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Philip Molyneux[a*], Qingwei Wang [b], Ru Xie [c] and Binru Zhao[c]

[a]College of Business, Abu Dhabi University, UAE; [b]Cardiff Business School, Cardiff University, Cardiff, UK; [c]School of Management, University of Bath, Bath, UK

ABSTRACT
This paper examines the relationship between bank marginal funding constraints and stock liquidity. Using bank credit default swap (CDS) spreads we show that increased funding constraints weaken bank stock liquidity (as measured by liquidity tightness, depth, and resilience). This effect strengthens during crises periods. Deteriorating bank stock liquidity is in turn priced into excess stock returns. In addition, we find that during liquidity crises, monetary expansion can break the relationship between funding costs and stock liquidity. Heightened monetary policy uncertainty, however, strengthens this relation.

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1. Introduction

Stock liquidity is desirable for banks. However, tight funding constraints can increase asset volatility and reduce stock liquidity (Brunnermeier 2009). These costs of illiquidity further affect stock return as investors require compensation for bearing them (Amihud 2002; Pastor and Stambaugh 2003; Brunnermeier and Pedersen 2009; and Acharya, Amihud, and Bharath 2013). In addition, an unexpected liquidity shock will raise future expected liquidity costs, which will drag down current stock prices. The effect also works in the other direction; changes in market liquidity, which lowers asset prices and erodes the financial institution's capital, can have a significant impact on the conditions of bank funding spreads. Under certain conditions, the interaction between funding and stock liquidity amplifies the impact of the initial negative shock and leads to illiquidity spirals (Brunnermeier and Pedersen 2009).

Several theoretical models establish a positive relationship between funding cost and market liquidity (Brunnermeier and Pedersen 2009). Brunnermeier and Pedersen (2009) suggest that increased funding spread lifts up market liquidity risk and the liquidity spiral exacerbates liquidity premium in asset pricing. Early empirical studies find that ex-ante asset return is an increasing function of expected illiquidity as investors require compensation for expected illiquidity (Amihud and Mendelson 1986, 1991; De Jong and Driessen 2012). Since asset illiquidity is persistent, an unexpected rise in illiquidity raises expected liquidity. Consequently, investors require higher expected asset returns, which makes asset prices fall (Amihud 2002).

In this paper, we provide empirical evidence for the impact of bank funding cost on stock liquidity risk. We use individual banks' spreads on their 5-year credit default swaps (CDS) to address bank funding costs. Bank stock liquidity is identified in three dimensions of liquidity: liquidity tightness, liquidity depth, and liquidity resilience. We find a sizeable, positive, and statistically significant relation between bank marginal funding costs and stock liquidity risk measured by all the three liquidity dimensions. In times of funding distress, the effect of rising funding costs on stock illiquidity is heightened due to the fact that investors rebalance their portfolios toward less risky and more liquid securities.

CONTACT Ru Xie r.xie@bath.ac.uk

*Present affiliation: Bangor Business School, Bangor University, Bangor, UK
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During liquidity crises, monetary authorities respond by cutting interest rates and increasing the money supply. In addition to traditional tools of monetary policy, the major central banks have adopted a range of unconventional monetary policies (UMP), guiding longer-term interest rate expectations, expanding the size of central bank balance sheets, and changing the composition of central bank asset holdings (Bernanke and Reinhart 2004; Brunnermeier and Sannikov 2016; Curdia and Woodford 2011; Del Negro et al. 2011; Drechsler, Savov, and Schnabl 2016). Recent literature has investigated the impact of such policies on real economic activity and inflation (Rodnyansky and Darmouni 2017; Chakraborty, Goldstein, and MacKinlay 2017). However, little is known about the effectiveness and pass-through of unconventional monetary policy to bank funding and market liquidity. Brunnermeier and Sannikov (2016) note that UMP can mitigate the destabilizing adverse feedback effects that precipitate crises by affecting asset prices held by constrained agents. Del Negro et al. (2011) investigate the effects of monetary interventions and support that unconventional policy can alleviate the crisis by swapping illiquid private paper for government liquidity. In this paper, we employ the monthly growth rate of central bank balance sheet size as a proxy for UMP in the wake of the crisis. We find that when we interact bank marginal funding costs with central bank balance sheet growth, the positive and substantial link between bank funding costs and stock illiquidity disappears. This suggests that monetary expansion interrupted the liquidity loop that existed between bank financing costs and stock liquidity. According to our findings, central banks can address systemic market liquidity risk in financial distress and break the vicious loop between funding costs and market illiquidity.

Monetary policy uncertainty can also have an impact on stock liquidity. Heightened policy uncertainty reduces investors' risk-bearing capacity as it increases market participants' expectations of future asset price volatility. Prior literature finds that monetary policy uncertainty is linked to greater stock price volatility and reduced investment (Baker, Bloom, and Davis 2015; Bernanke and Kuttner 2005). To gauge market uncertainty surrounding monetary policy stance we use the economic policy uncertainty index of Baker, Bloom, and Davis (2015), which provides the dynamic information on monetary uncertainty. We find positive and significant coefficients on the interaction terms, demonstrating that monetary policy uncertainty increases the liquidity loop between funding costs and stock illiquidity.

The interaction between bank funding costs and stock liquidity risk can lead to a liquidity loop, reflected in excess bank stock returns. An emerging literature on the interaction of funding liquidity and market liquidity provides further insight on the relationship between liquidity risk and asset pricing (Brunnermeier and Pedersen 2009; Acharya and Skeie 2011). Early empirical studies suggest that ex-ante asset returns are an increasing function of expected illiquidity as investors require compensation for bearing liquidity risk (Amihud and Mendelson 1986, 1991; De Jong and Driessen 2012). Developing a model in-line with Acharya and Pedersen (2005), we decompose bank stock liquidity into systematic and idiosyncratic components. Our results suggest that higher funding costs can push up stock illiquidity and stock liquidity risk is in-turn priced into bank stock returns. The strong link between bank funding costs and stock liquidity can amplify initial liquidity shocks leading to contagion and faster transmission of funding cost shocks to stock illiquidity.

Our paper contributes to the literature in a number of ways. First, we provide an empirical test of the theoretical model from Brunnermeier and Pedersen (2009) on funding and market liquidity. In addition, we find strong evidence that expansionary monetary policies are successful in breaking the vicious liquidity spiral. Last but not least, by decomposing liquidity risk into systematic and idiosyncratic liquidity risks, we demonstrate that bank idiosyncratic liquidity risk plays a more important role in bank stock performance.

