International Review of Economics and Finance 78 (2022) 141–152

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Measuring volatility persistence in leveraged loan markets in the presence of structural breaks☆,☆☆

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ARTICLE INFO

JEL classification:
C22
C50
C60
G15
G11
G20

Keywords:
Leverage loan indices
Persistence
Volatility
Fractional integration

ABSTRACT

This paper examines volatility persistence in leverage loan market price series for Australia, Canada, Europe, Japan, Singapore, UK and USA in the presence of structural breaks. To the best of our knowledge, this is the first empirical study to examine volatility persistence in the leveraged loan markets. To this end, using fractional integration methods, the results indicate that both absolute and squared returns display long memory features, with orders of integration confirming the long memory hypothesis. However, after accounting for structural breaks, we find a reduction in the degree of persistence in the leveraged loan market. The evidence of persistence in volatility implies that market participants who want to make gains across trading scales need to factor the persistence properties of leveraged loan price series in their valuation and forecasting models since that will help improve long-term volatility market forecasts and optimal hedging decisions.

1. Introduction

Innovativeness has powered financial market growth throughout history, and the leverage loan market has been fertile ground for financial innovation over several years. A leveraged loan is a commercial loan provided by a group of lenders. This loan is first structured, arranged, and administered by one or several commercial or investment banks, known as arrangers. It is then syndicated or sold to other banks and/or institutional investors (Yago & McCarthy, 2004). The global leveraged loan market has grown consistently since its inception in the 1980s to become a full-fledged asset class and an indispensable component of corporate finance, M&A, and leveraged buyout landscapes (Armstrong, 2003). Because leverage loans are considered less expensive, more efficient to administer

☆ Luis A. Gil-Alana gratefully acknowledges financial support from the Grant PID2020-113691RB-I00 funded by MCIN/AEI/ 10.13039/501100011033. An internal Project from the Universidad Francisco de Vitoria is also acknowledged. Additionally, we appreciate the support received from The University of Adelaide since this project commenced while Emmanuel was there.☆☆ Comments from the Editor and three anonymous reviewers are gratefully acknowledged.

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https://doi.org/10.1016/j.iref.2021.11.016
Received 30 November 2020; Received in revised form 14 July 2021; Accepted 25 November 2021
Available online 27 November 2021

than the traditional bilateral (one company, one lender) credit lines, the leveraged/syndicated loan market has become the means through which corporate borrowers tap banks and other institutional capital providers for loans (Gonzalez-Pedraz, 2019, pp. 1–13).

In both Europe and the United States, the markets for leveraged loans issued by non-financial corporates are about five times larger than high-yield bond markets. The S&P/LSTA Loan Index market size in the U.S. saw a tremendous growth of almost $1.2 trillion at year-end 2019 as against $619 billion at 2018's year-end due to continued demand by institutional investors and retail funds. Similarly, the European leveraged loan market grew to a record size in 2018, totalling €181 billion, an increase from €$139 billion at the outset of the year. While the European segment lacks the loan fund investor component that bolsters U.S. activity, collateralised loan obligation (CLO) issuance has boomed in this segment, driving the market (S&P Global Market Intelligence, 2019).

Despite such improvements, the leverage loan market poses risks for borrowers and lenders due to the market downturn. For example, period's market turmoil has exposed challenges to loan valuations based on market prices. For example, market prices of leveraged loans and loan indices may deviate from their economic fundamentals during periods of market stress if liquidity premia rise substantially. Difficulties in interpreting market price fluctuations and in valuing credit assets may amplify changes in liquidity premia and market stress as investors pull back the provision of liquidity to major financial institutions and leveraged loan markets. Another consequence of higher loan price volatility has been a fall in demand for triple-A tranches of collateralised loan obligation (CLOs). Some fund managers and banks that buy these tranches use mark to market accounting practices. The rising volatility of the prices of these tranches has deterred such mark to market investors (BIS, 2008). During the recent market turmoil sparked by the outbreak of COVID-19, the risk of defaults and decreases in ratings posed as a major challenge in the second half of 2020, when borrowers had to make more money to secure lender protection. The demand for leveraged loans tends to be marked by instability and volatility; as in the first half of 2020, US and European markets have seen spikes in loss and rate decreases, while M&A finance remains in limbo in Asia-Pacific. In Latin America, banks are concentrating on managing portfolios through the downturn and their core client base rather than directing resources into new activity (White & Case LLP, 2020).

Leveraged loans can be regarded as credit-risk-transfer instruments that permit financial market participants to tailor more precisely their credit-risk exposure. Participants of leveraged loans use the market as a source of investment products and to make portfolio adjustments while using the market perspective to better understand and evaluate underwriting of risk (Gonzalez-Pedraz, 2019, pp. 1–13). As leveraged loans are more administratively efficient for the borrower than a series of bilateral loan arrangements, Armstrong (2003) believes that borrowers can be more confident applying sophisticated portfolio-management techniques to their portfolios knowing that the market permits them to rebalance their portfolios as needed. Similarly, institutional investors can participate in the loan market with more assurance, given the availability of credit ratings and availability of quotations paving the way for them to market their portfolios.

Delving into volatility persistence in the leverage loan market is crucial because changes in volatility can affect the risk exposure of both borrowers and lenders. These changes may alter their respective investments in the leverage loan market. Thus, understanding volatility dynamics in this market is important for M&A-related transactions, recapitalization of a company's balance sheet, for refinancing debt and for funding general corporate purposes or financing projects among many others. Although volatility fluctuates over time, determining the persistence of these changes in volatility, which affect the leverage market, is crucial. In this study, we examine volatility persistence in the leverage loan market using data from Australia, Canada, Europe, Japan, Singapore the UK and USA using structural breaks/fractional integration methods. These methodologies are necessary as fractional integration works better on large data sequences while structural breaks lead to a better understanding of the true mechanisms driving changes in data. Failure to recognise structural breaks can lead to invalid conclusions, inaccurate forecasts and misleading policy recommendations (Hansen, 2001).

This paper offers several contributions to the scanty literature on leverage loan markets. To the best of our knowledge, this paper is the first study to examine extensively volatility persistence in the leverage loan market in the presence of structural breaks using a robust estimation approach. Specifically, this study makes a twofold contribution. First, it applies long memory techniques to provide evidence on the stochastic properties (in particular, the degree of persistence) of the leverage loan market price returns. Unlike the majority of methodologies employed in earlier studies focusing on various financial asset returns including stocks, bond, cryptocurrencies among others, this paper adopts a fractional integration framework that is much more general than the standard approaches based on the I(0)/I(1) dichotomy since it allows for fractional values of the integration/cointegration parameter and therefore does not impose restrictive assumptions on the dynamic behaviour of the individual series. Second, we examine the effects of structural breaks because failure to incorporate them may result in an overstatement of the degree of persistence of variance or in spurious estimation of long memory (Lamoureux & Lastrapes, 1990).

