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Liquidity on Eurozone stock markets: A non-linear approach

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Abstract

The purpose of this paper is to study the relationship between liquidity and returns in the main European stock markets for the period of January 2005- December 2020. Asset liquidity is measured by three correlated indicators (ROLL, CS and HL). The methodology adopted consists of constructing threshold autoregressive model (TAR) for market returns while using liquidity indicators as a transition variable. The distinction between the different regimes helps clarify the relationship between these variables. The results show that the detected thresholds are different depending on the stock market. We then find that the impact of the liquidity indicator on returns is different for regime 1 and regime 2, and we propose an economic explanation for this difference.

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Special issue “In memory of Professor Michel Terraza”

1 Introduction

Liquidity risk has attracted the attention of academic researchers and professionals in the past few years. Liquidity can refer to market liquidity, asset liquidity, fund liquidity, or portfolio liquidity. When referring to a financial asset, we consider it to be liquid when we can purchase and sell substantial quantities in a very short period of time without drastically changing its price.

In terms of risk, a distinction is made between funding liquidity risk (i.e. the risk that, over a given period of time, a financial institution may not be able to meet its short-term liabilities) and market liquidity risk which refers to the liquidity of assets and the inability to liquidate a position at the current market price.

Liquidity is a key feature for the proper functioning of financial markets. The financial crises of 2007-2008 is essentially characterized by a contagious contraction of liquidity in money and financial markets and have raised questions on the management of liquidity risk. Van Den End and Tabbae (2012) urged that the 2008 crisis began with a market liquidity shortage that caused a global economic slowdown. As a result, one of the challenges of financial regulation is to prevent systemic liquidity crises that can affect most financial institutions and markets.

The new ecosystems of financial markets (such as automated trading systems, high-frequency trading,...) have also raised new challenges regarding liquidity and have also highlighted the importance of regulation in stabilizing the market and preventing liquidity crisis. From financial market regulators perspective, Harris (2003) considers that one of their objectives is to ensure long-term liquidity which is essential for well-functioning equity markets. In terms of the regulatory framework, the "Regulation of National Markets" and the "Markets in Financial Instruments Directive" represent major changes in the structure of equity trading markets in the United States and the European Union respectively. These regulations allowed for competition among market participants and thereby a decrease in transaction costs which improved market liquidity. However, these regulations had also led to changes in market structure in a not necessarily positive way (market fragmentation, automated trading, opaque pools, high-frequency traders,...) which threatens market stability and the efficiency of the price formation process. Since then, many rules have been introduced in the banking sector to mitigate the liquidity risks of banks that had a substantial role in the financial crises. Basel III, released by the Basel Committee on Banking Supervision (BCBS) in January 2013, is one of the committee's fundamental changes to reinforce global liquidity regulation.

On the investor's side and as mentioned by Foucault et al. (2013), in a liquid market, short-term investors prefer liquid stocks with lower returns than non-liquid stocks. On the other hand, the long-term investor wants to invest in relatively less liquid stocks for higher returns.

Since they assume that the financial market is frictionless and that the exchanged assets are completely liquid, most traditional models in finance omit the liquidity component. Furthermore, a liquidity premium exists in the markets, according to various studies. For example, Amihud et al. (2006) found that liquidity has important effects on returns. The literature indicates that less liquid assets are allocated to investors with longer investment horizons and that expected asset returns are an increasing function of illiquidity (Constantinides, 1986). However, counterarguments are present in the literature as in Datar et al. (1998), and Brennan and Subrahmanyam (1996) who refute the impact of liquidity on markets. Therefore, given the divergent results on the relationship between liquidity and returns, this relationship needs to be examined in the European market.

In this study we focus on the main European stock market indices AEX, BFX, CAC 40, DAX, IBEX, SMI, FTSE MIB and the Euronext 100 benchmark. The aim of this study is to analyze the relationship between liquidity and returns on the European stock markets for the period from January 2005 to December 2020. A few studies have been done in the subject of relationship between returns and liquidity in these markets. Moreover, most of the studies use linear modeling, which does not capture the dynamics of liquidity.