The remainder of the paper is organized as follows. Section 2 introduces the liquidity measures. Section 3 describes the data and provides the empirical results. Section 4 concludes.

2. Construction of liquidity measures

There is an extensive literature on measuring bank funding costs. Measures such as margin requirements, the availability of external financing, rollover, and leverage risk have been used as proxies for bank funding costs (Brunnermeier and Pedersen 2009; Garleanu and Pedersen 2011; Acharya and Skeie 2011; Drehmann and Nikolaou, 2013). Other studies use Ted spread, the difference between the London Interbank Offered Rate (LIBOR) and a risk free rate as the funding spread (Cornett et al. 2011; Garleanu and Pedersen 2011; Boudt, Paulus, and

Rosenthal 2017). Ted spread represents the underlying short-term liquidity and credit risk of the bank. However, Libor is reported data, and it is now well known that banks may have under-reported their funding costs at times of market turmoil, which is evidenced by a weakening relationship between Libor and CDS spreads. CDS spreads capture high-frequency bank long-term variable-rate wholesale funding conditions in money markets. In setting the price for new lending, fund providers must factor in the cost of raising an additional unit of funding – the marginal funding cost, which is conditional on the bank's liquidity risk. CDS spreads closely mirror bank marginal funding costs in the money market with the higher the spread, the tighter the bank's funding constraints (Fecht and Grueber 2012). In this paper, we use bank-level panel data on bank CDS spreads as our key measure for bank marginal funding costs. Our measure is in-line with Fecht and Grueber (2012) and Beau et al. (2014), as well as the broad funding cost literature (Kroszner 2016).

In a seminal study, Kyle (1985) defines three dimensions of liquidity – tightness, depth and resilience, which is applied in several empirical studies (Harris 2003; Brunnermeier and Pedersen 2009; Garleanu and Pedersen 2011; Acharya and Skeie 2011). In our analysis, we examine whether funding constraints influence bank stock liquidity risk. Following Kyle (1985), we measure bank stock liquidity in three dimensions: tightness, depth and resilience. As a proxy for tightness, we take the relative spread (R-Spread), which is the quoted spread (the difference between the best ask and bid quotes) relative to the midpoint price (the average of the best ask and bid quotes). R-Spread measures the implicit cost of trading with a smaller R-Spread implying lower transaction cost:

$$R - Spread_{it} = \frac{(ask_{it} - bid_{it})}{((ask_{it} + bid_{it})/2)} \tag{1}$$

We follow Amihud (2002) and Acharya and Pedersen (2005) use the Amihud Illiquidity indicator (Amihud) to measure the depth dimension of bank stock liquidity. Amihud's (2002) illiquidity ratio measures the elasticity of liquidity. This is calculated as the daily measure of absolute asset returns to trading volume:

$$Amihud_{it} = \frac{|r_{it}|}{dvol_{it}} \tag{2}$$

where $r_{it}$is the return of stock i on day t and $dvol_{it}$is the trading volume for stock i on day t. The number of trading days for month t is D, and the mean level of illiquidity for month d is calculated as follows:

$$Amihud_{id} = \frac{1}{D_{id}} * \sum_{t=1}^{D_{id}} \frac{|r_{it}|}{dvol_{it}} \tag{3}$$

The time dimension of liquidity is commonly referred to as resilience. We use the measure of Roll (1984), which is an indicator of implied effective spread based on the negative autocorrelation produced by bounces between bid and ask quotes. Transaction costs cause negative serial dependence in successive observed market price changes and larger bid-ask bounces lead to higher negative covariance between adjacent price changes. This liquidity indicator includes the cost of trading that is based on the behaviour of prices. Roll's measure is calculated as the square root of the negative daily autocorrelation of individual stock returns, that is:

$$Roll_{it} = \sqrt{-cov(r_{it} r_{it-1})} \tag{4}$$

3. Empirical results

3.1. Data and summary statistics

Our dataset combines information from four main sources. Bank funding constraints measured by CDS spreads are obtained from Bloomberg; information to derive bank stock illiquidity is extracted from Datastream; bank-specific information is provided by Orbis BankFocus; and central bank balance size is collected from Datastream and national central banks. We use 5-year bank level CDS spreads as a proxy for bank's marginal funding costs. First, we match bank CDS spread data to stock market data from Datastream. To obtain bank-specific characteristics, we also match our data to bank balance sheet variables from Orbis BankFocus. The analysis focuses on the

Table 1. Summary statistics.

Sample:	All observations			High funding constraints period			Low funding constraints period		
Variable	N	Mean	Std.Dev.	N	Mean	Std.Dev.	N	Mean	Std.Dev.
Panel A: Bank Marginal Funding Spread and Stock Liquidity									
CDS (%)	3,848	2.019	3.609	1342	2.51	3.708	683	1.169	2.078
Amihud	5,720	1.075	1.980	1932	1.183	1.182	1265	0.957	1.888
R-Spread	5,094	0.402	3.155	1751	0.649	5.202	1103	0.318	0.872
Roll	3,213	0.577	0.310	1012	0.707	0.309	724	0.370	0.193
Panel B: Market Conditions and Stock Returns									
Sovereign_CDS (%)	5,400	2.163	2.942	1,802	2.027	2.796	1,183	2.081	2.600
Libor-OIS (%)	5,720	0.875	1.545	1,932	1.734	1.114	1,265	−0.596	1.381
R_i (%)	5,602	−2.299	1.758	1,892	−2.035	1.672	1,239	−3.055	1.598
R_m(%)	5,556	−2.269	1.746	1,892	−1.981	1.628	1,239	−3.067	1.592
MB	4,341	1.255	0.040	1,498	0.850	0.021	1,082	1.942	0.060
Panel C: Bank Balance Sheet data									
Size	4,341	19.566	0.985	1,498	19.643	0.993	1,082	19.315	0.958
Leverage	4,341	19.197	9.304	1,498	19.164	9.177	1,082	19.641	9.539
Funding (%)	4,125	0.433	0.196	1,424	0.427	0.201	1,027	0.437	0.187
ROAA	4,269	0.623	1.897	1,467	0.339	1.689	1,073	1.210	2.266
Cost to Income (%)	3,991	0.579	0.154	1,286	0.586	0.170	857	0.541	0.095
RWA	3,345	0.516	0.169	979	0.513	0.166	779	0.567	0.148
Panel D: Monetary Policy Uncertainty									
Baker_Index	5,720	118	42.135	1,932	140.097	37.119	1,265	70.433	7.962
CB_exp (%)	3,339	1.273	2.617	1,017	2.883	3.279	554	0.570	0.986

Note: This table reports the summary statistics and definitions of the key variables used in our analysis. The sample covers a time period of January 2003 to December 2012. The detailed definitions of each variable are provided in the OA Table A1. All variables are winsorized at the 1% and 99% level.

period from January 2003 to December 2012 for 10 years. Our primary data on bank marginal funding spread consist of daily CDS quotes for senior debt for 51 international banks. The summary statistics on CDS spreads for the sample banks are provided in appendix OA Table A2. We focus on mid-tier and top-tier international banking groups (by total assets) as only big banks' CDS are actively traded (see Chiaramonte and Casu 2013; Ashraf, Altunbas, and Goddard 2007).