From our empirical analysis, results show that the estimated values of d are close to 1 in each series indicating the original series are highly persistent. Results from the absolute and squared returns further confirm the long memory hypothesis since the estimated values of d are close to 1 and positive in almost all the series. Taking into account the effect of structural breaks, we find a significant reduction in the magnitude of the volatility persistence. The study as a result concludes that the volatility in leverage loan market is highly persistent.

The remaining part of the paper is organized as follows: Section 2 presents a brief understanding of the leverage loan market along with a summary of the relevant empirical literature. Section 3 describes the methodology while Section 4 presents the data and preliminary analysis. Section 5 and 6 present empirical results and the conclusion respectively.

2. Literature review

As used by market participants, "leveraged finance" usually refers to corporate debt with relatively high credit risk. Leveraged finance has long attracted policy attention because of the risks it poses for banks (BIS, 2008). In earlier years, portfolio credit losses were the main risk. In recent years, a wider variety of participants have appeared in the leveraged finance market, while the characteristics of loans and the channels for their distribution have changed, raising additional policy questions. For example, even if banks do not ultimately intend to hold the loans they underwrite, the issuance process can give rise to warehousing risk. This section surveys the limited literature in the leveraged finance market to serve as background and motivation for our study.

While several researchers concentrated on investor-based leverage (Acharya & Viswanathan, 2011; Adrian & Shin, 2010; Gromb & Vayanos, 2002), others have concentrated on asset based-leverage (Fostel & Geanakoplos, 2012; Cao, 2010; Brunnermeier & Pedersen, 2009; Geanakoplos, 2009; and; Simsek, 2010). These studies focused on the relationship between leverage and volatility as many conclude that low leverage usually results in high volatility. Not all these models present a theory of endogenous leverage; most of them assume a VaR = 0 rule and study the cyclical properties of leverage as well as its asset pricing implications. In Acharya and Viswanathan (2011) and Adrian and Shin (2010) the endogeneity of leverage relies on asymmetric information and moral hazard problems between lenders and borrowers.

In Cao (2010), Simsek (2010), Araujo et al. (2012), Fostel and Geanakoplos (2008), endogeneity does not rely on asymmetric information, rather financial contracts are micro founded by a collateralized loan market. Fostel and Geanakoplos (2011) argue that leverage is procyclical: leverage rises during normal times and falls during crisis times. Data on leverage and asset prices for the housing market and for AAA securities from 1998 to 2009 both show that leverage is pro-cyclical: prices rise as leverage increases, and prices fall as leverage decreases. In particular, both leverage and prices collapse during financial crisis. This has also been recorded by Adrian and Shin (2010) and Gorton and Metrick (2012).

A branch of theoretical literature with empirical emphasis by Fostel and Geanakoplos (2012) has explained how leverage is influenced by volatility in equilibrium, and why there is a positive relationship between leverage and asset prices. Their study shows how supply and demand determine equilibrium leverage and why higher volatility reduces leverage. Their model suggests that higher leverage increases asset prices. They suggested in their paper, 'the leverage cycle' that crises occur when there is bad news of a unique kind because the news raises tail volatility, as well as decreasing expectations, and hence reduces leverage. Prices then decline not only because of the lower expectations, but also because of the lower leverage. This inference that bad news is correlated with very high volatility seems quite plausible as they show history of the VIX index (the Chicago Board Options Exchange Volatility Index) a popular measure of the implied volatility of SP 500 index options. The results prove that a high value corresponds to a more volatile market and therefore more costly options.

Similarly, Berlin et al. (2020) use a quarterly time series of leverage loan issuance from 2003 through the end of 2017. Leverage loan issuance fell sharply around the financial crisis and subsequent recession. Leveraged loans, in particular, show several periods of sharp growth, including from 2006 through 2007 and from 2012 through early 2014. They attempt to find out whether the leveraged loan market has evolved to succeed the role of banks in monitoring and renegotiating loan contracts. Their analysis also indicates that nearly all leveraged loan borrowers remain subject to financial covenants and banks have retained their traditional role of monitoring while reducing the bargaining frictions that arise with the entry of nonbank lenders. Adrian et al. (2018) stipulates that the relaxation of investor protection in covenant-light loans helps borrower firms to increase their leverage, which also raises the potential losses in the event of default. Analysis of loans between 2016 and 2019 also proves that credit is not highly concentrated in specific sectors, although loans to businesses in the consumer discretionary, technology, financial, health and telecommunications sectors stand out.

However, while all of these papers focused on volatility in different dimensions, this study focuses on the persistence in volatility with regards to the leverage loan market under structural breaks using fractional integration and cointegration techniques.

3. Methodology

In the paper we use long range dependence or long memory methods and in particular we focus on fractional integration. The idea that is behind this technique is that the number of differences required in a time series to convert it to stationary I(0) may be any real value, and thus, it may potentially include fractional numbers.

In a classic paper by Nelson & Plosser (1982) and using ADF (Dickey & Fuller, 1979) tests, these authors found that fourteen US macro series were integrated of order 1, or I(1), implying that first differences were required to convert them to being stationary I(0). However, fifteen years later, Gil-Alana and Robinson (1997) examined an updated version of the same dataset, and using fractional integration methods, they found that all except one of the series were in fact I(d) with the value of d constrained between 0 and 1. Since then, this technique has been widely employed in the analysis of aggregated economic and financial data (see, e.g., Lima & Xiao, 2010; Gil-Alana & Moreno, 2012; Mensi et al., 2014; Ben Nasr et al., 2016; Abbritti et al., 2016; Gil-Alana & Mudida, 2018; Merhrdoust & Fallah, 2020; Gil-Alana et al., 2018; Gil-Alana, Abakah, & Rojo, 2020; Gil-Alana, Abakah, & Abakah, 2021; Abakah et al., 2020; etc.).

In the following section, we conduct the estimation of the following model,

$$y_t = \alpha + x_t; \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{1}$$

where y_t is the series of interest (log-prices and absolute and squared returns), α is an intercept, and x_t is an I(d) process where d can be any real value. Thus, u_t is I(0) and it will be specified as a white noise process and allowing for autocorrelation. In the latter case we use a non-parametric structure developed by Bloomfield (1973) that approximates ARMA models with very few parameters. We also consider the possibility of structural breaks by using both Bai and Perron's (2003) and Gil-Alana's (2008) approaches. Once the break dates have been determined, we will examine the degree of persistence associated with each subsample separately, and here, based on the shorter sample sizes, we also consider the possibility of a linear trend. Thus, the model examined will be the following one:

Table 1
Descriptive statistics.

