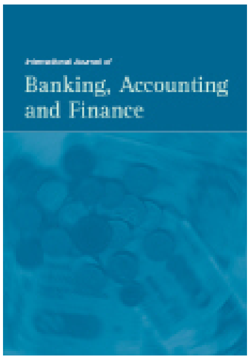


International Journal of Banking, Accounting and Finance

ISSN online: 1755-3849 - ISSN print: 1755-3830
https://www.inderscience.com/ijbaaf

Do idiosyncratic volatility and liquidity in stock returns still matter in post-global financial crisis? The UK evidence

Ghaith El-Nader, Yasmeen Al-Halabi

DOI: 10.1504/IJBAAF.2023.10053224

Article History:

Received:	10 September 2021
Accepted:	22 June 2022
Published online:	06 March 2023

Do idiosyncratic volatility and liquidity in stock returns still matter in post-global financial crisis? The UK evidence

Ghaith El-Nader* and Yasmeen Al-Halabi

Faculty of Business,
Yarmouk University,
Irbid-21163, Jordan
Email: ghaith.n@yu.edu.jo
Email: 2017720025@ses.yu.edu.jo
*Corresponding author

Abstract: This paper investigates the roles of idiosyncratic volatility and liquidity in explaining the variation in the UK stock returns following the aftermath of the global financial crisis. Results provide strong evidence of a positive idiosyncratic volatility premium across different return data intervals, implying that investors require compensation for higher idiosyncratic volatility stocks. Also, liquidity explains the positive idiosyncratic volatility-return relation and must be considered when seeking a move away from highly volatile stocks. Results of the industry analysis indicate that idiosyncratic volatility (liquidity) is relevant in explaining variations in six (seven) of the ten industry-level returns. The findings of this paper are important for active investors to understand how different industry volatilities are related, and therefore to increase their diversification capacity or speculate by timing their investment strategies.

Keywords: idiosyncratic volatility; liquidity; UK stock market.

Reference to this paper should be made as follows: El-Nader, G. and Al-Halabi, Y. (2023) 'Do idiosyncratic volatility and liquidity in stock returns still matter in post-global financial crisis? The UK evidence', *Int. J. Banking, Accounting and Finance*, Vol. 13, No. 3, pp.403–422.

Biographical notes: Ghaith El-Nader is an Assistant Professor of Finance at Yarmouk University. He received his MSc and PhD degrees from Swansea University, UK.

Yasmeen Al-Halabi obtained her MSc degree in Finance from Yarmouk University. Her research interests focus on portfolio management and asset pricing.

1 Introduction

Modelling and forecasting aggregate stock market volatility has attracted a great deal of attention in the finance literature given its important role in risk management and portfolio selection (see for example, Schwert, 1989; McMillan et al., 2000; Verma and Verma, 2007; Andrei and Hasler, 2015; Poshakwale et al., 2019). However, aggregate market return is only one element of an individual stock return; both industry-level and idiosyncratic firm-level shocks are significant elements as well. In fact, Campbell et al. (2001) (hereafter CLMX) show that the percentage of total volatility attributed to the idiosyncratic component is higher than the industry and market components. Recent empirical research has centred around the negative association between idiosyncratic volatility (IVOL) and stock returns documented by Ang et al. (2006, 2009). Also known as the IVOL puzzle, this negative relation calls into question both modern portfolio theory and Merton's (1987) investor recognition hypothesis, which assume a positive relation driven by investors holding under-diversified portfolios due to incomplete information. Despite the vast interest paid to understanding the behaviour and pricing of IVOL over the past two decades (see for example, Xu and Malkiel, 2003; Wei and Zhang, 2006; Fu, 2009; Angelidis, 2010; Brandt et al., 2010; Aboulamer and Kryzanowski, 2016; Alsanidis et al., 2019), the mixed evidence suggests that the issue is still far from consensus. Furthermore, the relevance of liquidity as a pricing factor in the cross-section of stock returns is well-documented (see for example, Amihud and Mendelson, 1986; Amihud, 2002; Pastor and Stambaugh, 2003; Avramov et al., 2006; Artikis, 2018). The general conclusion is that liquidity is negatively linked with stock returns, with the most common explanation being that illiquid stocks are more vulnerable to systematic liquidity risks and exhibit higher transaction costs.

The evidence that IVOL and liquidity are both important risk factors in asset pricing motivates us to investigate their combined impact in the aftermath of the financial crisis. It is well-documented that during periods of high uncertainty, investors increase their risk aversion and gravitate toward more liquid assets. However, it has also been demonstrated that the prices of illiquid and high IVOL stocks tend to recover to their original levels following recessions, and that the IVOL anomaly disappears following economic downturns (Malagon et al., 2018). We find strong evidence of a positive IVOL premium across different return intervals using a sample of all listed shares on the UK's FTSE-350 index from January 2009 to December 2018. This implies that investors hold under-diversified portfolios, and as a result, demand compensation for the IVOL of stocks. Further, the relationship between IVOL and stock returns is stronger than the relationship between liquidity and return, which supports previous evidence.

Our paper makes four main contributions. First, we add to the growing body of literature on the pricing of IVOL in the UK. Evidence of volatility spillovers during the financial crisis makes the UK market an appropriate environment for studying the risk-return relationship given its integration with the US stock market. Second, most existing research on the IVOL premium focuses on monthly stock holding intervals. These studies do not compare the IVOL premia at various return data frequencies. Khovansky and Zhylyevskyy (2013) provide an exception by investigating daily, monthly, quarterly, and annual return intervals. They document a positive (negative) IVOL premium on daily (other) return intervals. Malagon et al. (2015) provide another exception by decomposing the returns distribution over different timescales. They report that for investors with shorter (longer) investment horizons, the IVOL-return relationship is negative (positive). They concluded that investors with long-run investment horizons, as opposed to investors with short-run horizons should not be concerned about the IVOL puzzle. To the best of our knowledge, such a comparison has yet to be investigated in the UK context. Third, evidence on the combined importance of IVOL and liquidity in the UK is limited (see for example, Angelidis and Andrikopoulos, 2010; Cotter et al., 2015). These papers however do not provide information on these risk factors beyond the financial crisis period. Our paper investigates whether the significant reduction in stock market liquidity during the financial crisis influenced the post-crisis significance of IVOL. According to Malagon et al. (2018), prices of illiquid and high IVOL stocks tend to recover to their original levels following recessions, and thus the price correction may explain the absence of the IVOL anomaly. Fourth, we conduct our analysis at the industry level to determine how these effects differ across industries. Huang et al. (2014) documented increased herding during the financial crisis, especially in industry portfolios with higher IVOL.

Our findings of a positive IVOL premium across different return intervals are consistent with modern portfolio theory and the investor recognition hypothesis of Merton (1987) in that investors in the UK are under-diversified, and thus require compensation for the IVOL of securities. Further, we demonstrate that liquidity can help to clarify the positive IVOL-return relationship. During times of economic uncertainty, investors and portfolio managers must consider liquidity since it carries information about future macroeconomic fundamentals (Naes et al., 2011). Overall, our results support Wang's (2010) findings that investors can increase their chances of achieving full diversification by diversifying across industries, because different fundamental economic factors affect industries differently. Active investors must therefore understand these dynamics and how various industries are related to increase their diversification capacity. Our findings can also help policymakers' better deal with the effects of liquidity and volatility shocks on stock markets following crises periods.