As liquidity is a concept that combines many dimensions such as cost, volume and time, we use three different measures of liquidity in this study to analyze the dependence between liquidity and returns. On one hand, most empirical studies use a single measure of liquidity. However, this approach was criticized in particular by by Hasbrouck (2005), and Goyenko et al. (2009). On the other hand, this study covers the 2005 to 2020 period which had encountered four market crises: the 2008 subprime crisis, the 2011 debt crisis, the 2016 recession and more recently the 2019 Covid pandemic crisis. This would enable for an examination of how returns move during low liquidity periods and during violent market liquidity shocks.

The study is organized as follows: Section 2 highlights the literature review of empirical studies about liquidity and returns relationships. Section 3 presents the concept of liquidity and the measures used to quantify it and illustrates the theoretical framework of the analysis. Section 4 presents the data and results. Section 5 concludes.

2 Literature review

The concept of market liquidity has given rise to different axis of research. Some papers on the microstructure of financial markets have focused on studying the relationship between returns and liquidity. In this regard, Roll (1984), Amihud and Mendelson (1986) and Amihud and Mendelson (1991) were the first to study the relationship between low liquidity assets and their returns. Brennan and Subrahmanyam (1996) used the bid-ask spread as a measure of liquidity and found a significant negative relationship between average stock returns and liquidity. Amihud (2002) and Pástor and Stambaugh (2003) argued that stocks with more volatile liquidity have lower expected returns. Chan and Faff (2003) examined the role of liquidity in asset pricing. Amihud et al. (2006) conducted a comprehensive literature review on the relationship between liquidity and asset prices. They demonstrated that liquidity has wide-ranging effects on financial markets. Lesmond (2005) employed the five commonly used measures of liquidity in order to study 31 emerging markets. He noticed the presence of a liquidity premium in several markets. Bekaert et al. (2007) found that liquidity is an important factor in the valuation of assets traded in international markets. Using monthly data for the period 1990- 2009, Chiang and Zheng (2015) showed that stock returns are positively correlated with market illiquidity in G7 markets.This association between returns and liquidity has also been verified for different classes of assets as well. For example, we can list the studies of Czauderna et al. (2015) for German market, Smimou (2017) for gold market; Zheng and Su (2017) for oil market in China; Dinh (2017) on high frequency trading. Last but not least, Spiegel (2008) made a comparison amongst different markets in terms of liquidity.

On the other hand, several studies have found evidence of non-linearity for the relationship between returns and trading volume (which is also an indicator of liquidity). Hiemstra and Jones (1994) found a non-linear dynamic causal relationship between trading volume and stock index returns. Martens et al. (1998) used a TAR model to explain the transaction costs (or illiquidity costs) on futures prices. As a general observation, and as stated in most studies, the results obtained are often sensitive to the chosen liquidity proxy. It is therefore important to quantify liquidity accurately. Empirically, liquidity proxies are frequently used by researchers since high-frequency data that capture all facets of liquidity are not always available. Some authors have constructed their own proxies, as an example the Roll measure (Roll, 1984),Amivest (Amihud et al., 1997), Zeros (Lesmond et al., 1999) , Amihud (Amihud, 2002), PS (Pástor and Stambaugh, 2003), DSpread (Chung and Zhang, 2014), CHL (Abdi and Ranaldo, 2017), FHT (Fong et al., 2017). For a more detailed study on the effectiveness of these proxies, the reader can refer to Goyenko et al. (2009). Finally, we note that regardless of the measure used, liquidity has a significant impact on returns in most of the aforementioned papers.

3 Theoretical framework

3.1 Liquidity measures

Liquidity is not easy to define and measure. First, monetary liquidity refers to institutional liquidity and reflects the general financing conditions of the economy. Conversely, market and funding liquidity generally refers to private liquidity. Specifically, market liquidity is the ease with which financial assets can be traded (without causing large price fluctuations), while funding liquidity generally refers to the ability of financial institutions to fund their activities. Market liquidity covers several aspects: the depth or the existence of abundant orders at any price, the spread or the difference between the best bid and ask prices, the immediacy or the speed with which orders can be executed, and resiliency or how quickly prices return to their equilibrium value following a large consumption of liquidity. Because liquidity is multidimensional, researchers rely on one or a combination of these aspects to measure the liquidity risk.