Panel A: Descriptive Statistics of Leverage Loan Price Indices							
	Australia	Canada	Euro	Japan	Singapore	UK	USA
Mean	1295.1969	1336.3953	1419.0541	1143.1073	1167.611166	1744.5833	2309.177
Standard Dev	370.2771	376.9585	384.3006	305.27486	215.3889	512.2748	453.4192
Kurtosis	−1.147	−1.445	−1.238	−1.521	−0.868	−1.029	−0.771
Skewness	0.494	0.228	−0.031	−0.015	0.056	0.144	−0.311
Minimum	784.136	708.966	629.952	506.603	64	864.774	1202.254
Maximum	2128.903	1997.901	2138.539	1646.727	1599.734	2731.909	3081.266
Obs.	3410	3410	3410	3410	3410	3410	3410
Panel B: Descriptive Statistics of Absolute Returns							
	Australia	Canada	Euro	Japan	Singapore	UK	USA
Mean	0.0002	0.0002	0.0002	0.0001	0.0001	0.0003	0.0001
Standard Dev	0.0086	0.0063	0.0067	0.0078	0.0724	0.0067	0.0024
Kurtosis	34.1706	11.9113	9.9693	67.1539	1691.0186	12.5862	86.9359
Skewness	1.6473	0.1392	0.1378	2.2698	0.1879	0.7335	−4.4377
Minimum	−0.0706	−0.0513	−0.0463	−0.0554	−2.9770	−0.0412	−0.0382
Maximum	0.1459	0.0715	0.0640	0.1667	2.9863	0.0780	0.0328
Obs.	3410	3410	3410	3410	3410	3410	3410

Table 2
Estimates of d on the price indices: White noise errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	0.96 (0.94, 0.99)	0.94 (0.91, 0.96)	**0.94 (0.91, 0.96)**
CANADA	0.99 (0.96, 1.02)	0.99 (0.96, 1.01)	**0.99 (0.96, 1.02)**
EURO	1.01 (0.98, 1.03)	**1.04 (1.01, 1.07)**	1.04 (1.01, 1.07)
JAPAN	1.01 (0.98, 1.04)	**1.05 (1.03, 1.08)**	1.05 (1.03, 1.08)
SINGAPORE	1.00 (0.98, 1.03)	**1.10 (1.07, 1.13)**	1.10 (1.07, 1.13)
UK	0.99 (0.97, 1.02	1.00 (0.97, 1.03)	**1.00 (0.97, 1.03)**
USA	1.02 (0.99, 1.04)	**1.36 (1.34, 1.39)**	1.36 (1.34, 1.39)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 3
Estimates of d on the price indices: Autocorrelated errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	0.98 (0.94, 1.02)	0.95 (0.91, 1.00)	**0.95 (0.91, 0.99)**
CANADA	1.01 (0.97, 1.06)	1.02 (0.97, 1.08)	**1.02 (0.97, 1.08)**
EURO	1.04 (0.99, 1.08)	**1.09 (1.04, 1.14)**	1.09 (1.04, 1.14)
JAPAN	1.03 (0.99, 1.08)	**1.09 (1.05, 1.14)**	1.09 (1.05, 1.14)
SINGAPORE	1.03 (0.99, 1.08)	**1.11 (1.09, 1.19)**	1.12 (1.09, 1.19)
UK	0.99 (0.95, 1.04)	0.96 (0.92, 0.99)	**0.96 (0.92, 0.99)**
USA	1.04 (1.00, 1.09)	**1.38 (1.34, 1.43)**	1.38 (1.34, 1.43)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 4
Estimates of d on the log-price indices: White noise errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	1.00 (0.97, 1.02)	0.95 (0.92, 0.98)	**0.95 (0.92, 0.98)**
CANADA	1.00 (0.97, 1.03)	1.00 (0.97, 1.03)	**1.00 (0.97, 1.03)**
EURO	1.00 (0.97, 1.03)	**1.07 (1.05, 1.10)**	1.07 (1.05, 1.10)
JAPAN	1.00 (0.97 1.03)	**1.08 (1.05, 1.10)**	1.08 (1.05, 1.10)
SINGAPORE	1.00 (0.97 1.03)	**1.14 (1.11, 1.17)**	1.14 (1.11, 1.17)
UK	1.00 (0.97 1.03)	1.04 (1.01, 1.06)	**1.04 (1.01, 1.06)**
USA	1.00 (0.97 1.03)	**1.41 (1.38, 1.44)**	1.41 (1.38, 1.44)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 5
Estimates of d on the log-price indices: Autocorrelated errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	0.99 (0.96, 1.04)	0.95 (0.91, 0.99)	**0.95 (0.91, 0.99)**
CANADA	1.00 (0.96, 1.04)	0.97 (0.93, 1.02)	**0.97 (0.93, 1.02)**
EURO	1.00 (0.96, 1.04)	1.04 (1.00, 1.09)	**1.04 (1.00, 1.09)**
JAPAN	1.00 (0.96, 1.04)	**1.09 (1.05, 1.13)**	1.09 (1.04, 1.14)
SINGAPORE	1.00 (0.96, 1.04)	**1.16 (1.11, 1.20)**	1.16 (1.11, 1.20)
UK	0.99 (0.96.1.04)	0.97 (0.93 1.02)	**0.97 (0.93, 1.02)**
USA	0.99 (0.95, 1.04)	**1.37 (1.33, 1.42)**	1.37 (1.33, 1.42)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 6
Estimates of d in the absolute return series: White noise errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	0.22 (0.20, 0.23)	0.20 (0.18, 0.22)	**0.20 (0.18, 0.22)**
CANADA	0.21 (0.19, 0.23)	**0.19 (0.18, 0.21)**	0.19 (0.17, 0.21)
EURO	0.21 (0.20, 0.23)	**0.20 (0.19, 0.22)**	0.20 (0.18, 0.22)
JAPAN	0.20 (0.18, 0.22)	0.19 (0.17, 0.21)	**0.18 (0.16, 0.20)**
SINGAPORE	0.27 (0.25, 0.29)	**0.26 (0.24, 0.28)**	0.26 (0.24, 0.28)
UK	0.20 (0.18, 0.22)	**0.19 (0.17, 0.22)**	0.19 (0.17, 0.21)
USA	0.37 (0.35, 0.39)	**0.37 (0.34, 0.39)**	0.37 (0.34, 0.39)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 7
Estimates of d in the absolute return series: Autocorrelated errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	0.32 (0.30, 0.35)	0.30 (0.27, 0.33)	**0.28 (0.26, 0.33)**
CANADA	0.29 (0.26, 0.31)	0.25 (0.23, 0.28)	**0.24 (0.22, 0.27)**
EURO	0.30 (0.27, 0.32)	0.28 (0.25, 0.31)	**0.27 (0.25, 0.30)**
JAPAN	0.27 (0.24, 0.29)	0.24 (0.21, 0.27)	**0.23 (0.20, 0.26)**
SINGAPORE	0.29 (0.27, 0.32)	**0.27 (0.25, 0.30)**	0.27 (0.24, 0.31)
UK	0.27 (0.24, 0.30)	**0.24 (0.22, 0.27)**	0.24 (0.21, 0.27)
USA	0.38 (0.34, 0.41)	**0.37 (0.33, 0.41)**	0.36 (0.33, 0.40)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 8
Estimates of d in the squared return series: White noise errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	**0.11 (0.09, 0.13)**	0.11 (0.09, 0.13)	0.10 (0.08, 0.12)
CANADA	**0.16 (0.14, 0.18)**	0.16 (0.14, 0.18)	0.15 (0.13, 0.17)
EURO	**0.22 (0.20, 0.24)**	0.22 (0.20, 0.24)	0.22 (0.20, 0.24)
JAPAN	**0.04 (0.02, 0.07)**	0.04 (0.02, 0.07)	0.04 (0.01, 0.07)
SINGAPORE	**0.23 (0.21, 0.25)**	0.23 (0.21, 0.25)	0.23 (0.21, 0.25)
UK	**0.04 (0.01, 0.08)**	0.04 (0.01, 0.08)	0.04 (0.01, 0.08)
USA	**0.29 (0.27, 0.31)**	0.29 (0.27, 0.31)	0.29 (0.27, 0.31)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 9
Estimates of d in the squared return series: Autocorrelated errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	−0.05 (−0.09, 0.00)	**−0.05 (-0.09, 0.00)**	−0.05 (−0.10, −0.01)
CANADA	−0.03 (−0.07, 0.02)	**−0.03 (-0.07, 0.02)**	−0.03 (−0.07, 0.02)
EURO	**0.04 (0.00, 0.09)**	0.04 (0.00, 0.09)	0.04 (0.00, 0.09)
JAPAN	**0.09 (0.05, 0.13)**	0.09 (0.05, 0.13)	0.08 (0.05, 0.13)
SINGAPORE	**0.15 (0.11, 0.20)**	0.15 (0.11, 0.21)	0.15 (0.11, 0.20)
UK	−0.03 (−0.07, 0.02)	**−0.03 (-0.07, 0.02)**	−0.03 (−0.07, 0.02)
USA	**0.37 (0.33, 0.41)**	0.37 (0.33, 0.41)	0.37 (0.33, 0.41)