The structure of this paper is constructed as the following. Section 2 reviews the related literature. Section 3 presents the definition of variables and methodologies used. The analysis and results are discussed in Section 4. Finally, Section 5 concludes.

2 Literature review

The capital asset pricing model (CAPM) proposed by Sharpe (1964) and Lintner (1965) assumes that only market volatility is priced in equilibrium, and that any role of IVOL can be eliminated through diversification. However, Merton (1987) demonstrates that unsystematic or IVOL also influences stock returns. Because investors are unable to achieve full diversification due to institutional complexities and information costs, they demand higher returns to compensate them for higher IVOL, and thus IVOL should be a pricing factor in the cross-section of expected stock returns. Over the last two decades, the behaviour of IVOL and its significance in the variation of stock returns has attracted much interest, especially after CLMX identified a positive trend in IVOL. For example, Wei and Zhang (2006) attributed this trend to declining corporate earnings and rising earnings volatility. Brown and Kapadia (2007) and Fink et al. (2010) demonstrated the importance of the new listing effect in justifying the positive trend in IVOL. Brandt et al. (2010) contended that the increase in IVOL was an episodic phenomenon and demonstrated that the rise and subsequent reversal in IVOL is stronger amongst low-priced stocks with high retail ownership. Yin et al. (2019) recently argued that the IVOL puzzle is a problem of investment horizon specification. They observed that this relationship was negative in both the short and long runs, but positive in the intermediate run.

Furthermore, the role of liquidity in the IVOL and return relationship has received less attention. Spiegel and Wang (2005) demonstrated that IVOL (liquidity) levels increased (decreased) stock returns. They noted that firms with high IVOL have less liquidity, which is consistent with inventory control models. Han and Lesmond (2011) demonstrated the importance of microstructure influences in estimating IVOL and demonstrated that return reversals and liquidity effects drive the IVOL-return relationship. Similarly, Bradrania et al. (2015) demonstrated that the IVOL premium is driven by liquidity after returns for microstructure noise are corrected. Vidal-Garcia et al. (2016) and Dinh (2017) provided strong evidence that IVOL has a greater effect on the performance of mutual funds as compared to systematic risks. Malagon et al. (2018) observed that greater IVOL (less liquid) stocks were more sensitive to liquidity shocks, particularly during times of financial uncertainty with significant liquidity dry ups, but that these stocks' prices recovered to their original levels following recessions. In the UK context, Angelidis and Tessaromatis (2008) found that IVOL of small stocks predicted the small capitalisation premium between 1979 and 2003, yet business cycle and liquidity variables were found to be unrelated to IVOL. Angelidis and Andrikopoulos (2010) showed that IVOL spillovers from large-cap to small-cap stocks between 1987 and 2007 can be forecasted by illiquidity shocks in size-based portfolios. They provided evidence of asymmetric liquidity spillovers, which supports the perception that market-wide information is firstly absorbed in the trading behaviour of large-cap stocks before being transmitted to small-cap stocks. Cotter et al. (2015) found the relation to be dependent on whether the market excess return is negative or positive and showed that the negative pricing of IVOL between 1990 and 2009 was due to its association with market volatility particularly during recessions[1], while liquidity risk exposures indicated that conditional pricing of IVOL is dependent on the general state of the economy.

3 Data and variables

3.1 Sample

Our dataset is obtained from Thomson Reuters DataStream and includes all listed shares on the FTSE-350 index for the period of January 2009 to December 2018.[2] This index represents the 350 largest firms listed on the London Stock Exchange (LSE). It represents around 89% of the trading volume on LSE and is considered broad enough to cover a wide range of industries, therefore allowing us to obtain an accurate description of the UK stock market.

3.2 Variables

3.2.1 Idiosyncratic volatility

We employ daily stock returns to compute monthly IVOL measures following the volatility decomposition method of CLMX. This method implicitly assumes that systematic risks are captured by the industry return and that firms have unit betas in relation to their respective industries (Bekaert et al., 2012). It extends the CAPM to decompose the total return volatility of a stock into three components: market, industry and firm specific. In addition to these components adding up to total return volatility, it has the additional benefit of removing firm-specific betas, which can be unstable over time (Fink et al., 2010). To calculate the firm-specific residual, we subtract the daily industry-i return from the daily firm-f return:

$$\zeta_{f,i,t} = Ret_{f,i,t} - Ret_{i,t} \tag{1}$$

The month-t IVOL of stock-f in industry-i is computed by summing the squared firm residuals:

$$Vol_{f,i,t} = \sum\nolimits_{s \in t} \zeta^2_{f,i,t} \tag{2}$$

We next construct the weighted average of IVOL for each individual industry by using monthly *IVOL* estimates for all stocks:[3]

$$Vol_{i,t} = s \sum\nolimits_{f \in i} w_{f,i,t} Vol_{f,i,t} \tag{3}$$

where $w_{f,i,t}$ denotes the month-t weight of industry-i measured by market capitalisation. Finally, we calculate the weighted average of the industry *IVOL* to reach the average idiosyncratic volatilities across all the stocks in a particular year. Specifically:

$$Vol_t = \sum\nolimits_i w_{i,t} Vol_{i,t} \tag{4}$$

where $w_{i,t}$ denotes the month-t weight of stock-f in industry-i. As indicated by CLMX, this technique guarantees that firm-specific covariances aggregate out based on the assumption that $\left(\sum\nolimits_{f \in i} w_{f,i,t} \beta_{f,i} = 1\right)$.

3.2.2 Liquidity

To measure liquidity, we employ the Amihud (2002) illiquidity ratio which is computed as the ratio of absolute daily stock return to daily trading volume, averaged over the trading days of a particular month. Specifically:

$$Amihud_{f,t} = Average\left(|Ret_{f,t}| \big/ V_{f,t} \right) \tag{5}$$

where $Ret_{f,t}$ represents the daily return, and $V_{f,t}$ is the respective daily volume in GBP. This measure is intuitively appealing because it quantifies the price/return response to a given trade size and determines the price impact of the order flow.

3.2.3 Control variables

Based on previous literature (see for example, Angelidis and Tessaromatis, 2008; Brandt et al., 2010; Malagon et al., 2018), we include a number of firm characteristics that are regarded as key factors in explaining the variation of stock returns. These include the dividend yield, leverage, return on equity and firm size.

3.2.4 Regression model

We examine the impact of IVOL and liquidity on stock returns using the following regression model:

$$Ret_t = \alpha_0 + \alpha_1 IVOl_{t-1} + \alpha_2 Liq_{t-1} + \alpha_3 DY_{t-1} + \alpha_3 ROE_{t-1} + \alpha_3 Lev_{t-1} + \alpha_3 Sz_{t-1} + \varepsilon_t \quad (6)$$

where *Ret* denotes stock return, *IVOL* represents IVOL following the CLMX method, *Liq* denotes liquidity calculated using the Amihud illiquidity measure, *DY* is the dividend yield, *ROE* is the return on equity, *Lev* denotes leverage and *Sz* is firm size. ε_t is the error term. Table 1 gives a detailed description of all variables.