Table 1 presents summary statistics for the key variables in our sample.[1] Columns 1–3 provide summary statistics for the whole sample. Columns 4–6 and 7–9 give summary statistics for the sub-samples of high and low funding constraints, respectively. High funding constraints period is defined as when VIX is in the 75th percentile in the sample. Low funding constraints period is defined as when VIX is in the 25th percentile in the sample. To reduce the effects of outliers, all of our variables are winsorized at the 1% level. Panel A of Table 1 shows summary statistics for bank marginal funding cost and stock illiquidity. The median value of bank CDS spreads in our sample is 202 basis points. The average values for the R_spread, Amihud, and Roll measures are 0.402, 1.075 and 0.577, respectively. Panel B of Table 1 presents summary statistics on market conditions and bank stock returns, as well as sovereign CDS spread (Sovereign_CDS), Libor-OIS (Libor-OIS), excess bank stock returns (R_i), excess market stock returns (R_m) and the market to book value ratio (MB). Changes in sovereign CDS may affect bank marginal funding costs and stock liquidity. We control for sovereign CDS and Libor-OIS, which are important determinants of overall stock illiquidity. The mean values of Sovereign CDS spread and Libor-OIS in our sample are 216 basis points and 88 basis points, respectively. We also control for excess bank stock returns and excess market returns. The mean values of excess stock returns and excess market returns are −2.30% and 1.79%, respectively. The growth opportunities of banks are controlled for by the market to book ratio. The average MB ratio in our sample is 1.255 and this is comparable to other studies (Gopalan, Kadan, and Pevzner 2012).

Furthermore, we include size, leverage and funding structure as bank-specific controls. Bank size (Size) is defined as the natural logarithm of total assets and is used to control for different characteristics across relatively large and smaller banks, as well as economies of scale. Some investment banks that rely on leverage face higher funding costs and stock liquidity risk when market liquidity is tight (Brunnermeier 2009). Banks that rely on

Table 2. Correlation matrix.

	R_spread	Amihud	Roll	CDS	Libor-OIS	R_i	R_m	MB	Size	Leverage	Funding	ROAA
R-Spread	1.000											
Amihud	−0.022	1.000										
Roll	0.005	0.019	1.000									
CDS	0.048*	0.106*	0.273*	1.000								
Libor-OIS	0.017	0.096*	0.276*	0.088*	1.000							
R_i	0.045*	−0.059*	0.129*	0.204*	−0.064*	1.000						
R_m	0.047*	−0.060*	0.151*	0.248*	−0.045*	0.978*	1.000					
MB	0.061*	−0.136*	−0.027	−0.087*	0.070*	0.228*	0.229*	1.000				
Size	−0.109*	0.192*	0.021	−0.062*	0.155*	0.090*	0.099*	0.018	1.000			
Leverage	−0.064*	0.099*	−0.017	−0.035	−0.043*	0.035*	0.040*	0.019	0.323*	1.000		
Funding	0.001	0.013	−0.086*	−0.077*	0.116*	−0.086*	−0.092*	0.094*	−0.156*	−0.312*	1.000	
ROAA	0.156*	−0.075*	−0.142*	−0.240*	−0.155*	0.007	−0.009	0.079*	−0.222*	−0.245*	0.205*	1.000

Note: This table presents the correlation matrix for the main variables in our sample. The detailed definitions of each variable are provided in the OA Table 1. All variables are winsorized at the 1% and 99% level. * denotes statistical signifcance at the 5% level.

short-term wholesale funding instead of traditional retail deposits face excessive exposure to liquidity risk. Consequently, we control for bank leverage (Leverage) and funding structure (Funding) to isolate these effects. In addition, we include bank cost income ratio (Cost Income), return on average assets (ROAA), and risk weighted asset to total asset (RWA) as control variables. Panel C of Table 1 presents summary statistics of bank balance sheet data.

Monetary policy can directly improve liquidity conditions in the interbank market (Diamond and Rajan 2006; Freixas, Martin, and Skeie 2011; Allen, Carletti, and Gale 2009). In this paper, we take the growth rate of the size of central bank balance sheets as a proxy for UMP in the wake of the crises. To take into consideration market participants' uncertainty about monetary policy, we proxy monetary policy uncertainty by the index of Baker, Bloom, and Davis (2015). Panel D of Table 1 presents summary statistics of monetary policy expansion and uncertainty.

Table 2 presents the correlation matrix of the main variables in our empirical analysis. It shows a positive and significant correlation between CDS spread and the three dimensions of liquidity measured by R Spread, Amihud and Roll. The results also demonstrate a positive and significant correlation between bank stock liquidity, excess stock return, excess market return and Libor-OIS. On the opposite, bank market to book ratio, size, leverage, ROAA, cost income ratio, funding structure and RWA are negatively associated with bank stock liquidity.

(a) The impact of bank funding constraints on stock liquidity

We begin our empirical analysis by testing whether there is a positive or negative relation between bank funding constraint and stock liquidity. We run the following regression model:

$$Stock\_Liq_{i,\,t} = \alpha_1 CDS_{i,t-1} + \beta_t X_{it-1} + \upsilon_t + \eta_i + \epsilon_{i,\,t} \tag{5}$$

where the dependent variable of $Stock_Liq_{i,t}$is the three dimensions of liquidity: proxied by relative spread (R-Spread), Amihud illiquidity measure (Amihud), and the Roll's measure (Roll). CDS is the bank individual CDS spread. X is a vector of control variables, including Libor-OIS, excess stock return, excess market return, market to book ratio, bank size, leverage, funding structure, and profitability. Our main interest is the size, sign and statistical significance of the coefficients α_1, which captures the impact of bank CDS spread on stock liquidity risk. All of the independent variables are lagged by one month. In addition, we include year-month, bank-fixed effects in our model to account for bank and time-invariant heterogeneities. The regression models are estimated with robust standard errors clustered by bank, to correct for autocorrelation and heteroscedasticity (Pedersen 2009).