The Bid-Ask spread is an indicator of liquidity which is difficult to obtain. difficult. Nonetheless, there are a number of proxy measures derived from price (or return) data that might provide useful information on the market liquidity. In this paper, we have estimated three measures capturing the Bid-Ask spread, namely: Roll's measure (Roll, 1984), the spread measure CS (Corwin and Schultz, 2012) and the simple high-low ratio.

Roll's measure is exclusively based on the series of the price. We calculate the covariance between two successive price changes:

$$Cov(\triangle p_t, \triangle p_{t-1}) = \frac{-s^2}{4} \tag{1}$$

$$Roll_t = \hat{s} = 2.\sqrt{-Cov(\triangle p_t, \triangle p_{t-1})} \tag{2}$$

where $\triangle$ is the differential operator, p_t is the price of the asset on day t. In case of positive covariance, we take the absolute values with a negative sign added (Lesmond (2005)).

The high-low estimator is the relative difference between the highest price (H_t)

and the lowest price (L_t) observed during the day:

$$HL_t = \frac{H_t - L_t}{H_t} \tag{3}$$

This indicator could provide an indication of the liquidity of an asset since the ratio of *high/ low* prices for a day reflects both the variance of the stock and its Bid-Ask spread.

The CS spread measure was introduced by Corwin et Schultz who used *high* and *low* prices using a two-day interval. They showed that the variance is twice as large when the *high-low* ratios are calculated over two days, but the Bid-Ask spread remains unchanged. Then, they estimate it by eliminating the price volatility component. The spread can therefore be calculated using the one-day and two-day *high-low* ratios:

$$CS_t = (\sqrt{2} + 1).(\sqrt{\beta_t} - \sqrt{\gamma_t}) \tag{4}$$

β_t given by the sum over two consecutive days of the log-squared ratio between high and low prices, and γ_t is given by the log-ratio between the high price over two consecutive days, and the low price over two days:

$$\beta_t = \sum_{j=-1}^{0} \left(ln \frac{H_{t+j}}{L_{t+j}} \right)^2 \tag{5}$$

$$\gamma_t = \left(ln \frac{max(H_t, H_{t-1})}{min(L_t, L_{t-1})} \right)^2 \tag{6}$$

3.2 TAR model

Time series present, in many cases, characteristics that linear models, particularly ARIMA models, do not take into account: (i) for some economic variables, the bullish and bearish phases do not necessarily have the same properties, (ii) some economic variables present asymmetric cycles, (iii) some series are defined by the occurrence of jumps, (iiii) some processes are irreversible in time. The nonlinear models proposed in the literature have allowed to account for these characteristics. Among these models, the threshold autoregressive models (TAR) developed by Tong and Lim (2009) had a significant influence in economics, particularly in modeling cycles and forecasting economic variables. (Tong (1990) gives a summary of these models and argues that there is no linear model that can explain cyclical dynamics. The TAR model is an extension of the linear regression model with structural changes. The transition variable is used to distinguish the different regimes that may exist, based on a threshold value. When constructing a TAR model, it is important to ensure that all the variables incorporated into the TAR modeling are stationary. In this study, we use the Phillips and Perron (1988) test (PP). Considering a time series Y_t , the PP test allows to verify the null hypothesis H_0 of unit root (or non-stationarity) against the alternative hypothesis $H_1 : |\phi_j| < 1$. This test estimates three models by the least squares method (OLS). The first model is a model with constant and drift (7). The second model is with constant and without drift (8). Finally, the third model is without constant and drift (9).

$$\Delta Y_t = \alpha + \beta t + \rho Y_{t-1} + \epsilon_t \tag{7}$$

$$\Delta Y_t = \alpha + \rho Y_{t-1} + \epsilon_t \tag{8}$$

$$\Delta Y_t = \rho Y_{t-1} + \epsilon_t \tag{9}$$

with ϵ_t independent and identically distributed of variance σ_t. A stationary process Y_t that follows a two-regime threshold model is defined as follows:

$$\mathrm{y}_t = \begin{cases} \beta_0^{(1)} + \beta_i^{(1)} X_{it} + \varepsilon_i^{(1)} & if \quad S_{t-d} < s \\ \beta_0^{(2)} + \beta_i^{(2)} X_{it} + \varepsilon_i^{(2)} & if \quad S_{t-d} \geq s \end{cases} \tag{10}$$