Table 1 Definition of variables

Variable	*Notation*	*Definition*
Stock returns	*Ret*	Stock returns calculated from adjusted closing prices
Idiosyncratic volatility	*IVOL*	Idiosyncratic volatility estimated from the CLMX model
Liquidity	*Liq*	Average ratio of absolute daily return to daily trading volume
Dividend yield	*DY*	Dividends per share over stock price
Return on equity	*ROE*	Net income scaled by total equity
Leverage	*Lev*	Total liabilities scaled by total assets
Size	*Sz*	Natural logarithm of market capitalisation

4 Empirical results

4.1 Main results

Panel A of Table 2 displays the summary statistics for the sample firms. The mean return (*Ret*) is 0.019 and has a standard deviation of 0.024. The monthly average *IVOL* is 0.012 and has a standard deviation of 0.021. Figure 1 displays the time-series plots of aggregate annual IVOL. Overall, we do not detect a behavioural trend in IVOL, but rather a few episodes of spikes which reversed itself. The high level of IVOL during 2009 can be attributed to effect of the global financial crisis.

Table 2 Summary statistics and correlation matrix

Panel A: summary statistics							
Variable	*Mean*	*SD*	*Min.*	*25th*	*Median*	*75th*	*Max.*
Ret	0.019	0.024	–0.212	–0.025	0.013	0.054	0.164
IVOL	0.012	0.021	0.000	0.007	0.011	0.028	0.196
Amihud	0.113	0.231	0.000	0.014	0.054	0.161	0.259
DY	0.034	0.023	0.000	0.013	0.024	0.037	0.141
ROE	0.118	0.146	–0.291	0.021	0.109	0.204	0.544
Lev	0.189	0.193	0.000	0.035	0.150	0.494	0.986
Sz	14.51	1.458	7.490	11.29	14.23	16.07	18.12

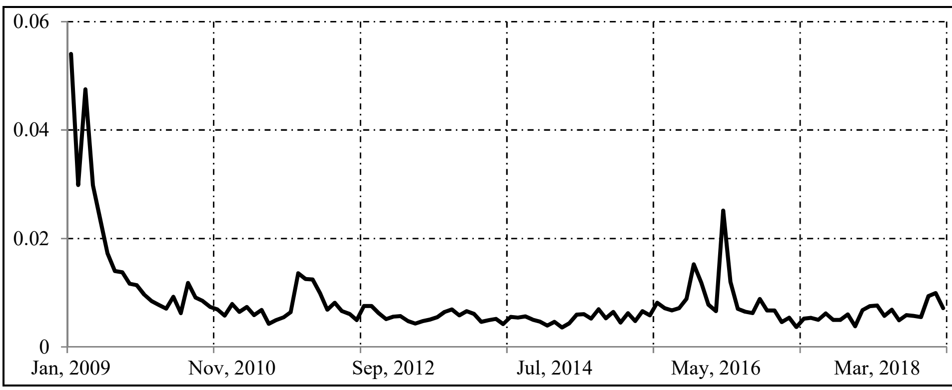
Note: This table displays the main statistics of the variables (Panel A) and the correlation matrix (Panel B).

Table 2 Summary statistics and correlation matrix (continued)

Panel B: correlation matrix							
Variable	*Ret*	*IVOL*	*Amihud*	*DY*	*ROE*	*Lev*	*Size*
Ret	*1*						
IVOL	0.073	*1*					
Amihud	0.024	0.159	*1*				
DY	–0.061	0.092	0.013	*1*			
ROE	0.044	–0.079	–0.069	–0.013	*1*		
Lev	–0.014	0.047	–0.084	0.102	–0.043	*1*	
Sz	0.029	v0.133	–0.441	0.058	0.119	0.163	*1*

Note: This table displays the main statistics of the variables (Panel A) and the correlation matrix (Panel B).

Figure 1 Aggregate IVOL



Note: This figure displays the annual average standard deviation for every month between January 2009 to December 2018 calculated using the CLMX methodology.

Figures of industry volatilities are available in Appendix 1 and are calculated following the CLMX method. The *Amihud* illiquidity ratio has a mean value of 0.113 and a standard deviation of 0.231. On average, the sample firms have a dividend yield of 3.4% and a return on equity ratio of approximately 12%. The capital structure shows a use of around 19% in debt financing. Further, Panel B reports the pairwise correlation between the variables and shows that stock returns (*Ret*) are positively correlated with all the variables except the dividend yield (*DY*) and leverage (*Lev*).

The key findings in Table 3 show that *IVOL* and illiquidity (*Amihud*) are significant in explaining the variation in stock returns across different regression model specifications. The regression coefficient of *IVOL* is 0.124 in specification 1 and increases to 0.226 in specification 3 when control variables are added. The positive and highly significant *IVOL* coefficients indicate that investors require a premium for higher IVOL stocks because their portfolios are under-diversified; this finding is in line with Fu (2009), Huang et al. (2010) and Bradrania et al. (2015). Further, the regression coefficient of *Amihud* is 0.062 in specification 2 and rises to 0.119 in specification 4 when adding our control variables. The positive and highly significant *Amihud* coefficients suggest that investors demand higher returns for less liquid stocks, which is in line with the findings of Spiegel and Wang (2005) and Bradrania et al. (2015), among others. Furthermore, our regression estimates in specifications 5 and 6 show that the positive relationship between IVOL and stock returns is stronger than the liquidity-return relationship. From the adjusted R-square of specification 5, we see that both variables account for 26.5% of the variation in stock returns. Our control variables are also important factors in explaining stock return variations. Specifically, we find that smaller and less leveraged firms with higher profitability and dividend yields earn higher returns.

Table 3 Determinants of stock returns

	Monthly intervals					
Variable/specification	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.033***	0.029***	–0.030***	0.026**	0.021***	–0.023***
	(0.005)	(0.009)	(0.008)	(0.011)	(0.008)	(0.009)
IVOL	0.124***	–	0.226***	–	0.179***	0.246***
	(0.039)		(0.057)		(0.052)	(0.058)
Amihud	–	0.062**	–	0.119***	0.083***	0.154***
		(0.030)		(0.034)	(0.034)	(0.033)
DY	–	–	–0.028	0.017**	–	0.024**
			(0.015)	(0.008)		(0.012)
ROE	–	–	0.047***	0.039**	–	0.047***
			(0.021)	(0.019)		(0.018)
Lev	–	–	–0.029**	–0.009	–	–0.027**
			(0.014)	(0.006)		(0.013)
Sz	–	–	–0.045***	–0.022***	–	–0.051***
			(0.011)	(0.005)		(0.019)
Adj. R^2	0.212	0.246	0.321	0.269	0.265	0.326

Notes: Our sample includes all shares listed on the FTSE-350 index over the period from 2009:01 to 2018:12. Independent variables are in lagged form. Robust standard errors are reported in parentheses. *** and ** indicate statistical significance at 1% and 5% levels, respectively.