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 10
Estimates of d on the log squared returns: White noise errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	0.31 (0.29, 0.33)	**0.28 (0.26, 0.29)**	0.27 (0.26, 0.29)
CANADA	0.32 (0.30, 0.34)	**0.28 (0.27, 0.30)**	0.28 (0.26, 0.30)
EURO	0.31 (0.29, 0.33)	**0.27 (0.25, 0.28)**	0.27 (0.25, 0.28)
JAPAN	0.31 (0.29, 0.33)	**0.28 (0.26, 0.29)**	0.28 (0.26, 0.29)
SINGAPORE	0.34 (0.32, 0.35)	**0.30 (0.28, 0.31)**	0.30 (0.28, 0.31)
UK	0.21 (0.18.0.24)	0.10 (0.08, 0.12)	**0.09 (0.07, 0.11)**
USA	0.26 (0.24, 0.28)	0.26 (0.24, 0.28)	**0.26 (0.24, 0.28)**

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 11
Estimates of d on the log squared returns: Autocorrelated errors.

Country	No terms	Intercept	Intercept + time trend
AUSTRALIA	0.45 (0.42, 0.48)	**0.40 (0.37, 0.42)**	0.40 (0.37, 0.42)
CANADA	0.46 (0.44, 0.39)	**0.40 (0.37, 0.43)**	0.40 (0.37, 0.43)
EURO	0.45 (0.43, 0.48)	**0.40 (0.37, 0.42)**	0.40 (0.37, 0.42)
JAPAN	0.46 (0.44, 0.48)	**0.41 (0.38, 0.43)**	0.41 (0.38, 0.43)
SINGAPORE	**0.47 (0.43, 0.49)**	0.40 (0.38, 0.43)	0.40 (0.38, 0.43)
UK	0.34 (0.29, 0.38)	0.15 (0.12, 0.18)	**0.13 (0.11, 0.17)**
USA	0.38 (0.35, 0.42)	0.35 (0.32, 0.38)	**0.36 (0.32, 0.40)**

In parenthesis, the 95% confidence band of the non-rejection values of d.

Table 12
Break dates for the absolute returns.

Country	Number of breaks	Break dates	95% Confidence Limits		Bai and Perron's Multiple Structural Change Test $SupF_T$ $SupF_T$
AUSTRALIA	*4/Obs.*				
	516	*28/02/2012*	*253*	*779*	*672.26**
	1036	*03/08/2012*	*1028*	*1044*	*245.22**
	1641	*30/06/2015*	*1530*	*1752*	*523.52**
	2362	*17/04/2018*	*2354*	*2370*	*477.4**
CANADA	*3/Obs.*				
	514	*18/03/2009*	*404*	*624*	*1597.13**
	1127	*15/12/2014*	*1114*	*1140*	*773.82**
	1641	*16/04/2018*	*1572*	*1710*	*1027.54**
EURO	*4/Obs.*				
	514	*18/03/2009*	*175*	*853*	*530.88**
	1053	*26/08/2011*	*879*	*1227*	*342.98**
	1564	*15/12/2014*	*1542*	*1586*	*237.8**
	2075	*18/04/2018*	*2062*	*2088*	*184.6**
JAPAN	*4/Obs.*				
	514	*18/03/2009*	*507*	*521*	*1077.36**
	1119	*13/07/2011*	*1112*	*1126*	*496.18**
	1641	*05/06/2013*	*1580*	*1702*	*358.21**
	2505	*03/11/2016*	*2490*	*2520*	*469.98**
SINGAPORE	*4/Obs.*				
	514	*18/03/2009*	*40*	*988*	*5361.09**
	1265	*02/02/2012*	*791*	*1739*	*12447**
	1978	*21/06/2016*	*1977*	*1979*	*8267.09**
	2489	*10/04/2018*	*2488*	*2490*	*6186.06**
UK	*3/Obs.*				
	514	*18/03/2009*	*508*	*520*	*681.53**
	1151	*22/08/2011*	*719*	*1583*	*737.69**
	1852	*22/06/2016*	*1443*	*2261*	*1028.24**
USA	*5/Obs.*				
	515	*16/03/2009*	*502*	*528*	*46.53**
	1178	*04/10/2011*	*1145*	*1211*	*163.05**
	1813	*10/03/2014*	*1768*	*1858*	*157.33**
	2324	*24/02/2016*	*2309*	*2339*	*151.02**
	2838	*13/02/2018*	*2362*	*3314*	*146.19**

Table 13
Break dates for the squared returns.