Where X_{it} are the explanatory variables, S_t is the transition variable, s is the threshold, d is the lag and the regression in this model is piecewise linear. A TAR model is defined when the model is piecewise autoregressive such that: $X_{it} = (Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p})$.
The model requires the estimation of several parameters: the number of regimes, the lag parameter d, the threshold value and the autoregressive coefficients of each regime. The choice of the number of delays p is made based on information criteria as in a linear model. The threshold is defined using the sequential least squares method. In order to check the linear model specification, we use the RESET (Regression Error Specification) test of Ramsey (1969) where we test the hypothesis of linearity against an undefined alternative.
In our study, we model the returns of the European stock market indices by a TAR model. The transition variable corresponds to the liquidity of the entire European market represented by the Euronext 100 index. In order to check for the robustness of the analysis, we use several measures of liquidity.

$$r_t = \begin{cases} \beta_0^1 + \sum_{i=1}^{p} \beta_i^1 r_{t-i} + \varepsilon_t^1 & si \quad L_{t-d} < s_1 \\ \beta_0^2 + \sum_{i=1}^{p} \beta_i^2 r_{t-i} + \varepsilon_t^2 & si \quad s_1 \leq L_{t-d} < s_2 \\ \quad\quad\ldots & \\ \quad\quad\ldots & \\ \beta_0^k + \sum_{i=1}^{p} \beta_i^k r_{t-i} + \varepsilon_t^l & si \quad L_{t-d} \geq s_{k-1} \end{cases} \tag{11}$$

4 Results and discussion

4.1 Data and description statistics

Our sample is represented by seven European stock market indices from 2005 to 2020 (4165 daily observations for each index). To have an overview of the studied indices, Table 1 describes the composition of the indices, and Figure 1 gives the cumulative return curve. We notice a great variability in the cumulative returns. The cumulative returns are positive for all the indices except IBEX and FTSE. We note also that there is a correlation between these indices.

Index	Country	Composition
AEX	Netherlands	25 largest Dutch companies listed on the Amsterdam stock exchange.
BFX	Belgium	Index of the 20 main companies of the Brussels stock exchange
CAC40	France	40 French companies with the highest market capitalization on the Paris stock exchange
DAX	Germany	30 most important companies listed on the Frankfurt Stock Exchange
IBEX	Spain	35 large companies by market capitalization on the Madrid Stock Exchange
SMI	Switzerland	Top 20 Swiss blue chips listed on the Swiss Exchange
FTSE MIB	Italy	40 largest publicly traded stocks.
EURONEXT100		the stock market index of the most highly capitalized stocks traded on Euronext.

Table 1: Description of the market indices used in the analysis.

The DAX index outperformed the other indices between 2005 and 2020. In addition to the DAX, the SMI and the AEX performed slightly better than the overall Euronext index (yellow). The IBEX and FTSE indices did not show the same dynamics. The latter incurred a net loss on the price between 2005 and 2020. For

Figure 1: Evolution of the cumulative returns of the indices

the CAC 40, BFX and BX indices, even though they made up for the losses incurred during the 2008 crisis and the debt crisis in 2016, the Covid 2019 pandemic caused the cumulative returns to fall even further. The Covid 19 crash affected all indices. Table 2 reports a number of descriptive statistics for the stock market indices (explanatory variables) in this analysis. The means are almost equal to 0. The maximum values vary between 10% and 15%, while the minimum values vary between -11% and -18%. On the other hand, the FTSE index seems to be the most volatile. The returns of the European stock indices have a negative skewness coefficient, so their distributions are left skewed. All series have leptokurtic distributions because their Kurtosis coefficients are greater than 3.