4.2 Additional results

We next offer further analysis on the effect of IVOL and liquidity on stock returns using different data frequencies. Since volatility is persistent (Engle, 1982), we anticipate that past-IVOL should be predictive even when longer periods are utilised to calculate IVOL. Khovansky and Zhylyevskyy (2013) find a positive IVOL premium on daily return data, but a negative premium on quarterly and annual data. Malagon et al. (2015) find a negative (positive) IVOL-return relationship for shorter (longer) investment horizons. We document similar results between Table 3 and Table 4. Instead of calculating *IVOL* over the previous month (t – 1, t), we follow Ang et al. (2009) and use daily returns over the previous 3 and 12 months denoted by (t – 3, t) and (t – 12, t) for quarterly and annual intervals, respectively. Our results show that *IVOL* has a significant and positive coefficient estimate regardless of the data interval used, implying that IVOL is indeed priced and commands a positive and significant premium even at longer holding periods. However, the magnitude of the *IVOL* coefficients declines with longer formation periods, decreasing from 0.078 in Panel A to 0.058 in Panel B of specification 1.

Table 4 Determinants of stock returns using different data frequencies

Panel A: quarterly intervals						
Variable/specification	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.021***	0.007	0.018**	0.012***	0.016**	0.013***
	(0.009)	(0.005)	(0.009)	(0.005)	(0.008)	(0.005)
IVOL	0.078**	–	0.101**	–	0.093***	0.136***
	(0.037)		(0.049)		(0.040)	(0.051)
Amihud	–	0.042***	–	0.051***	0.048**	0.086***
		(0.018)		(0.021)	(0.023)	(0.033)
DY	–	–	0.028**	0.015	–	0.028**
			(0.014)	(0.009)		(0.013)
ROE	–	–	0.064***	0.051***	–	0.065***
			(0.026)	(0.020)		(0.027)
Lev	–	–	–0.011	–0.024**	–	–0.015
			(0.008)	(0.011)		(0.010)
Sz	–	–	–0.037***	–0.029***	–	–0.032***
			(0.014)	(0.012)		(0.007)
Adj. R^2	0.404	0.368	0.402	0.379	0.416	0.443
Panel B: annual intervals						
Variable/specification	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.041**	0.029**	0.028***	0.015**	0.026**	0.019***
	(0.020)	(0.015)	(0.009)	(0.007)	(0.012)	(0.005)
IVOL	0.058**	–	0.081***	–	0.064***	0.095***
	(0.027)		(0.031)		(0.024)	(0.039)
Amihud	–	0.033***	–	0.042**	0.040**	0.063**
		(0.014)		(0.020)	(0.019)	(0.031)
DY	–	–	0.019**	0.012**	–	0.025**
			(0.009)	(0.006)		(0.012)
ROE	–	–	0.043**	0.054***	–	0.056***
			(0.021)	(0.019)		–0.008
Lev	–	–	–0.031**	–0.013	–	–0.037***
			(0.015)	(0.009)		(0.017)
Sz	–	–	–0.021**	–0.025***	–	0.011
			(0.010)	(0.011)		(0.008)
Adj. R^2	0.483	0.452	0.627	0.599	0.531	0.602

Notes: Our sample includes all shares listed on the FTSE-350 index over the period from 2009:01 to 2018:12. Independent variables are in lagged form. Robust standard errors are in parentheses. *** and ** indicate statistical significance at 1% and 5% levels, respectively.

Furthermore, the *Amihud* coefficient is significant and positive in both panels, confirming that investors demand higher returns for illiquid stocks. More importantly, we find that *IVOL* and *Amihud* both account for 41.6% (53.1%) of the variation in stock returns in Panel A (Panel B) of specification 5. Even at longer time intervals, the positive relationship between stock returns and *IVOL* remains stronger and more robust than the liquidity-volatility relationship. Lastly, our control variables are found to be significant in explaining the variation in stock returns, with the signs being consistent with our previous findings.

4.3 Industry-level results

Building on the interesting exploration of the US industry volatility by CLMX, we next explore the impact of IVOL and liquidity on stock returns at industry levels. To do so, we classify firms according to the Industry Classification Benchmark (ICB). Table 5 displays the regression results. *IVOL* is found to be important in explaining the variation in six of the ten industry-level returns. In particular, the coefficient estimate of IVOL is highest in the consumer goods industry (0.171). This is not surprising given that these stocks are highly sensitive during different economic cycles, suffering more during recessions but exhibiting increased sensitivity during economic upturns. Furthermore, *Amihud* is significant in explaining the variation in seven industry-level returns, with the financial industry appearing to be the most liquid (0.036). This finding is not surprising given that financial institutions saw large deposit inflows from investors during and after the financial crisis (DeYoung and Jang, 2016). Finally, while the importance of our control variables varies by industry, they generally indicate that smaller and less leveraged firms with higher profitability and dividend yields earn higher returns. Overall, our findings support Wang's (2010) contention that, while investors frequently do not hold well-diversified portfolios due to a lack of information, transaction costs, or wealth constraints, they can better diversify their portfolios by investing across industries, as different industries exhibit different exposures to various fundamental economic factors.

4.4 Robustness tests

In this section, we conduct further analyses to ensure our baseline results are robust to alternative measures of IVOL and liquidity. We report the results in Table 6. Specifically, we calculate IVOL based on the CAPM as follows:

$$Ret_{f,t} - R_{ft} = \alpha_i + \beta_t \left(Rm_t - Rf_t \right) + \varepsilon_{f,t} \tag{7}$$

where $Ret_{f,t}$ is the daily firm-*f* return, Rf is the daily risk-free rate, Rm is the daily market return, β_t is the slope coefficient that captures systematic risk and $\varepsilon_{f,t}$ is the error term. The month-*t* idiosyncratic volatility (*IVOL-CAPM*) of firm-*f* is the standard deviation of the daily residuals from the estimated model. In addition, we employ the Amivest ratio as an alternative liquidity measure. Specifically:

$$Amivest_{f,t} = Sum\left(V_{f,t} \big/ \left| Ret_{f,t} \right| \right) \tag{8}$$

where $V_{f,t}$ denotes the daily trading volume in GBP and $Ret_{f,t}$ is the respective daily firm-*f* return.