Country	Total Number of breaks	Break dates	95% Confidence Limits		Bai and Perron's Multiple Structural Change Test $SupF_T$
AUSTRALIA	-				
CANADA	*5/Obs.*				
	571	*05/06/2009*	*334*	*808*	*17.46**
	1111	*11/07/2011*	*−1930*	*4152*	*10.09***
	1641	*03/10/2012*	*670*	*2612*	*9.42***
	2343	*12/07/2013*	*1764*	*2922*	*7.62***
	2886	*16/07/2015*	*2481*	*3291*	*6.74***
EURO	*5/Obs.*				
	514	*18/03/2009*	*364*	*664*	*38.31**
	1027	*09/09/2011*	*535*	*1519*	*25.22**
	1624	*18/06/2013*	*942*	*2306*	*17.2**
	2135	*12/03/2015*	*1826*	*2444*	*13.95**
	2715	*24/08/2017*	*−280*	*5710*	*11.52**
JAPAN	*4/Obs.*				
	810	*06/05/2010*	*658*	*962*	*29.36**
	1424	*30/12/2014*	*881*	*1967*	*15.61**
	2005	*04/06/2015*	*1266*	*2744*	*13.07**
	2531	*22/02/2018*	*1347*	*3715*	*10.62**
SINGAPORE	*2/Obs.*				
	514	*22/03/2016*	*400*	*628*	*1447.77**
	1169	*08/03/2018*	*1102*	*1236*	*604.37**
UK	*4/Obs.*				
	571	*05/06/2009*	*329*	*813*	*21.53**
	1089	*12/07/2012*	*−925*	*3103*	*12.81**
	1602	*20/05/2013*	*692*	*2512*	*13.9**
	2315	*03/05/2018*	*665*	*3965*	*9.97**
USA	*4/Obs.*				
	612	*03/08/2009*	*427*	*797*	*113.1**
	1365	*10/08/2011*	*1349*	*1381*	*207.69**
	1876	*29/07/2013*	*1863*	*1889*	*120.66**
	2387	*20/04/2018*	*2020*	*2754*	*99.26**

$$y_t = \alpha + \beta t + x_t; \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{2}$$

where α and β are the coefficients associated to the intercept and the linear time trend.

The estimation of the differencing parameter d is conducted by means of using a simple version of the tests of Robinson (1994). These tests are very general, including not only the standard case of fractional integration, but also allowing for seasonal and cyclical differentiation. The functional form of the version of the tests used in this work can be found in Gil-Alana and Robinson (1997).

4. Data and empirical analysis

We obtain daily S&P Leverage Loan Price Indices for Australia, Canada, Europe, Japan, Singapore, UK and USA from 30th March 2007 to 23rd April 2020 from DataStream leading to 3411 observations. These countries were selected based on availability of data. Daily returns of indices are in log form.

Table 1 presents summary statistics for the daily returns of Leveraged Loan prices and their corresponding returns. From Table 1 Panel A, we find that for the period examined, the USA Leveraged Loan market is the leading market evidenced by the highest price index. From Panel B we find that the daily returns of Leveraged Loan Indices are positive for all series under examination. The UK area recorded the highest returns with Singapore and the USA recording the lowest returns. On skewness, results further report significant negative skewness for the USA. Negative (Positive) skewness connotes the tendency of higher negative (positive) returns without matching the tendency of positive (negative) returns. On kurtosis, all the series examined in this study recorded kurtosis which exceeded the threshold 3, thus it can be surmised that the returns series of Leverage Loan prices for the period have flatter tails compared to what might be anticipated from a normally distributed series[1].

We start by estimating d in the original series, using the model given by equation (1).

Tables 2, 4, 6, 8, 10 and 14 refer to the case of white noise errors, while the results in Tables 3, 5,7, 9, 11 and 15 assume auto-correlation for the error terms.

Focusing first on the original data, and for the case of no autocorrelation, we find in Table 2 mean reversion in the case of Australia; the UK and Canada show evidence of I(1), with orders of integration about 1 in the remaining cases. In the case of autocorrelation, in Table 3, mean reversion is only found in Australia and the UK, the values of d being 0.95 (Australia) and 0.96 (UK). Results from the log

[1] The squared returns project a similar outlook and is available upon request.

Table 14
Probable cause of break dates in each country.

Country	Probable causes of break dates in each country.
AUSTRALIA	The Monetary Policy committee of The Reserve Bank of Australia since 1990 to date agreed that the appropriate target for monetary policy is to achieve an inflation rate of 2–3 per cent, on average, over time. Hence it is not surprising we observed no break dates for the squared returns.
CANADA	No reasons found.
EURO	a] The European Central Bank (ECB) engaged in large-scale purchase of covered bonds in May 2009, and purchased around 250 billion euros of sovereign bonds from targeted member states in 2010 and 2011. b] a] Quantitative Easing by European Central Bank in 2015.
JAPAN	a] On 4 April 2013, the Bank of Japan announced that it would expand its asset purchase program by 60–70 trillion Yen a year. b] On 31 October 2014, the Bank of Japan announced the expansion of its bond buying program, to now buy ¥80 trillion of bonds a year. c] In 2011 Japan's public debt was about 230 percent of its annual Gross Domestic Product, the largest percentage of any nation in the world. In order to address the Japanese budget gap and growing national debt, in June 2012 the Japanese Diet passed a bill to double the national consumption tax to 10%.[2] The new bill increases the tax to 8% by April 2014 and 10% by October 2015. However, it was delayed until at least October 2019.
SINGAPORE	Unlike many other central banks such as the Federal Reserve System, the European Central Bank or the Bank of England, the Bank of Singapore does not regulate the monetary system via interest rates to influence the liquidity in the system. Instead, it chooses to do it via the foreign exchange mechanism, which it has been doing since 1981. In doing so it manages the Singapore dollar versus a number of currencies that they do not reveal publicly – a Singapore dollar nominal effective exchange rate (S$ NEER). We attribute the break dates in Singapore leverage market to the following decisions of Monetary Authority of Singapore (MAS) (MAS, 2016; 2018). a] zero percent rate of appreciation of SGD NEER band in October 2016. b] slightly increase rate of appreciation of SGD NEER band in October 2018.
UK	a] Quantitative easing in the UK in 2009 and 2012. b] UK's vote to leave the European Union in June 2016 which saw the MPC cut the base rate from 0.5% to 0.25%, the first change since March 2009.
USA	a] Quantitative Easing 1, December 2008 to March 2010. b] Zero Interest Rate Policy, December 2008 to December 2015. c] Quantitative Easing 2, November 2010 to June 2011. d] Operation Twist 2011. e] Quantitative Easing 3, September 2012 to December 2013.