Table 3 reports the OLS estimation results between bank marginal funding cost and stock illiquidity. All the results include bank and year-month fixed effects. The independent variable of interest, bank marginal funding cost, is measured by a bank's five-year CDS spread. We use the lagged bank's five-year CDS spread to alleviate

Table 3. Impact of bank marginal funding costs on stock illiquidity.

Independent variable:	R_spread (1)	Amihud (2)	Roll (3)
CDS	0.024***	0.079***	0.007***
	(0.005)	(0.011)	(0.002)
Libor-OIS	−0.101*	0.076	0.017
	(0.051)	(0.123)	(0.018)
R_i	−0.004	−0.041	−0.071***
	(0.028)	(0.039)	(0.023)
R_m	0.065	−0.072	0.072***
	(0.050)	(0.104)	(0.024)
MB	−3.735***	0.252	0.188
	(1.019)	(0.479)	(0.257)
Size	0.372**	0.248	−0.069
	(0.172)	(0.244)	(0.054)
Leverage	−0.009	0.009	0.008**
	(0.011)	(0.008)	(0.004)
Funding	0.632*	−0.233	0.030
	(0.322)	(0.377)	(0.161)
ROAA	0.005	−0.020	−0.012***
	(0.012)	(0.014)	(0.003)
Bank fixed effects	Y	Y	Y
Year-Month fixed effects	Y	Y	Y
Intercept	−6.898**	−4.162	1.768
	(3.400)	(4.995)	(1.083)
Number of Obs.	2428	2709	1374
Adj_R^2	0.165	0.207	0.537

Note: This table reports the results of the impact of bank marginal funding costs on stock illiquidity controlling for market liquidity and other factors. The dependent variables are bank stock liquidity risk measured by the three liquidity dimensions of liquidity tightness (R-Spread), liquidity depth (Amihud), and liquidity resilience (Roll). Please see OA Table 1 for the detailed description of the variables. Standard errors are clustered by bank and are in parentheses. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

endogenous concerns. The dependent variables are bank stock liquidity measured by its three dimensions – tightness (R-Spread), depth (Amihud) and resilience (Roll). The results reported in regressions demonstrate a sizeable, positive and statistically significant relation between bank marginal funding costs and stock liquidity risk measured by all the three liquidity dimensions (R_spread, Amihud and Roll). For example, a one standard deviation increase in funding costs results in a 3.17% increase in R spreads, a 3.57% increase in stock illiquidity proxied by Amihud (2002) measure, and a 2.25% increase in stock illiquidity using resilience (Roll) measure.

Although we employed lagged independent variables in all of our regressions to minimize concerns about reverse causality, this may not entirely eliminate the issue of endogeneity between bank CDS spread and stock liquidity risk. To further alleviate the endogeneity issue we apply the generalized method of moments (GMM) estimator to investigate the impact of bank funding constraints on stock illiquidity. The estimated results in Table 4, confirms a positive and significant relation between bank funding costs and stock illiquidity, which indicates that increases in bank marginal funding costs can trigger a rise in stock liquidity risk. Furthermore, the results are economically significant.

During financial crises, investors withdraw their funds from the collective cash pools due to heightened uncertainty and increased risk aversion. Such withdrawals can lead to a huge shortage of liquidity, which forces financial firms to fire-sell securities to meet increased liquidity demand. In Table 5 we investigate the impact of bank marginal financing costs on stock illiquidity over three time periods: severe funding constriant period, normal funding constriant period, and low funding constraint period. Following earlier work (e.g. Nagel 2012; Lou, Yan, and Zhang 2013; Jame 2018), we use VIX as a measure of funding distress. A period is considered a high funding cost period if the VIX is more than the 75th percentile value in our sample period. A period is classified as normal a funding period if the VIX in our sample period is between the 75th and 25th percentiles. A low funding cost period is defined as one in which the VIX is less than the 25th percentile value. Columns (1)

Table 4. Impact of bank marginal funding costs on stock illiquidity: using a GMM framework.

Independent variable:	R_spread (1)	Amihud (2)	Roll (3)
CDS	0.012***	0.077***	0.010***
	(0.004)	(0.009)	(0.002)
Market controls	Y	Y	Y
Bank characteristics controls	Y	Y	Y
Number of Obs.	2429	2709	1370
Intercept	0.575**	−11.551***	1.232***
	(0.231)	(0.903)	(0.169)
Number of Obs.	2429	2709	1370

Note: This table reports the estimation results between bank funding constraints and stock illiquidity using the GMM framework. According to Newey and West (1987), the standard errors are adjusted and are included in parentheses. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5. Sub-sample analysis – high funding cost period versus low funding cost period.

	R-Spread(1)	Amihud(2)	Roll(3)	R-Spread(4)	Amihud(5)	Roll(6)	R-Spread(7)	Amihud(8)	Roll(9)
Independent variable:	Severe funding constraint period			Normal funding constraint period			Low funding constraint period		
CDS	0.047***	0.054***	0.010***	0.013**	0.081***	0.005*	−0.037	0.776	0.348
	(0.008)	(0.010)	(0.003)	(0.006)	(0.010)	(0.003)	(0.884)	(0.644)	(0.428)
Market controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank characteristics controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of Obs.	885	996	441	1069	1191	644	472	521	287
Adj_R^2	0.167	0.111	0.427	0.140	0.167	0.432	0.521	0.504	0.230

Note: This table reports results of the impact of bank marginal funding costs on stock illiquidity over high funding cost period, normal funding cost period and low funding cost period. Standard errors are clustered by bank and are in parentheses. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

to (3) find positive and highly statistically significant coefficients on CDS for the high-cost period. Columns (4) to (5) show the outcomes for the normal funding cost period. The results suggest a positive, but less significant relationship between bank marginal funding costs and stock illiquidity. In periods of non-crisis (columns 7-9), there's no evidence of relation between bank marginal funding costs and liquidity risk. These results suggest that the impact of bank funding cost shocks on stock liquidity is stronger in financial stress periods due to the fact that investors rebalance their portfolios toward less risky and more liquid securities (Acharya, Amihud, and Bharath 2013; Beber, Brandt, and Kavajecz 2009). The results are in-line with earlier theoretical studies of Brunnermeier and Pedersen (2009) and Acharya, Amihud, and Bharath (2013).