Table 5 Determinants of stock returns across different industries

Variable/industry	*Financials*	*Basic materials*	*Technology*	*Consumer goods*	*Consumer services*
Intercept	–0.012	0.034**	0.042***	0.034**	0.029
	(0.007)	(0.017)	(0.019)	(0.016)	(0.018)
IVOL	0.129***	0.015	0.063**	0. 171***	0.028
	(0.051)	(0.009)	(0.031)	(0.072)	(0.017)
Amihud	0.036**	0.051**	0.018	0.078**	0.045**
	(0.017)	(0.025)	(0.013)	(0.036)	(0.023)
DY	0.043***	0.033**	0.026**	0.024***	0.009
	(0.021)	(0.016)	(0.012)	(0.009)	(0.006)
ROE	0.045**	0.014	0.033***	0.035**	0.028
	(0.022)	(0.009)	(0.015)	(0.017)	(0.16)
Lev	–0.029**	–0.019**	–0.014	–0.048***	–0.024**
	(0.014)	(0.009)	(0.008)	(0.020)	(0.012)
Sz	–0.016	–0.044***	–0.030**	–0.050**	–0.051***
	(0.009)	(0.016)	(0.014)	(0.024)	(0.021)
Adj. R^2	0.284	0.233	0.247	0.324	0.227
Variable/industry	*Healthcare*	*Industrials*	*Oil and gas*	*Utilities*	*Telecommunication*
Intercept	0.029**	0.038**	0.048***	0.036**	0.022
	(0.014)	(0.018)	(0.020)	(0.018)	(0.018)
IVOL	0.055**	0.024	0.147***	0.051**	0.021
	(0.026)	(0.015)	(0.047)	(0.025)	(0.013)
Amihud	0.024	0.021	0.041**	0.046**	0.071***
	(0.019)	(0.014)	(0.019)	(0.023)	(0.030)
DY	–0.027**	–0.009	–0.031***	–0.027**	–0.032***
	(0.013)	(0.006)	(0.009)	(0.013)	(0.011)
ROE	0.034**	0.041***	0.046***	–0.011	0.037**
	(0.016)	(0.018)	(0.020)	(0.008)	(0.018)
Lev	–0.007	–0.029**	–0.043***	–0.041***	–0.015
	(0.004)	(0.014)	(0.017)	(0.016)	(0.009)
Sz	–0.033***	–0.048***	–0.009	–0.025**	–0.023**
	(0.014)	(0.019)	(0.005)	(0.012)	(0.011)
Adj. R^2	0.256	0.189	0.262	0.272	0.207

Notes: Our sample includes all shares listed on the FTSE-350 index over the period from 2009:01 to 2018:12. Independent variables are in lagged form. Robust standard errors are in parentheses. *** and ** indicate statistical significance at 1% and 5% levels, respectively.

Table 6 Determinants of stock returns using different proxies and data frequencies

Panel A: monthly intervals						
Variable/specification	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.013**	0.009	0.011***	0.024***	0.011***	0.018**
	(0.006)	(0.005)	(0.005)	(0.007)	(0.005)	(0.009)
IVOL-CAPM	0.098***	–	0.199***	–	0.183**	0.211***
	(0.034)		(0.063)		(0.057)	(0.062)
Amivest	–	–0.040**	–	–0.047***	–0.078**	–0.099***
		(0.019)		(0.017)	(0.038)	(0.035)
DY	–	–	0.039**	–0.023	–	0.038**
			(0.019)	(0.015)		(0.018)
ROE	–	–	0.077***	0.005	–	0.049**
			(0.025)	(0.003)		(0.024)
Lev	–	–	–0.016**	–0.017**	–	–0.017
			(0.008)	(0.008)		(0.010)
Sz	–	–	–0.050***	–0.027**	–	–0.032**
			(0.021)	(0.013)		(0.015)
Adj. R^2	0.198	0.176	0.342	0.223	0.214	0.349
Panel B: quarterly intervals						
Variable/specification	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.043**	0.009	0.026***	0.011	0.025**	0.013***
	(0.021)	(0.006)	(0.008)	(0.006)	(0.012)	(0.004)
IVOL-CAPM	0.043***	–	0.132***	–	0.058***	0.139***
	(0.013)		(0.058)		(0.019)	(0.048)
Amivest	–	–0.019**	–	–0.034**	–0.028**	–0.039**
		(0.009)		(0.016)	(0.013)	(0.019)
DY	–	–	0.042**	0.037**	–	0.040**
			(0.021)	(0.018)		(–0.019)
ROE	–	–	0.051***	0.067**	–	0.059***
			(0.019)	(0.031)		(0.022)
Lev	–	–	–0.046**	–0.048***	–	–0.055***
			(0.022)	(0.013)		(0.024)
Sz	–	–	–0.021**	–0.008	–	–0.019
			(0.010)	(0.005)		(0.011)
Adj. R^2	0.436	0.320	0.442	0.367	0.431	0.489

Notes: Our sample includes all shares listed on the FTSE-350 index over the period from 2009:01 to 2018:12. Independent variables are in lagged form. Robust standard errors are in parentheses. *** and ** indicate statistical significance at 1% and 5% levels, respectively.

Table 6 Determinants of stock returns using different proxies and data frequencies (continued)

Panel C: annual intervals						
Variable/specification	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.061**	0.009	0.049***	0.025**	0.008	0.014**
	(0.029)	(0.005)	(0.017)	(0.012)	(0.006)	(0.007)
IVOL-CAPM	0.022**	–	0.063***	–	0.045***	0.099**
	(0.011)		(0.025)		(0.012)	(0.047)
Amivest	–	–0.015**	–	–0.021***	–0.017**	–0.027**
		(0.007)		(0.009)	(0.008)	(0.013)
DY	–	–	0.039**	0.028	–	0.038**
			(0.018)	(0.016)		(0.019)
ROE	–	–	0.007	0.024***	–	–0.011
			(0.005)	(0.009)		(0.007)
Lev	–	–	–0.025**	–0.018**	–	–0.020***
			(0.012)	(0.009)		(0.008)
Sz	–	–	–0.052***	–0.032	–	–0.044**
			(0.019)	(0.024)		(0.021)
Adj. R^2	0.436	0.389	0.568	0.545	0.508	0.648

Notes: Our sample includes all shares listed on the FTSE-350 index over the period from 2009:01 to 2018:12. Independent variables are in lagged form. Robust standard errors are in parentheses. *** and ** indicate statistical significance at 1% and 5% levels, respectively.

Table 7 Determinants of stock returns across different industries using alternative proxies

Variable/industry	*Financials*	*Basic materials*	*Technology*	*Consumer goods*	*Consumer services*
Intercept	0.038***	0.025**	0.015	0.042***	0.029**
	(0.014)	(0.012)	(0.009)	(0.018)	(0.014)
IVOL-CAPM	0.134***	0.024	0.059**	0. 212***	0.054**
	(0.038)	(0.016)	(0.028)	(0.069)	(0.027)
Amivest	–0.085**	–0.059***	–0.019	–0.048***	–0.039**
	(0.041)	(0.023)	(0.011)	(0.021)	(0.019)
DY	0.037***	0.023**	0.021***	0.024**	0.013
	(0.016)	(0.011)	(0.009)	(0.012)	(0.007)
ROE	0.058***	0.030**	0.048***	0.021	0.018
	(0.024)	(0.014)	(0.021)	(0.013)	(0.11)
Lev	–0.027**	–0.023**	–0.009	–0.051***	–0.022**
	(0.013)	(0.011)	(0.005)	(0.019)	(0.011)
Sz	–0.047***	–0.031**	–0.030**	–0.049***	–0.039***
	(0.020)	(0.015)	(0.015)	(0.016)	(0.017)
Adj. R^2	0.267	0.351	0.168	0.283	0.172

Notes: Our sample includes all shares listed on the FTSE-350 index over the period from 2009:01 to 2018:12. Independent variables are in lagged form. Robust standard errors are in parentheses. *** and ** indicate statistical significance at 1% and 5% levels, respectively.