	AEX	BFX	CAC40	DAX	FTSE	IBEX	SMI
Mean	0,000141	5,30E-05	8,87E-05	0,000279	-8,18E-05	-2,93E-05	0,000148
Median	0,000461	0,00021	0,000202	0,000599	0,000267	0,000264	0,000294
Maximum	0,100283	0,092213	0,105946	0,107975	0,108742	0,134836	0,107876
Minimum	-0,113758	-0,153275	-0,130983	-0,130549	-0,185461	-0,151512	-0,101339
Std. Dev.	0,012737	0,012537	0,01374	0,013476	0,015594	0,014551	0,010848
Skewness	-0,399007	-0,701995	-0,284769	-0,252126	-0,696141	-0,384326	-0,428802
Kurtosis	13,2703	14,52187	11,74779	11,74111	13,5376	13,42658	13,3373
Jarque-Bera	18415,53	23380,35	13336,36	13303,91	19606,66	18968,87	18672,28

Table 2: Descriptive statistics of stock market indexes.

As indicated in Figure 2, the characteristics of a nonlinear process appear to be present. The irregular amplitude of the peaks and dips suggests temporal irreversibility and asymmetry. Table 3 gives the mean and median of the European indices in phases of 5 years each. Compared to the total period 2005-2020, the averages and medians per period are not the same. This suggests that returns fluctuate according to economic

	Période totale		Période 2005-2009		Période 2010-2014		Période 2015-2020	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
AEX	0,000141	0,000461	-2.86E-05	0.000585	0.000181	0.000201	0.000249	0.000518
BFX	5,30E-05	0,00021	-0.000119	0.000238	0.000206	7.69E-05	6.89E-05	0.000235
CAC40	8,87E-05	0,000202	2.28E-05	0.000176	6.29E-05	0.000111	0.000165	0.000322
DAX	0,000279	0,000599	0.000258	0.000884	0.000382	0.000584	0.000212	0.000366
FTSE	-8,18E-05	0,000267	-0.000218	0.000585	-0.000154	0.000000	9.31E-05	0.000351
IBEX	-2,93E-05	0,000264	0.000210	0.000694	-0.000115	0.000000	-0.000158	0.000130
SMI	0,000148	0,000294	0.000107	0.000490	0.000243	0.000236	0.000102	0.000168

Table 3: Descriptive statistics of indices by cycle.

	AEX	BFX	CAC40	DAX	FTSE	IBEX	SMI
AEX	1,000	0,844	0,908	0,876	0,804	0,791	0,783
BFX	0,844	1,000	0,863	0,827	0,794	0,790	0,729
CAC40	0,908	0,863	1,000	0,910	0,852	0,848	0,793
DAX	0,876	0,827	0,910	1,000	0,808	0,794	0,771
FTSE	0,804	0,794	0,852	0,808	1,000	0,838	0,678
IBEX	0,791	0,790	0,848	0,794	0,838	1,000	0,682
SMI	0,783	0,729	0,793	0,771	0,678	0,682	1,000

Table 4: Correlations between European index returns.

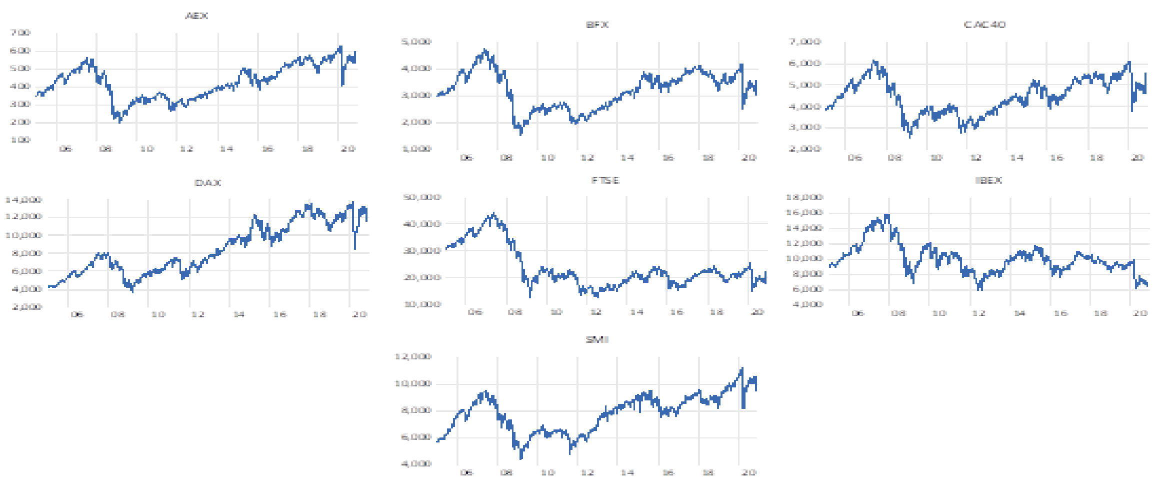

Figure 2: Evolution of European market indices.

cycles. This is true for all indices, which are, by the way, positively correlated (Table 4).