3.2. Can monetary policy break the vicious liquidity loop?

The strong effect of bank marginal funding costs on stock illiquidity can deepen the initial liquidity shock, leading to more direct contagion and faster transmission from funding liquidity risk to market liquidity risk. Little is known about the effectiveness and pass-through of UMP to bank funding costs and stock liquidity. In this section, we employ the monthly growth rate of central bank balance sheet size as a proxy for UMP in the wake of the crisis.[2] The results in Table 6 show that the positive and significant relationship between bank funding costs and stock illiquidity disappears after interacting bank marginal funding costs with central bank balance sheet expansion. This indicates that monetary expansion can break the relation between bank funding costs and their stock liquidity risk. In our analysis, we find that central banks are in a position to tackle systemic market liquidity risk in turbulent times and can break the vicious circle between funding costs and market illiquidity.

Table 6. Impact of monetary expansion.

Independent variable:	R-Spread (1)	Amihud (2)	Roll (3)
CDS∗CB_exp	−0.274	−0.099	0.046
	(0.163)	(0.175)	(0.077)
CDS	0.028***	0.083***	0.006*
	(0.007)	(0.006)	(0.003)
CB_exp	2.680	0.299	−0.065
	(1.755)	(2.158)	(0.667)
Market controls	Y	Y	Y
Bank characteristics controls	Y	Y	Y
Bank fixed effects	Y	Y	Y
Year-Month fixed effects	Y	Y	Y
Intercept	−2.389	−2.845	3.580**
	(5.569)	(7.482)	(1.531)
Number of Obs.	1646	1879	948
Adj_R^2	0.125	0.279	0.505

Note: This table reports results of the impact of monetary expansion (through unconventional monetary policy – UMP) on the relationship between bank funding spreads and stock illiquidity. The dependent variables are bank stock illiquidity measured by the three liquidity dimensions of tightness (R-Spread), depth (Amihud) and resilience (Roll). Independent variable is the interaction term CDS∗CB_exp. CB_exp is the monthly change of central bank total assets. Standard errors are clustered by bank and are in parentheses. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7. Impact of monetary policy uncertainty.

	High monetary uncertainty			Low monetary uncertainty		
Independent variable:	R-Spread	Amihud	Roll	R-Spread	Amihud	Roll
CDS	0.032***	0.064***	0.008***	0.201	0.040	0.055
	(0.007)	(0.009)	(0.002)	(0.154)	(0.127)	(0.065)
Market controls	Y	Y	Y	Y	Y	Y
Bank characteristics controls	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y
Year-Month fixed effects	Y	Y	Y	Y	Y	Y
Intercept	−12.872*	−5.807	4.235*	−14.583	0.888	3.131
	(6.386)	(4.928)	(2.369)	(12.648)	(3.106)	(2.593)
Number of Obs.	1403	1566	737	1020	1138	631
Adj_R^2	0.234	0.083	0.466	0.246	0.429	0.578

Note: This table reports results of the impact of monetary uncertainty on the relationship between bank funding costs and stock illiquidity. The dependent variables are bank stock liquidity measured by the three liquidity dimensions of tightness (R-Spread), depth (Amihud) and resilience (Roll). Baker_Index is the economic policy uncertainty index of Baker, Bloom, and Davis (2015). We split the sample into high and low monetary uncertainty groups based on the median value of economic policy uncertainty index. The detailed description of each variable is listed in the OA Table A1. Standard errors are clustered by bank and are in parentheses. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

On the other hand, the literature also finds that monetary policy uncertainty is associated with greater stock price volatility and reduced investment (Baker, Bloom, and Davis 2015; Bernanke and Kuttner 2005). Consequently, market liquidity may be influenced by greater monetary policy uncertainty, as this tends to reduce investors' risk-bearing capacity (Mueller, Tahbaz-Salehi, and Vedolin 2017). In Table 7, we split our sample into two subsamples based on the median value of the economic policy uncertainty index of Baker, Bloom, and Davis (2015) in our sample. In the high monetary policy uncertainty group, the estimated coefficients on *CDS* are positive and statistically significant. However, the estimated coefficients on *CDS* become insignificant in the low monetary policy uncertainty group. As the results suggest, the relation between funding costs and bank stock illiquidity heightens with monetary policy uncertainty.

3.3. The price of liquidity risk

Variation in stock liquidity comes from both systematic and idiosyncratic sources. Developing a model in-line with Acharya and Pedersen (2005), we decompose bank stock liquidity into systematic and idiosyncratic components. We use a time series regression model for each bank stock to decompose daily variation in individual stock illiquidity into systematic and idiosyncratic components. We also compute several measures of systematic liquidity risk motivated by the models of Pastor and Stambaugh (2003) and Acharya and Pedersen (2005).

Using daily data within a month, we regress bank-specific stock illiquidity on changes in aggregate illiquidity and excess market returns:

$$c_{it} = \alpha_i + \beta^C_{ci}\Delta C_{Mt} + \beta^R_{ci}(R_{Mt} - r_{ft}) + \varepsilon_{it} \tag{6}$$

where $R_{Mt} - r_{ft}$ is the excess market return on day t and C_{Mt} is the aggregate market illiquidity on day t measured by the Libor-OIS spread. We also regress bank-level excess stock returns on changes in market illiquidity and the excess market return.

$$r_{it} - r_{ft} = \alpha_i + \beta^C_{ri}\Delta C_{Mt} + \beta^R_{ri}(R_{Mt} - r_{ft}) + \epsilon_{it} \tag{7}$$

where $r_{it} - r_{ft}$ is the bank excess stock return on day t. The four slope coefficients in Equations (5) and (6) are used as measures of systematic liquidity risk. β^C_{ci} is the sensitivity of the asset's illiquidity to the aggregate illiquidity; β^R_{ci} is the sensitivity of a security's illiquidity to the market return; β^C_{ri} is the sensitivity of a security's return to the aggregate illiquidity; and β^R_{ri} is the sensitivity of a security's return to the market return, which is the market beta.