Table 7 Determinants of stock returns across different industries using alternative proxies (continued)

Variable/industry	*Healthcare*	*Industrials*	*Oil and gas*	*Utilities*	*Telecommunication*
Intercept	–0.008	0.039***	0.048***	0.031**	0.011
	(0.005)	(0.015)	(0.021)	(0.015)	(0.006)
IVOL-CAPM	0.064**	0.015	0.206***	0.037	0.039
	(0.031)	(0.008)	(0.068)	(0.019)	(0.023)
Amivest	–0.021	0.009	–0.028	–0.034	–0.063***
	(0.016)	(0.007)	(0.016)	(0.019)	(0.027)
DY	–0.025**	–0.029**	–0.038***	–0.016	–0.030***
	(0.012)	(0.014)	(0.015)	(0.009)	(0.011)
ROE	0.048***	0.043***	0.037**	0.008	0.041**
	(0.019)	(0.016)	(0.018)	(0.005)	(0.020)
Lev	–0.018	–0.025**	–0.029**	–0.057***	–0.029**
	(0.011)	(0.012)	(0.014)	(0.023)	(0.014)
Sz	–0.025**	–0.042***	–0.009	0.013	–0.015
	(0.012)	(0.017)	(0.006)	(0.011)	(0.008)
Adj. R^2	0.244	0.273	0.223	0.179	0.247

Notes: Our sample includes all shares listed on the FTSE-350 index over the period from 2009:01 to 2018:12. Independent variables are in lagged form. Robust standard errors are in parentheses. *** and ** indicate statistical significance at 1% and 5% levels, respectively.

Our regression results echo our previous findings in Table 3 and Table 4. Overall, the *IVOL-CAPM* coefficient estimates are significantly positive across all panels, with a declining coefficient magnitude across longer formation periods. In specification 1, *IVOL-CAPM* falls from 0.098 in Panel A to 0.043 in Panel B and to 0.022 in Panel C. In addition, the *Amivest* regression coefficient is significant and negative across all panels. Taken together, it is clear from specifications 5 and 6 that the IVOL-return association continues to be stronger and more robust than the liquidity-return relationship across all panels.

Moreover, results of the industry analysis in Table 7 are very similar to our findings in Table 5. *IVOL-CAPM* is significant in explaining the variation in six of the ten industry-level returns, with the highest coefficient estimate being in the consumer goods industry (0.212), closely followed by the oil and gas industry (0.206). While *Amivest* is only significant in explaining the variation in five of the industry level returns, the financial industry remains the most liquid with a significant coefficient estimate of –0.085 and thus is consistent with our previous findings. As a final robustness check, we sort stocks into quintiles of value weighted portfolios ranked by their monthly mean returns. This process generates five value-weighted portfolios, with portfolio 1 (5) having the lowest (highest) return. Our IVOL and liquidity measures' respective means are reported. Between 2009 and 2018, the quintile portfolios are rebalanced once a year. Appendix 2 displays a summary of these findings. We discover compelling evidence that both measures of IVOL and the Amihud illiquidity measure are a monotonic positive function of stock returns. The increase in stock returns is associated with higher (lower) IVOL (liquidity), thus supporting our overall findings.

5 Conclusions

Over the last two decades, there has been a growing interest in the behaviour, features, and pricing of IVOL. This is hardly unexpected considering its significance in asset pricing and portfolio management. Moreover, it has been suggested that prices of illiquid and high IVOL equities tend to rebound to their previous levels during recessions (Malagon et al., 2018), and that the IVOL anomaly is missing following recessions. As a result, this paper investigated whether the significant dry-up of stock market liquidity during the financial crisis influenced the post-crisis relevance of IVOL. We document strong evidence that IVOL has a significant and positive effect on the UK stock returns for the post-financial-crisis period, implying that investors require a premium in compensation for higher IVOL stocks. We also show that liquidity can clarify the positive IVOL-return relationship. Because liquidity has an information element associated with future macroeconomic fundamentals (Naes et al., 2011), investors should consider illiquidity when seeking a general flight to safety during periods of high uncertainty. Our findings support the argument put forward by Spiegel and Wang (2005) in that IVOL has a stronger association with stock returns as compared to liquidity. Moreover, we find that the positive IVOL premium is consistent across different return intervals. Even at lower frequencies, fully diversified portfolios are still difficult to attain, possibly due to stocks with high IVOL being undervalued by investors, and hence such stocks can be accompanied by higher subsequent returns (Stambaugh et al., 2015). Finally, we document that IVOL (liquidity) is relevant in explaining variations in six (seven) of the ten industry-level returns. These findings support Wang's (2010) contention that investors can improve their odds of obtaining full diversification by diversifying across industries, as various fundamental economic factors affect industries differently. Active investors must thus understand these dynamics and how different industry volatilities are connected to increase their diversification capacity or speculate by timing their investing and hedging methods. Our findings can also help policymakers address the consequences of volatility and liquidity shocks on stock markets more effectively.

References

Aboulamer, A. and Kryzanowski, L. (2016) 'Are idiosyncratic volatility and MAX priced in the Canadian market?', *Journal of Empirical Finance*, Vol. 37, pp.20–36.

Alsanidis, N., Christiansen, C., Lambertides, N. and Savva, C.S. (2019) 'Idiosyncratic volatility puzzle: influence of macro-finance factors', *Review of Quantitative Finance and Accounting*, Vol. 52, No. 2, pp.381–401.

Amihud, Y. (2002) 'Illiquidity and stock returns: cross-section and time-series effects', *Journal of Financial Markets*, Vol. 5, No. 1, pp.31–56.

Amihud, Y. and Mendelson, H. (1986) 'Asset pricing and the bid-ask spread', *Journal of Financial Economics*, Vol. 17, No. 2, pp.223–249.

Anand, A., Irvine, P., Puckett, A. and Venkataraman, K. (2013) 'Institutional trading and stock resiliency: Evidence from the 2007–2009 financial crisis', *Journal of Financial Economics*, Vol. 108, No. 3, pp.773–797.

Andrei, D. and Hasler, M. (2015) 'Investor attention and stock market volatility', *The Review of Financial Studies*, Vol. 28, No. 1, pp.33–72.

Ang, A., Hodrick, R.J., Xing, Y. and Zhang, X. (2006) 'The cross-section of volatility and expected returns', *The Journal of Finance*, Vol. 61, No. 1, pp.259–299.

Ang, A., Hodrick, R.J., Xing, Y. and Zhang, X. (2009) 'High idiosyncratic volatility and low returns: international and further US evidence', *Journal of Financial Economics*, Vol. 91, No. 1, pp.1–23.

Angelidis, T. (2010) 'Idiosyncratic risk in emerging markets', *Financial Review*, Vol. 45, No. 4, pp.1053–1078.

Angelidis, T. and Andrikopoulos, A. (2010) 'Idiosyncratic risk, returns and liquidity in the London Stock Exchange: a spillover approach', *International Review of Financial Analysis*, Vol. 19, No. 3, pp.214–221.

Angelidis, T. and Tessaromatis, N. (2008) 'Idiosyncratic volatility and equity returns: UK evidence', *International Review of Financial Analysis*, Vol. 17, No. 3, pp.539–556.