Source: Central Bank websites of individual countries.

transformed data, reported in Tables 4 and 5 depict similar results to those in Tables 2 and 3 though evidence of mean reversion ($d < 1$) is now only found in the case of Australia.

Next we examine volatility by looking at the absolute return and squared returns. For the absolute returns, if the errors are uncorrelated (Table 6) evidence of long memory ($d > 0$) is found in all series. However, if autocorrelation is permitted (in Table 7), we obtain similar findings with all values of d being strictly positive which support the long memory hypothesis. Considering the case of squared returns, in the absence of no autocorrelation, we observe in Table 8 that the estimates of d are positive. However, when autocorrelation is permitted (Table 9), we note negative values of d for Australia ($d = -0.05$), Canada ($d = -0.03$) and the UK ($d = -0.03$) which supports the hypothesis of anti-persistence ($d < 0$), though the confident bands indicate that the I(0) hypothesis cannot be rejected. For the remaining series, the values of d are all strictly positive which reveals evidence of mean reversion though for some cases, we cannot reject the null hypothesis of I(0) or short memory. In addition, and following authors such as Starica and Granger (2005), we also look at the log-squared returns (Tables 10 and 11 respectively for the two cases of white noise and autocorrelated errors) and evidence of long memory and mean reversion ($0 < d < 1$) were found in all cases, the highest values corresponding to the case of Singapore and the lowest one to the UK.

We also used alternative approaches that account for other deterministic terms and potential breaks in the data (Hou & Perron, 2014) and the results were almost identical to those reported here across the tables. Nevertheless, in what follows, we want to deeper investigate if breaks are present in the data and if this is the case, if these have had any influence in the degree of persistence of the data. As earlier mentioned, we use first the approach developed in Bai and Perron (2003) for detecting multiple breaks in time series, and then we also consider the methodology proposed in Gil-Alana (2008), which is basically an extension of Bai and Perron (2003) to the fractional case. The number of breaks and the breaks dates for each case are presented in Table 12 and Table 13 for the absolute returns and squared returns respectively.

We observe in Table 12 that for the absolute returns, three breaks take place in the cases of Canada and the UK; four breaks for Australia, Europe, Japan and Singapore and five breaks in the case of the USA. For the squared returns, four break dates occur for Japan, the UK and the USA; five breaks for Canada and Europe; two breaks in the case of Singapore, and no breaks in the case of Australia. With respect to the break dates, most of them occur at similar dates, namely, the beginning and middle of 2009; middle 2011; the middle of 2016 and/or the beginning of 2018; Once the break dates have been determined, we examine the degree of persistence associated with each subsample, and here, based on the shorter sample sizes, we also consider the possibility of a linear trend. Thus, the model examined is (2). We estimate d under three set-ups: i) when α and β are assumed to be 0 a priori, that is, imposing no deterministic terms in the model, ii) with $\beta = 0$ a priori, that is, allowing for an intercept, and iii) allowing for a linear time trend by estimating α and β freely from the data. Table 14 provides some explanantions for the potential breaks in the data.

The results in terms of the estimation of d for each of these three cases and each subsample are reported across Table 15 (absolute

Table 15
Estimates of d in the absolute return series: White noise errors.

Country	Subs.	No terms	Intercept	Intercept + time trend
AUSTRALIA	1st	0.15 (0.08, 0.26)	0.18 (0.10, 0.28)	**0.14 (0.05, 0.27)**
	2nd	0.19 (0.16, 0.22)	0.17 (0.15, 0.20)	**0.16 (0.13, 0.19)**
	3rd	0.09 (0.06, 0.13)	0.10 (0.06, 0.14)	**0.06 (0.02, 0.10)**
	4rd	0.11 (0.06, 0.16)	0.07 (0.04, 0.11)	**−0.05 (-0.10, 0.01)**
	5th	0.37 (0.32, 0.43)	0.37 (0.32, 0.43)	**0.36 (0.30, 0.43)**
CANADA	1st	0.14 (0.11, 0.19)	0.17 (0.13, 0.21)	**0.11 (0.06, 0.16)**
	2nd	0.19 (0.16, 0.21)	0.15 (0.13, 0.18)	**0.10 (0.07, 0.13)**
	3rd	0.08 (0.04, 0.13)	0.06 (0.02, 0.10)	**0.02 (-0.02, 0.06)**
	4rd	0.32 (0.28, 0.36)	**0.32 (0.28, 0.36)**	0.31 (0.28, 0.36)
EURO	1st	0.17 (0.14, 0.21)	0.20 (0.16, 0.24)	**0.11 (0.07, 0.17)**
	2nd	0.07 (0.01, 0.13)	**0.05 (0.01, 0.09)**	0.05 (0.01, 0.10)
	3rd	0.20 (0.17, 0.24)	0.17 (0.15, 0.20)	**0.16 (0.13, 0.19)**
	4rd	0.14 (0.10, 0.19)	0.10 (0.06, 0.14)	**0.05 (0.01, 0.10)**
	5th	0.31 (0.27, 0.35)	0.31 (0.27, 0.36)	**0.30 (0.26, 0.35)**
JAPAN	1st	0.16 (0.12, 0.20)	0.18 (0.14, 0.23)	**0.14 (0.09, 0.19)**
	2nd	0.18 (0.12, 0.25)	0.13 (0.07, 0.19)	**0.11 (0.05, 0.17)**
	3rd	0.26 (0.22, 0.31)	0.23 (0.19, 0.28)	**0.17 (0.12, 0.24)**
	4rd	0.05 (0.02, 0.10)	0.06 (0.02, 0.10)	**0.04 (0.00, 0.09)**
	5th	0.29 (0.26, 0.33)	**0.28 (0.25, 0.32)**	0.28 (0.25, 0.32)
SINGAPORE	1st	0.27 (0.22, 0.33)	0.29 (0.24, 0.35)	**0.25 (0.19, 0.32)**
	2nd	0.20 (0.16, 0.25)	**0.18 (0.14, 0.22)**	0.18 (0.15, 0.23)
	3rd	0.14 (0.11, 0.17)	0.14 (0.11, 0.17)	**0.12 (0.09, 0.15)**
	4rd	0.10 (0.04, 0.16)	0.07 (0.03, 0.13)	**0.03 (-0.02, 0.09)**
	5th	0.36 (0.32, 0.41)	0.36 (0.32, 0.41)	**0.36 (0.31, 0.40)**
UK	1st	0.18 (0.15, 0.22)	0.20 (0.17, 0.24)	**0.11 (0.07, 0.17)**
	2nd	0.10 (0.03, 0.17)	**0.05 (0.01, 0.10)**	0.02 (−0.04, 0.08)
	3rd	−0.01 (−0.03,0.04)	**−0.01 (-0.04, 0.04)**	−0.01 (−0.05, 0.04)
	4rd	0.25 (0.21, 0.29)	**0.23 (0.19, 0.27)**	0.23 (0.19, 0.27)
USA	1st	**0.45 (0.39, 0.53)**	0.46 (0.39, 0.53)	0.45 (0.38, 0.53)
	2nd	0.49 (0.44, 0.55)	**0.44 (0.39, 0.50)**	0.43 (0.38, 0.49)
	3rd	0.25 (0.19, 0.31)	0.22 (0.17, 0.29)	**0.21 (0.15, 0.28)**
	4rd	**0.37 (0.31, 0.45)**	0.38 (0.32, 0.45)	0.38 (0.32, 0.45)
	5th	0.42 (0.37, 0.47)	0.36 (0.31, 0.42)	**0.34 (0.28, 0.40)**
	6th	0.32 (0.29, 0.36)	0.32 (0.29, 0.36)	**0.32 (0.28, 0.35)**