Figure 3 shows a substantial increase in all three measures of liquidity during the economic downturns of 2008-09, 2010-11, 2016, and 2020. In general, market liquidity has improved but it remains vulnerable during some periods. Liquidity exhibits a property of persistence: unlike returns, shocks in 2008, 2010, 2016, and 2020 did not

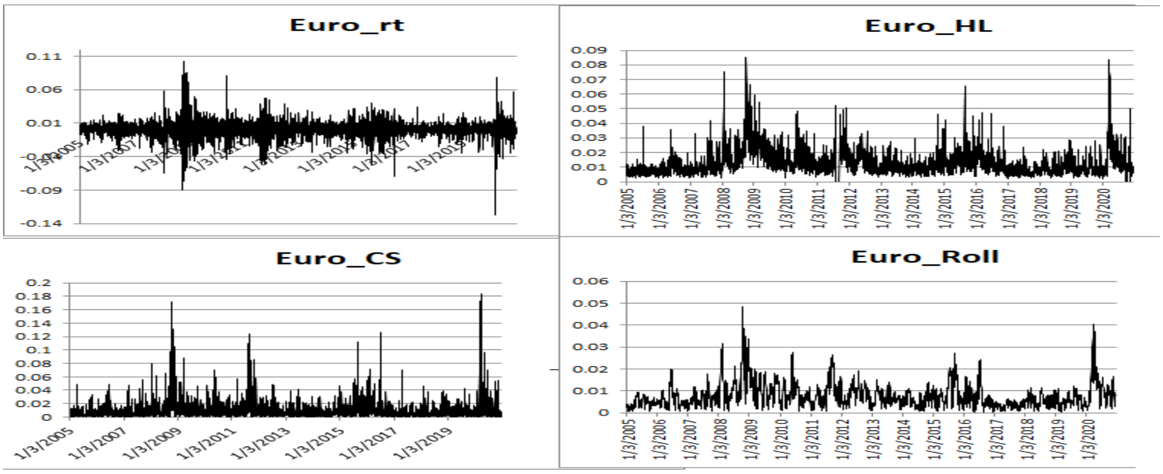

Figure 3: Evolution of returns and liquidity of the Euronext100 index.

fade in the same year. This can be interpreted as the persistence of investors risk aversion. Amihud (2002) asserts that liquidity persists over time, meaning that if a market is now illiquid, it is less likely to improve quickly.

	EURO_Rt	EURO_CS	EURO_HL	EURO_Roll
Mean	0.000124	0.009461	0.012450	0.007975
Median	0.000437	0.005640	0.010194	0.006517
Maximum	0.103216	0.183788	0.085328	0.048585
Minimum	-0.127517	0.000000	0.000000	7.66E-05
Std. Dev.	0.012589	0.013084	0.008673	0.005717
Skewness	-0.397412	4.961394	2.469839	1.952500
Kurtosis	12.69135	42.47103	13.27366	8.574594
Jarque-Bera	16409.06	287458.6	22551.46	8039.339

Table 5: Descriptive statistics on returns and liquidity of the Euronext100 index.

	EURO_CS	EURO_HL	EURO_Roll
EURO_CS	1,000	0,369	0,246
EURO_HL	0,369	1,000	0,381
EURO_Roll	0,246	0,381	1,000

Table 6: Correlations between returns and liquidity of the Euronext100 index.

Table 5 shows the descriptive statistics of the returns and liquidity of the Euronext100. Liquidity is measured by the CS, HL and Roll indicators. Unlike the distribution of returns, the distribution of liquidity for the Euronext100 index is right skewed.