To estimate the idiosyncratic liquidity component, we use a time series regression to decompose daily variation in individual stock illiquidity into systematic and idiosyncratic components. More specifically, we regress daily bank-level illiquidity on daily aggregate liquidity risk measured by Libor-OIS spreads, the sovereign CDS spreads and the excess market returns. The idiosyncratic volatility of a stock is the standard deviation of the regression residuals e_{it} in Equation (8):

$$c_{it} = b_{0i} + b_{1i}C_{Mt} + b_{2i}S\_CDS_{it} + b_{3i}(R_{Mt} - r_{ft)} + e_{it} \tag{8}$$

where S_CDS_{it} is the sovereign CDS spreads.

As the mean level of illiquidity and the standard deviation of the residuals from Equation (8) are highly correlated we control for the mean level of illiquidity (Akbas, Armstrong, and Petkova 2011). For every month we compute a coefficient of variation by dividing the idiosyncratic volatility of liquidity by the mean level of illiquidity:

$$idio\_illiq_{id} = \frac{\sigma(e_{it})_d}{illiq_{id}} \tag{9}$$

In line with the theoretical model from Acharya and Pedersen (2005), we employ the following regression model with both idiosyncratic and systematic liquidity risk included:

$$r_{id} - r_{fd} = \gamma_0 + \gamma_1 idio\_illiq_{id} + \gamma_3\beta^C_{ci} + \gamma_4\beta^R_{ci} + \gamma_5\beta^C_{ri} + \gamma_6\beta^R_{ri} + \mu_{id} \tag{10}$$

where: $idio\_illiq_{id}$ is bank idiosyncratic volatility of bank stock liquidity. We conduct the cross-sectional asset pricing tests in a generalized method of moments (GMM) framework following Cochrane (2005). The equation is estimated by the GMM estimation method and the standard errors are adjusted according to the Newey and West (1987) adjustments for serial correlation and heteroscedasticity.

The results in Table 8 indicate that idiosyncratic liquidity risk has a negative contemporaneous relation with bank excess stock returns. The coefficients on three idiosyncratic liquidity risk measures (idio_Amihud, idio_rspread, and idio_Roll) are negative and significant, which suggests that idiosyncratic liquidity shocks are negatively associated with asset prices. Among the four liquidity betas, the market beta that measures the covariance between a bank's stock return and the market return is significantly positively priced. None of the other betas in the model are significantly priced. Overall, the results indicate that higher funding costs can push up

Table 8. The price of stock liquidity risk: idiosyncratic vs systematic liquidity.

Independent variable:	Excess stock returns		
Idio_Amihud	−0.148***		
	(0.027)		
Idio_Rspread		−0.075***	
		(0.009)	
Idio_Roll			−0.605***
			(0.192)
β_{ci}^{R}	40.727	20.205	−9.962
	(30.629)	(30.858)	(42.254)
β_{ri}^{R}	8.240***	7.981***	7.303***
	(0.715)	(0.735)	(0.966)
β_{ci}^{C}	−19.297	−16.521	−15.797
	(15.464)	(16.186)	(21.072)
β_{ri}^{C}	4.937	4.707	4.53(5.551)
	(3.884)	(4.061)	
Intercept	−3.287***	−3.019***	−3.161***
	(0.091)	(0.101)	(0.127)
Number of Obs.	3376	3163	1754

Note: In this table, we examine the impact of idiosyncratic and systematic liquidity risk on excess stock returns. Idio_Amihud is the bank idiosyncratic volatility of illiquidity measured by the Amihud Index, Idio_Rspread is the bank idiosyncratic volatility of illiquidity measured by relative spread. Idio_Roll is the bank idiosyncratic volatility of illiquidity measured by Roll's index. β_{ci}^{C} is the sensitivity of the asset's illiquidity to aggregate illiquidity; β_{ci}^{R} is the sensitivity of a security's illiquidity to the market return; β_{ri}^{C} is the sensitivity of a security's return to the aggregate illiquidity; and β_{ri}^{R}. is the sensitivity of a security's return to the market return, which is the market beta. The t-statistics below the coefficients are estimated using a GMM framework with standard errors adjusted according to Newey and West (1987). Robust errors are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

stock illiquidity and stock liquidity risk is in-turn priced into bank stock returns. The strong link between bank funding costs and stock liquidity can amplify initial liquidity shocks leading to contagion and a faster transmission of funding cost shocks to stock liquidity.

The negative contemporaneous relationship does not mean that bank idiosyncratic risk is negatively priced in stock returns. This is due to liquidity persistence and an unexpected rise in illiquidity raises expected illiquidity. Consequently, investors require higher expected asset returns. The higher risk compensation required by investors pushes down current asset prices and leads to a negative contemporaneous relationship between liquidity risk and asset prices.

To further investigate the relationship between liquidity risk and excess bank stock return, and to differentiate the impact of expected vs. unexpected liquidity risk on bank stock returns, we take the residuals of an AR (1) model of the illiquidity measures as our proxy of unexpected liquidity risk. The measure of unexpected liquidity risk follows Amihud (2002) and Banti and Phylaktis (2015). The results in Table 9 suggest a strongly negative and significant relationship between unexpected liquidity risk and excess stock returns, confirming that unexpected market illiquidity lowers contemporaneous stock prices due to the liquidity risk premium required by investors. We also find a positive and significant relationship between expected liquidity risk measured by R_spread and excess stock returns, which suggests that investors require compensation for being exposed to expected liquidity risks Table 9.

4. Conclusion

In this paper, we examine the relation between bank marginal funding costs and stock illiquidity. We show that higher funding cost reduces bank stock liquidity. During crisis periods, the relation between funding costs and stock liquidity heightens. Further, our analysis links liquidity risk to asset pricing with further implications for the pricing of such risks. We find that increased bank marginal funding cost weakens bank stock liquidity and this in turn is priced into excess stock returns. Decomposing liquidity risk into systematic and idiosyncratic

Table 9. The price of stock liquidity risk: expected liquidity risk vs unexpected liquidity risk.