In parenthesis, the 95% confidence band of the non-rejection values of d.

returns) and Table 16 (squared returns), and we have marked in bold in the tables the most adequate specification for each case according to the significance of the estimated coefficients of these deterministic terms.

Starting with the absolute returns, we observe in Table 15 that the time trend is required for all sub-samples in the case of Australia; the first to third sub-samples for Canada; first and last sub-samples for Euro; first to fourth sub-samples for Japan; first and fourth sample for Singapore, first sample for the UK and last sample for the USA. However, in the majority of cases the intercept is sufficient to describe the deterministic part. Focusing on d, most of the estimates are once more positive, and evidence of short memory or I(0) behaviour is only found in four of the 34 subsamples examined. Except for the US, the highest degrees of persistence are obtained during the last subsamples. We attribute the highest degree of persistence observed in the US during the subsamples to the impact of the large-scale asset purchases (LSAPs), colloquially known as quantitative easing (QE), on commercial bank lending in the US. We make this claim because, Rodnyansky & Darmouni (2017), using a difference-in-differences identification strategy found strong effects of the third round of quantitative easing (QE3) on credit with results showing that highly affected commercial banks increase lending by 3% relative to their counterparts. The plots below (Fig. 1) show the daily price series and returns of USA leverage loan market with the period of US quantitative easing circled. Focusing on the three rounds of Quantitative Easing: 1 (QE1, December 2008 to March 2010); Quantitative Easing 2 (QE2, November 2010 to June 2011) and Quantitative Easing 3 (QE3, September 2012 to December 2013), we observe a significant impact of QE on credit markets which may have influenced the high degree of persistence observed in the case of USA.

The plot below shows the daily price series and returns of USA leverage loan market with the period of US quantitative easing circled. Focusing on the three rounds of Quantitative Easing, we observe a significant impact of QE on the credit markets.

Table 16 refers to the squared returns. Once more the time trend is required in a number of cases, at the beginning of the sample in the cases of Canada, Euro, the UK and during the last subsamples for the USA, the UK, and Japan. Focusing on the estimated values of d, in Table 16, we notice a reduction with respect to the previous case in the degree of persistence in the cases of all series under

Table 16
Estimates of d in the absolute return series: Autocorrelated errors.