Artikis, P.G. (2018) 'Liquidity as an asset pricing factor in the UK', *Journal of Financial Management, Markets, and Institutions*, Vol. 6, No. 2, pp.1–24.

Avramov, D., Chordia, T. and Goyal, A. (2006) 'Liquidity and autocorrelations in individual stock returns', *The Journal of Finance*, Vol. 61, No. 5, pp.2365–2394.

Bekaert, G., Hodrick, R.J. and Zhang, X. (2012) 'Aggregate idiosyncratic volatility', *Journal of Financial and Quantitative Analysis*, Vol. 47, No. 6, pp.1155–1185.

Bradrania, M.R., Peat, M. and Satchell, S. (2015) 'Liquidity costs, idiosyncratic volatility, and expected stock returns', *International Review of Financial Analysis*, Vol. 42, pp.394–406.

Brandt, M.W., Brav, A., Graham, J.R. and Kumar, A. (2010) 'The idiosyncratic volatility puzzle: time trend or speculative episodes?', *The Review of Financial Studies*, Vol. 23, No. 2, pp.863–899.

Brown, G. and Kapadia, N. (2007) 'Firm-specific risk and equity market development', *Journal of Financial Economics*, Vol. 84, No. 2, pp.358–388.

Campbell, J.Y., Lettau, M., Malkiel, B.G. and Xu, Y. (2001) 'Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk', *The Journal of Finance*, Vol. 56, No. 1, pp.1–43.

Cotter, J., O'Sullivan, N. and Rossi, F. (2015) 'The conditional pricing of systematic and idiosyncratic risk in the UK equity market', *International Review of Financial Analysis*, Vol. 37, pp.184–193.

DeYoung, R. and Jang, K.Y. (2016) 'Do banks actively manage their liquidity?', *Journal of Banking & Finance*, Vol. 66, pp.143–161.

Dinh, M.T. (2017) 'The returns, risk, and liquidity relationship in high frequency trading: evidence from the Oslo stock market', *Research in International Business and Finance*, Vol. 39, pp.30–40.

Engle, R.F. (1982) 'Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation', *Econometrica*, Vol. 50, No. 4, pp.987–1008.

Fatum, R. and Yamamoto, Y. (2016) 'Intra-safe haven currency behavior during the global financial crisis', *Journal of International Money and Finance*, Vol. 66, pp.49–64.

Fink, J., Fink, K.E., Grullon, G. and Weston, J.P. (2010) 'What drove the increase in idiosyncratic volatility during the internet boom?', *Journal of Financial and Quantitative Analysis*, Vol. 45, No. 5, pp.1253–1278.

Fu, F. (2009) 'Idiosyncratic risk and the cross-section of expected stock returns', *Journal of Financial Economics*, Vol. 91, No. 1, pp.24–37.

Hameed, A., Kang, W. and Viswanathan, S. (2010) 'Stock market declines and liquidity', *The Journal of Finance*, Vol. 65, No. 1, pp.257–293.

Han, Y. and Lesmond, D. (2011) 'Liquidity biases and the pricing of cross-sectional idiosyncratic volatility', *The Review of Financial Studies*, Vol. 24, No. 5, pp.1590–1629.

Huang, T.C., Lin, B.H. and Yang, T.H. (2014) 'Herd behavior and idiosyncratic volatility', *Journal of Business Research*, Vol. 68, No. 4, pp.763–770.

Huang, W., Liu, Q., Rhee, S.G. and Zhang, L. (2010) 'Return reversals, idiosyncratic risk, and expected returns', *The Review of Financial Studies*, Vol. 23, No. 1, pp.147–168.

Khovansky, S. and Zhylyevskyy, O. (2013) 'Impact of idiosyncratic volatility on stock returns: a cross-sectional study', *Journal of Banking & Finance*, Vol. 37, No. 8, pp.3064–3075.

Lintner, J. (1965) 'Security prices, risk, and maximal gains from diversification', *The Journal of Finance*, Vol. 20, No. 4, pp.587–615.

Malagon, J., Moreno, D. and Rodriguez, R. (2015) 'Time horizon trading and the idiosyncratic risk puzzle', *Quantitative Finance*, Vol. 15, No. 2, pp.327–343.

Malagon, J., Moreno, D. and Rodriguez, R. (2018) 'Idiosyncratic volatility, conditional liquidity, and stock returns', *International Review of Economics & Finance*, Vol. 53, pp.118–132.

McMillan, D., Speight, A. and Apgwilym, O. (2000) 'Forecasting UK stock market volatility', *Applied Financial Economics*, Vol. 10, No. 4, pp.435–448.

Merton, R.C. (1987) 'A simple model of capital market equilibrium with incomplete information', *The Journal of Finance*, Vol. 42, No. 3, pp.483–510.

Naes, R., Skjeltorp, J.A. and Odegaard, B.A. (2011) 'Stock market liquidity and the business cycle', *The Journal of Finance*, Vol. 66, No. 1, pp.139–176.

Pastor, L. and Stambaugh, R.F. (2003) 'Liquidity risk and expected stock returns', *Journal of Political Economy*, Vol. 111, No. 3, pp.642–685.

Poshakwale, S.S., Chandorkar, P. and Agarwal, V. (2019) 'Implied volatility and the cross section of stock returns in the UK', *Research in International Business and Finance*, Vol. 48, pp.271–286.

Schwert, G.W. (1989) 'Why does stock market volatility change over time?', *The Journal of Finance*, Vol. 44, No. 5, pp.1115–1153.

Sharpe, W.F. (1964) 'Capital asset prices: a theory of market equilibrium under conditions of risk', *The Journal of Finance*, Vol. 19, No. 3, pp.425–442.

Spiegel, M.I. and Wang, X. (2005) *Cross-sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk*, Unpublished Working Paper, Yale University.

Stambaugh, R.F., Yu, J. and Yuan, Y. (2015) 'Arbitrage asymmetry and the idiosyncratic volatility puzzle', *The Journal of Finance*, Vol. 70, No. 5, pp.1903–1948.

Verma, R. and Verma, P. (2007) 'Noise trading and stock market volatility', *Journal of Multinational Financial Management*, Vol. 17, No. 3, pp.231–243.

Vidal-Garcia, J., Vidal, M. and Nguyen, D.K. (2016) 'Do liquidity and idiosyncratic risk matter? Evidence from the European mutual fund market', *Review of Quantitative Finance and Accounting*, Vol. 47, No. 2, pp.213–247.

Wang, Z. (2010) 'Dynamics and causality in industry-specific volatility', *Journal of Banking & Finance*, Vol. 34, No. 7, pp.1688–1699.

Wei, S.X. and Zhang, C. (2006) 'Why did individual stocks become more volatile?', *The Journal of Business*, Vol. 79, No. 1, pp.259–292.

Xu, Y. and Malkiel, B.G. (2003) 'Investigating the behavior of idiosyncratic volatility', *The Journal of Business*, Vol. 76, No. 4, pp.613–645.

Yin, L., Shu, T. and Su, Z. (2019) 'Common idiosyncratic volatility and returns: from an investment horizon perspective', *International Journal of Finance & Economics*, Vol. 24, No. 1, pp.370–390.

