidity preference theory that argue for a liquidity premium associated with holding less liquid assets. Therefore, banks are recommended to hold significant liquidity buffers to take advantage of opportunities when they present themselves. Also, this confirms the recommendation by the BASEL III that advocates for higher liquidity positions. BASEL III encourages banks to hold more than 100% for both the Liquidity coverage ratio and the Net stable funding ratio.

The market wide liquidity level as measured by ALMI was found to be negatively related with bank stock returns. Meaning a contrarian strategy bears positive results, that is when the market is awash with money the banks stocks negatively perform. Therefore, in periods of high market wide liquidity, short positions in banks stocks may be optimal. Banks are recommended to keep lower liquidity buffers in times of high market wide liquidity because cash may be associated with very high opportunity cost.

Other results indicate that the global financial crises of 2007-2009 had significant influence on banks' stock returns. Also, there is a significant linkage between banks stock returns and the traditional factors, the broad market index, HML and SMB.

Overall, liquidity was found to have a deterministic influence on stock returns. This was the case for bank level liquidity as measured by BLMI and the market wide liquidity as measured by ALMI. Therefore, liquidity plays a role in asset pricing models and can be tested empirically. More importantly, the aggregate liquidity mismatch index provided a good macro-prudential liquidity measure which could be included in various financial economics models.

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