	Excess stock returns					
Independent variable:	Unexpected stock illiquidity			Expected stock illiquidity		
AR_Amihud	−0.154***					
	(0.048)					
AR_Rspread		−0.815***				
		(0.278)				
AR_Roll			−0.755*			
			(0.420)			
Amihud				−1.272*		
				(0.670)		
R-Spread					4.552	
					(7.003)	
Roll						4.222
						(4.846)
betaR_liquidity_d	34.328	−0.867	7.242	16.506	−384.522	38.695
	(25.144)	(31.245)	(31.717)	(39.953)	(611.644)	(62.053)
betaR_return_re	6.311***	6.686***	6.122***	−0.731	2.767	−5.585
	(0.576)	(0.668)	(0.919)	(3.739)	(7.317)	(11.554)
betaC_liquidity_d	−9.401	−6.402	5.098	−3.829	−46.292	−23.534
	(12.009)	(13.652)	(16.104)	(22.253)	(124.285)	(21.686)
betaC_return_re	7.506***	4.735	6.582*	9.201	10.227	7.869
	(2.877)	(3.461)	(3.714)	(6.888)	(8.786)	(4.815)
Intercept	−3.865***	−3.829***	−3.696***	9.268	2.309	−5.707**
	(0.308)	(0.354)	(0.411)	(6.919)	(9.964)	(2.708)
Number of Obs.	5108	4868	3829	5108	4560	2852

Note: In the Table, we take the residuals of an AR (1) model of the liquidity measures as our proxy of unexpected liquidity risk. AR_Amihud is the residuals of an AR(1) model of bank stock illiquidity measured by the Amihud Index. AR_Rspread is the residuals from an AR(1) model of bank stock illiquidity measured by relative spread, AR_Roll is the residuals of an AR(1) model of bank stock illiquidity measured by Roll's index. The dependent variable is bank excess stock return. The t-statistics are below the reported coefficients and are estimated using a GMM framework with standard errors adjusted according to the Newey and West (1987) procedure. Standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

elements, we show that asset prices are more sensitive to idiosyncratic liquidity risk, which drags down asset prices. Specifically, unexpected market illiquidity lowers contemporaneous stock prices due to the liquidity risk premium required by investors. As liquidity risk is persistent, expected liquidity risk is positively associated with ex ante stock excess returns.

Furthermore, we find that during liquidity crises, the conduct of monetary expansion can break the relation between funding costs and stock liquidity. In contrast monetary policy uncertainty strengthens the relation between funding costs and stock liquidity. These findings provide important monetary policy indications. A positive and significant impact of funding constraints on market illiquidity can amplify the effect of the initial funding liquidity shock. Expansionary monetary policy with lower interest rate and quantitative easing can mitigate the liquidity crisis. This indicates that monetary expansion can break the relation between bank funding costs and their stock liquidity risk. A liquidity risk shock demonstrated by a hike in bank idiosyncratic and unexpected liquidity risk will push down bank stock prices. In this context, proactive and prudent macroeconomic policies can play an important role in breaking the vicious loop of a liquidity crisis.

Notes

1. The detailed description and data source of the variables are provided in the OA Table A1.
2. See Gambacorta, Hofmann, and Peersman (2014), Lambert and Ueda (2014), and Alessandri and Nelson (2015) who use central bank balance sheet size as an indicator of the extent of UMP.

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No potential conflict of interest was reported by the author(s).

Notes on contributors

Philip Molyneux is an Emeritus Professor at Bangor Business School, Bangor University. His main area of research is on the structure and efficiency of banking markets and he has published widely in this area. He has also published a variety of texts on banking areas and in the past has acted as a consultant to: New York Federal Reserve Bank, World Bank, European Commission, UK Treasury; Citibank Private Bank, Barclays Wealth, McKinsey & co, Credit Suisse and various other international banks and consulting firms.

Qingwei Wang is an associate professor (Reader) in finance at Cardiff Business School, Cardiff. He previously worked as a Lecturer in Finance at Bangor Business School, and a researcher at the Centre for European Economic Research (ZEW, Mannheim, Germany). He has engaged in projects with Deutsche Bank, German Federal Ministry of Economics and Labour, and German Science Foundation. He is the former director of Cardiff Empirical Finance Group, the director of Centre for China Business Research, the co-director of Cardiff Fintech Research Group, and an associate editor of Finance Research Letters and The European Journal of Finance. He has published in many journals, including Journal of International Business Studies, Journal of Empirical Finance, European Financial Management, and International Journal of Forecasting.

Dr ***Ru Xie*** is an Associate Professor of Finance at School of Management, University of Bath. She specialises in empirical banking and finance studies. Her research output has attracted policy-makers' attention and has been featured in more than 100 major media outlets including Financial Times, Bloomberg, CNN, NBC, Fortune etc. Her previous research has been published in leading international academic journals including the Review of Finance, Journal of Banking and Finance, the European Financial Management, the Journal of Financial Services Research, and the International Review of Financial Analysis.

Binru Zhao is an PhD student at School of Management, University of Bath. He recently received a job offer of Lecturer in Finance from Bangor Business School.

ORCID

Qingwei Wang http://orcid.org/0000-0002-3695-7846
Ru Xie http://orcid.org/0000-0002-9461-4956

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Appendix

Table A1. Variable definition and data source.

Variable	Definition	Source
CDS (%)	Bank level 5-year senior credit default swap spread in percentage.	Bloomberg
Amihud	The Amihud illiquidity ratio is defined as the absolute return of stock i on day t relative to the dollar trading volume (in billions) for stock i on day t.	Datastream
R-Spread	Relative spread is defined as the difference between the ask quote and bid quote relative to the average of the ask quote and bid quote.	Datastream
Roll	Relative spread is defined as the difference between the ask quote and bid quote relative to the average of the ask quote and bid quote.	Datastream
Sovereign_CDS (%)	The daily 5-year sovereign credit default spreads in percentage.	Datastream
Libor-OIS (%)	The difference between the 3-month Libor rate and OIS.	Datastream
R_i (%)	Excess stock return of bank i on day t.	Datastream
R_m (%)	Excess market return of country k on day t.	Datastream
MB	Market to book value.	Orbis BankFocus
Size	The logarithm of bank total assets.	Orbis BankFocus
Leverage	Bank total assets relative to total equity.	Orbis BankFocus
Funding (%)	The percentage of deposit funding to total liabilities.	Orbis BankFocus
ROAA	The return on average asset.	Orbis BankFocus
Baker_Index	The economic policy uncertainty index of Baker, Bloom, and Davis (2015).	https://www.policyuncertainty.com
CB_exp (%)	The monthly change of central bank total assets in percentage.	Datastream
Cost to Income	The cost to income ratio	Orbis BankFocus
RWA	Risk weighted assets to total assets	Orbis BankFocus

Table A2. Summary statistics on CDS spreads for sample banks.