Notes

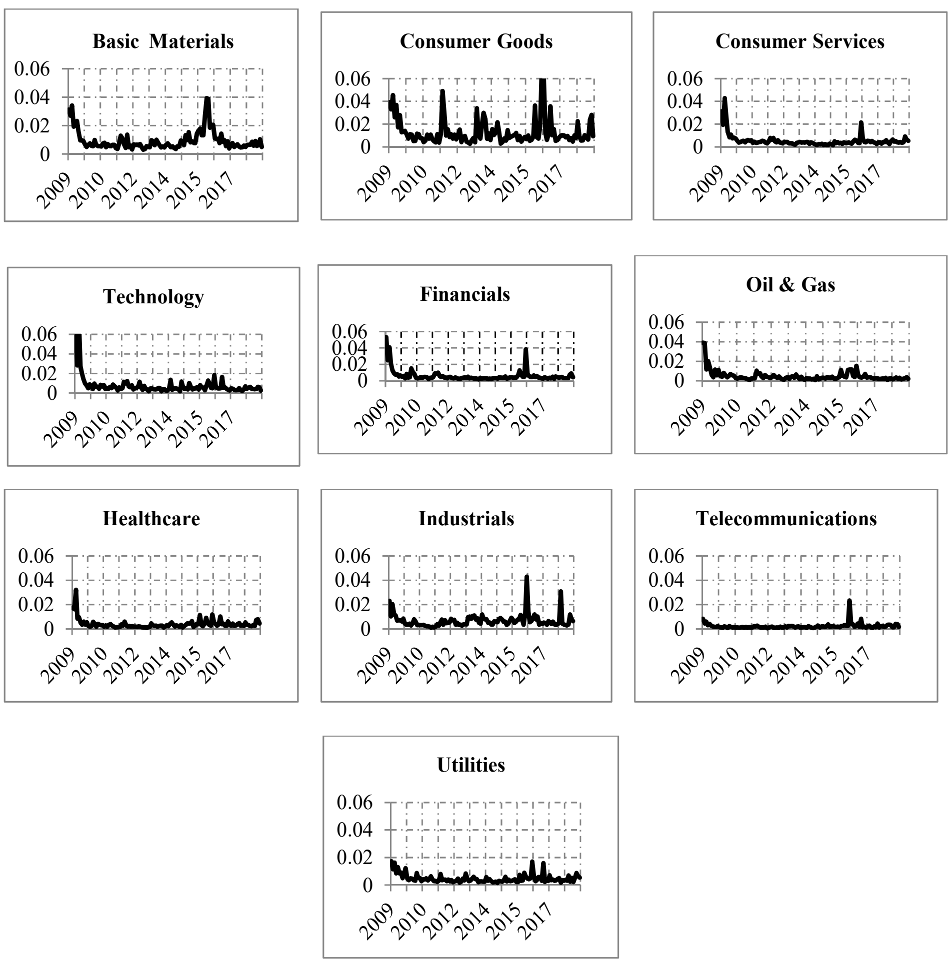
1 Stock market volatility, as witnessed during the financial crisis can have widespread repercussions on the economy, with events of liquidity dry ups being mainly attributed to panic selling (Anand et al., 2013) and capital constraints encountered by financial intermediaries (Hameed et al., 2010).

2 Since our research focuses on the post-crisis period, we choose our sample period from early 2009 following Fatum and Yamamoto (2016) to focus on the immediate aftermath of the financial crisis, while allowing us to shed some light on the concluding stages of the crisis.

3 Individual firms are aggregated into their respective industries according to the ICB which include ten industries: financials, basic materials, technology, consumer goods, consumer services, healthcare, industrials, oil and gas, utilities and telecommunication.

Appendix 1

ICB average volatilities – CLMX method



Appendix 2

The relationship between stock returns, idiosyncratic volatility and liquidity

Year	*Ret*	*IVOL-CLMX*	*IVOL-CAPM*	*Amihud*	*Amivest*
2009					
1 (low)	0.009	0.015	0.163	0.175	21.57
2	0.026	0.016	0.181	0.178	16.94
3	0.042	0.018	0.197	0.179	14.92
4	0.062	0.021	0.231	0.315	13.82
5 (high)	0.117	0.032	0.258	0.347	13.40
2010					
1 (low)	–0.01	0.001	0.104	0.126	23.90
2	0.007	0.004	0.105	0.130	16.65
3	0.017	0.006	0.108	0.140	16.20
4	0.027	0.009	0.112	0.142	15.79
5 (high)	0.055	0.011	0.114	0.176	11.39
2011					
1 (low)	–0.027	0.005	0.107	0.144	21.16
2	–0.008	0.007	0.107	0.154	13.52
3	0.000	0.007	0.109	0.199	11.39
4	0.008	0.009	0.120	0.219	11.02
5 (high)	0.031	0.011	0.143	0.257	14.13
2012					
1 (low)	–0.006	0.004	0.106	0.100	21.99
2	0.008	0.004	0.107	0.131	15.99
3	0.015	0.005	0.109	0.140	15.87
4	0.024	0.006	0.110	0.143	14.15
5 (high)	0.044	0.008	0.126	0.224	14.06
2013					
1 (low)	–0.012	0.002	0.102	0.104	20.69
2	0.009	0.003	0.104	0.111	19.62
3	0.019	0.004	0.105	0.125	16.55
4	0.030	0.005	0.109	0.137	15.61
5 (high)	0.048	0.008	0.118	0.212	15.41
2014					
1 (low)	–0.018	0.003	0.105	0.044	21.96
2	0.001	0.004	0.105	0.014	21.59
3	0.009	0.004	0.107	0.014	16.09
4	0.017	0.005	0.112	0.016	14.79
5 (high)	0.031	0.007	0.137	0.050	13.87

The relationship between stock returns, idiosyncratic volatility and liquidity (continued)

Year	*Ret*	*IVOL-CLMX*	*IVOL-CAPM*	*Amihud*	*Amivest*
2015					
1 (low)	–0.025	0.004	0.106	0.076	23.84
2	–0.002	0.005	0.108	0.089	22.51
3	0.006	0.006	0.109	0.117	15.29
4	0.015	0.008	0.109	0.127	13.49
5 (high)	0.033	0.008	0.111	0.134	13.14
2016					
1 (low)	–0.023	0.005	0.107	0.065	20.07
2	–0.003	0.007	0.107	0.082	18.75
3	0.006	0.008	0.109	0.084	17.36
4	0.016	0.009	0.142	0.109	16.56
5 (high)	0.048	0.018	0.160	0.127	16.18
2017					
1 (low)	–0.013	0.002	0.103	0.048	30.21
2	0.005	0.004	0.104	0.057	24.57
3	0.014	0.005	0.106	0.072	22.43
4	0.023	0.008	0.107	0.066	19.35
5 (high)	0.037	0.010	0.109	0.110	13.31
2018					
1 (low)	–0.028	0.005	0.107	0.055	24.77
2	–0.012	0.005	0.109	0.056	26.15
3	–0.004	0.006	0.110	0.076	19.46
4	0.003	0.007	0.111	0.088	17.79
5 (high)	0.018	0.009	0.115	0.096	15.11