Country	Subs.	No terms	Intercept	Intercept + time trend
AUSTRALIA	1st	**0.11 (0.09, 0.13)**	0.11 (0.09, 0.13)	0.10 (0.08, 0.12)
CANADA	1st	0.13 (0.10, 0.18)	0.14 (0.10, 0.19)	**0.12 (0.07, 0.17)**
	2nd	0.10 (0.06, 0.15)	0.09 (0.04, 0.12)	**0.02 (-0.02, 0.07)**
	3rd	0.08 (0.02, 0.15)	0.06 (0.01, 0.13)	**0.01 (-0.04, 0.08)**
	4rd	0.18 (0.12, 0.27)	0.16 (0.10, 0.24)	**0.10 (0.03, 0.20)**
	5th	−0.01 (−0.23, 0.06)	**0.00 (-0.06, 0.06)**	0.00 (−0.05, 0.08)
	6th	0.26 (0.06, 0.29)	**0.26 (0.23, 0.29)**	0.26 (0.23, 0.29)
EURO	1st	0.17 (0.14, 0.22)	0.18 (0.14, 0.23)	**0.13 (0.09, 0.19)**
	2nd	0.14 (0.09, 0.21)	**0.13 (0.08, 0.29)**	0.14 (0.09, 0.21)
	3rd	0.13 (0.09, 0.18)	0.11 (0.07, 0.16)	**0.01 (-0.04, 0.07)**
	4rd	0.06 (0.01, 0.12)	0.06 (0.01, 0.12)	**0.05 (0.00, 0.11)**
	5th	0.10 (0.06, 0.16)	**0.09 (0.04, 0.14)**	0.03 (−0.02, 0.09)
	6th	0.27 (0.23, 0.31)	**0.27 (0.23, 0.31)**	0.26 (0.22, 0.31)
JAPAN	1st	0.16 (0.13, 0.20)	**0.17 (0.13, 0.21)**	0.17 (0.13, 0.21)
	2nd	−0.01 (−0.03, 0.04)	**−0.01 (-0.05, 0.04)**	−0.01 (−0.05, 0.04)
	3rd	−0.04 (−0.19, 0.14)	−0.05 (−0.11, 0.11)	**−0.09 (-0.21, 0.06)**
	4rd	0.07 (0.03, 0.12)	0.07 (0.03, 0.11)	**0.06 (0.01, 0.11)**
	5th	0.25 (0.21, 0.30)	0.26 (0.22, 0.30)	**0.24 (0.20, 0.29)**
SINGAPORE	1st	0.13 (0.10, 0.15)	**0.12 (0.10, 0.15)**	0.12 (0.10, 0.15)
	2nd	0.07 (0.01, 0.13)	**0.05 (0.01, 0.11)**	0.01 (−0.05, 0.07)
	3rd	0.31 (0.27, 0.37)	0.32 (0.27, 0.37)	**0.31 (0.26, 0.36)**
UK	1st	0.12 (0.09, 0.16)	0.13 (0.10, 0.17)	**0.08 (0.04, 0.13)**
	2nd	0.04 (−0.01, 0.09)	0.03 (−0.01, 0.07)	**−0.03 (-0.07, 0.02)**
	3rd	0.00 (−0.06, 0.09)	**0.00 (-0.06, 0.09)**	−0.02 (−0.10, 0.07)
	4rd	0.13 (0.09, 0.318	**0.13 (0.09, 0.18)**	0.13 (0.09, 0.18)
	5th	0.22 (0.17, 0.28)	0.22 (0.18, 0.28)	**0.21 (0.16, 0.27)**
USA	1st	0.29 (0.23, 0.35)	**0.29 (0.24, 0.35)**	0.29 (0.23, 0.35)
	2nd	0.38 (0.32, 0.45)	**0.37 (0.31, 0.44)**	0.37 (0.31, 0.44)
	3rd	0.18 (0.11, 0.26)	0.17 (0.10, 0.25)	**0.18 (0.11, 0.27)**
	4rd	0.32 (0.28, 0.36)	**0.32 (0.28, 0.36)**	0.32 (0.28, 0.36)
	5th	0.28 (0.24, 0.33)	0.28 (0.24, 0.33)	**0.27 (0.23, 0.32)**

In parenthesis, the 95% confidence band of the non-rejection values of d.

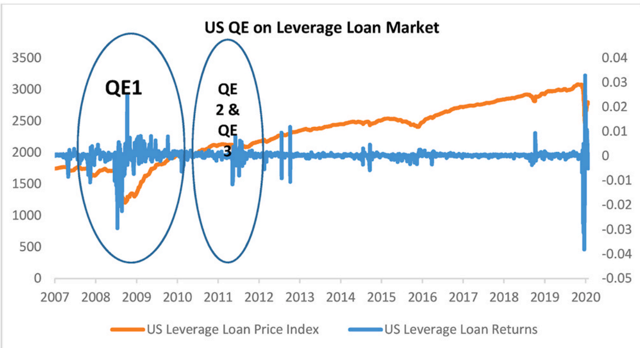

Fig. 1. Plots of leverage loan price series and returns of USA.

examination. There are now eight cases where the I(0) hypothesis cannot be rejected and as in the previous case, the highest degree of persistence takes place at the last subsamples in all countries except the US.

5. Conclusions

This paper uses fractional integration methods including the possibility of structural breaks to investigate the degree of persistence in leveraged loan markets (Australia, Canada, Europe, Japan, Singapore, the UK and the USA) for the period 30th March 2007 to 23rd

April 2020. Succinctly, results obtained for the original series indicate that all them are highly persistent with values of d close to 1 in all cases. In fact, the only evidence of mean reversion is found in the Australian case and even in this case, the estimate of d is very close to 1 implying very long lasting effects of shocks. Focusing on the absolute and squared returns, the estimates of d indicate positive values in most cases, which clearly supports the long memory hypothesis. This further indicates that the leveraged loan market is still inefficient, implying that abnormal returns could be obtained by investors in the leveraged loan market through technical trading strategies. After documenting the presence of persistence in the leverage loan market, we run further tests to investigate whether structural breaks in the data could have any effect on the extent of persistence, and provide some evidence indicating that the degree of persistence is somehow reduced when we take into account structural breaks. In fact, short memory is found in some of the subsamples and the highest degrees of persistence seem to take place during the last subsamples.

The findings documented in this study offer several implications for market participants, investors and policy markets as they seek to make gains, understand the long memory properties and regulate the leverage loan market respectively. First, our empirical findings surmise the significance of accounting for the long memory property in an empirical analysis that considers the economics and financial benefits of leverage loan market returns such as optimal hedging estimation, risk portfolio management, and potential option valuation. Secondly, the evidence of high persistence in volatility suggests that market analysts, participants and analysts who aim to make gains in the leverage loan market across trading scales need to factor the persistence properties of leverage loan market returns in their valuation and forecasting models since that will help improve long-term volatility market forecasts and optimal hedging decisions. Lastly, the findings also offer market participants and analysts an interesting opportunity to get benefits from the inefficiencies in the leverage loan market. As such, they can potentially improve the risk-adjusted performance of their portfolios by using long memory-based frameworks. Additionally, recent market events have demonstrated that enhancing transparency and strengthening risk management practices require special attention. For example, more timely disclosure of balance sheet information might enhance transparency and improve creditors' ability to monitor borrower credit quality. According to the Bank of International Settlement 2019 report, The Bank of England's 2018 stress test, which looked at the impact of a severe economic downturn on UK banks' holdings of leverage loans, found that they had relatively low levels of lower risk to CLO exposures, but that does not mean that banks in other parts of the world are immune to a leveraged loan stress. In view of this, we suggest that, in the area of risk management, improvements in stress testing need to be given greater attention. We recommend further studies using robust econometric estimations techniques such as regime switching copulas (e.g., Tiwari et el., 2020), Diebold & Yilmaz, 2012, and Baruník et al., 2017) spillover frameworks (e.g., Le et al., 2020), non-linear Fourier unit roots (e.g. Abakah et al., 2018) among other models to be employed to investigate other stylized facts such as dependence in newly constituted leverage loan markets.

Author statement

Emmanuel Joel Aikins Abakah proposed the original idea of the manuscript. He conducted the Introduction and literature review along with the interpretation of the results and conclusions. **Luis A. Gil-Alana** was responsible for the programming, computation and interpretation of the results and conclusion along with a complete overview of the manuscript. **Emmanuel Kwesi Arthur** collaborated with the introduction, literature review and conclusions. **Aviral Kumar Tiwari** participated in the literature review, interpretation of the results, conclusions and a final overview of the manuscript.

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