Bank	Country	Obs.	Mean (bps)	Std. Dev.	Min (bps)	Max (bps)
Alliance & Leicester PLC	UK	832	217.96	84.66	86.09	723.75
Allied Irish Banks PLC	Ireland	1979	826.70	1552.71	9.50	5547.48
Australia & New Zealand Banking Group Ltd	Australia	2241	103.26	89.27	6.75	354.25
Banca Monte dei Paschi di Siena SpA	Italy	2492	222.61	303.40	11.94	1395.76
Banca Popolare di Milano	Italy	2198	223.03	313.46	14.63	1340.57
Banco Bilbao Vizcaya Argentaria S.A.	Spain	2498	170.17	209.38	11.89	825.27
Banco Espirito Santo SA	Portugal	2468	322.42	432.38	13.00	1854.23
Banco Popular Espanol SA	Spain	412	41.24	75.33	12.50	323.85
Banco Santander SA	Spain	2584	159.07	181.85	12.13	732.31
Bank of America Corp	US	1069	281.78	142.08	112.50	736.01
Bank of Tokyo-Mitsubishi UFJ Ltd	Japan	1676	115.79	80.83	10.50	312.67
Barclays Bank PLC	UK	2492	134.18	139.75	7.81	542.04
Bayerische Landesbank	Germany	448	285.32	85.15	54.15	564.96
BNP Paribas SA	France	2674	109.88	135.38	8.63	620.52
Caja de Ahorros y Monte de Piedad de Madrid	Spain	957	360.17	211.76	17.25	924.79
Caja de Ahorros y Pensiones de Barcelona	Spain	947	468.91	213.73	132.72	1022.16
Citigroup Inc	US	1660	216.82	197.29	13.69	1028.63
Commerzbank AG	Germany	2675	195.38	207.25	13.81	1051.61
Commonwealth Bank of Australia	Australia	2244	102.73	87.86	6.67	354.53
Credit Agricole SA	France	1188	263.82	172.29	22.82	724.99
Credit Suisse Group AG	Switzerland	2454	107.15	91.21	11.97	370.21
DBS Bank Ltd	Singapore	2425	68.93	58.17	7.94	321.78
Deutsche Bank AG	Germany	2684	109.82	98.81	13.82	482.53
Dexia Credit Local SA	France	807	833.17	633.93	42.00	2185.78
DNB Bank ASA	Norway	599	128.76	53.43	33.75	301.60
Erste Group Bank AG	Austria	1192	319.31	141.04	52.38	771.73
Fortis Bank SA/NV	Belgium	1051	223.11	126.83	88.43	796.51
HBOS PLC	UK	1607	245.00	189.98	1.00	755.51
HSBC Bank PLC	UK	2446	82.60	72.15	7.67	303.92
ING Bank NV	Netherlands	2502	112.75	112.36	7.09	467.83
Intesa Sanpaolo SpA	Italy	2501	159.90	208.81	10.73	981.26
JPMorgan Chase & Co	US	1728	98.15	68.15	19.32	320.00
KBC Bank NV	Belgium	599	263.33	108.74	102.95	497.50
Lloyds TSB Bank PLC	UK	2491	174.70	199.33	6.06	758.63
Merrill Lynch & Co Inc	US	931	322.66	150.57	45.50	822.50
Mizuho Corporate Bank Ltd	Japan	2458	125.91	93.76	11.38	375.44
Morgan Stanley	US	406	154.95	137.16	25.75	802.00
National Australia Bank Ltd	Australia	2308	101.66	88.90	6.75	354.53
Natixis	France	1001	333.25	121.82	161.45	577.10
Nordea Bank AB	Sweden	948	162.08	59.27	72.30	285.33
Raiffeisen Zentralbank Oesterreich AG	Austria	1044	362.17	122.17	132.65	881.16
Skandinaviska Enskilda Banken AB	Sweden	984	228.97	94.91	102.60	495.74
Societe Generale SA	France	2668	132.73	169.13	9.04	796.44
Standard Chartered Bank	UK	1085	200.85	90.26	104.21	555.00
Sumitomo Mitsui Banking Corp	Japan	2393	106.29	79.93	11.10	354.11
Svenska Handelsbanken AB	Sweden	922	132.62	50.76	60.46	253.28
Swedbank AB	Sweden	337	199.80	78.54	112.64	458.11
UBS AG	UK	280	216.58	75.26	122.46	453.48
UniCredit SpA	Italy	2774	173.33	232.64	11.66	1153.40
Wells Fargo & Co	US	1029	165.03	67.86	90.95	522.50
Westpac Banking Corp	Australia	2252	101.87	88.34	6.50	354.25

Note: This table presents statistics of senior 5-year CDS spreads (in basis points) for 51 banks in our sample period.

Table A3. Robustness Check: Is the relationship driven by other bank financial characteristics?

Independent variable:	R_spread (1)	Amihud (2)	Roll (3)
CDS	0.056**	−0.048	0.039***
	(0.026)	(0.036)	(0.008)
Libor-OIS	0.012	0.075	0.025
	(0.067)	(0.153)	(0.016)
R_i	−0.048	−0.047	−0.059**
	(0.044)	(0.045)	(0.028)
R_m	0.047	0.003	0.033
	(0.061)	(0.067)	(0.033)
MB	−6.810**	0.971	−0.409
	(2.927)	(2.707)	(0.699)
Size	0.725**	0.209	−0.240***
	(0.304)	(0.357)	(0.067)
Leverage	−0.609	1.175	0.513*
	(0.829)	(1.052)	(0.275)
Funding	1.011*	−0.420	−0.069
	(0.536)	(0.460)	(0.249)
ROAA	0.090*	−0.002	−0.023***
	(0.053)	(0.027)	(0.005)
Cost to Income	0.413	0.866	0.054
	(0.249)	(0.519)	(0.113)
RWA	0.450**	−0.026	−0.146***
	(0.178)	(0.156)	(0.044)
Bank fixed effects	Y	Y	Y
Year-Month fixed effects	Y	Y	Y
Intercept	−15.156**	−3.677	5.238***
	(6.352)	(7.247)	(1.376)
Number of Obs.	1647	1869	1000
Adj_R^2	0.114	0.228	0.472

Note: This tables report the regression results with additional control variables (Cost to Income and RWA). We also controlled market characteristics (Libor-OIS, R_i, R_m, and MB) and bank characteristics (Size, Leverage, Funding, and ROAA). All specifications include bank fixed effects and year-month fixed effects. Standard errors are clustered by bank and are in parentheses. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.