The Jarque-Bera statistic asymptotically follows a $khi - squared$ distribution with 2 degrees of freedom. For $\alpha = 5\%, \chi^2_{0.05}(2) = 5.99$, all series have a $Jarque - Bera$ statistic greater than 5.99, the hypothesis of normality is therefore rejected. A correlation analysis between the different indicators of liquidity of the Euronext100 index is listed in Table 6. We see that the liquidity measures move in the same direction.

4.2 TAR estimation

The first step is to estimate the appropriate autoregressive model for the returns of each of the European stock market indices (AEX, BFX, CAC40, DAX, FTSE, IBEX, SMI). Then, we build for each index the threshold model with sharp transition. The transition variable is the liquidity of the European market as a whole represented by the Euronext100 index. This liquidity is measured in three different ways, and this will allow us to compare both the value of the estimated thresholds between the different stock market indices and between the different liquidity measures. For each series, we verify stationarity by using the PP test following the three models described in equations (7), (8) and (9). We reject the null hypothesis of the existence of a unit root in each model for both 5% and 10% risk levels. This leads us to assert that these series are stationary.
The application of the RESET test indicates that the p-values associated with the F-stat and the Log likelihood ratio are lower than 5%. We reject the null hypothesis: our linear model is misspecified. We assume that for returns, a regime-switching model might be more appropriate. The linear model has many limitations characterized by the non-robustness of the model, the presence of heteroskedasticity, the autocorrelation of the residuals and the presence of breakpoints that lead us to believe that the returns are non-linear. The results of the identification of autoregressive models of the index returns as well as the different breakpoints estimated from the liquidity variable are listed in Table 7. We note that four indices have a single break date while the AEX index has two break dates. In general, the transition thresholds are lower for exchanges with lower trading volume in euros (FTSE, IBX) and are higher for indices with high trading volume (CAC40, DAX)(see Table 7).

This result suggests a high threshold value for the transition from high to low liquidity. In resilient markets, liquidity shocks are absorbed gradually, without significantly affecting prices. When a shock to the market dries up liquidity, participants become increasingly concerned about the market's ability to reconstitute liquidity. Weakly resilient markets, where liquidity shocks are absorbed very slowly, impede trading

		AEX	BFX	CAC40	DAX	FTSE	IBEX	SMI
Transition variable	Breackdate	10/17/2008 6/26/2013		12/09/2008	3/23/2009	11/29/2016		03/11/2009
Euro_CS	TAR model threshold	0.01574336	0.01628864	0.015962	0.01600916	0.01455536	0.01079798	0.01010449
Euro_HL		0.01680356	0.01642202	0.01680356	0.01922726	0.01709983	0.01680356	0.01922726
Euro_Roll		0.01086033	0.01086033	0.011473488	0.01276025	0.008683775	0.009144933	0.01103319

Table 7: Estimation of autoregressive models and breakdates.

because transactions become more expensive to execute when bid-ask spreads are wider. Similarly, a highly resilient market, with a strong ability to absorb liquidity shocks gradually, attracts market participants and thus promotes trading. The CS and HL liquidity measures (calculated over 1 and 2 days) have higher thresholds than those calculated with the Roll measure (calculated over a longer period).
Detailed estimates for each regime-switching model are provided in Table 8 below. After the autoregressive model is estimated for each stock index, the threshold model with sharp transition is estimated. The two regimes are determined on the basis of the transition variable "market liquidity" (represented by three proxies: Euro_CS, Euro_HL and Euro_Roll). When the liquidity index is below or above a certain threshold, we are respectively in a regime of high or low market liquidity. Indeed, the higher the value of the proxy (CS, ROLL, HL), the less liquid the market is. The analysis is therefore carried out by defining two groups of observations: on the one hand, observations for which the market is in a period of high liquidity (regime 1), and on the other hand, observations for which the market is in a phase of low liquidity (regime 2).
After comparing the different thresholds for the different market indices whose transition variable is the liquidity measure, we look closely at the effect of each measure in detecting the threshold within the same market. First of all, we notice that the threshold detected by the HL proxy is higher than that of CS and ROLL for all market indices. For the AEX market returns, we are in the presence of two regimes, when the liquidity measured by the CS proxy on the European EURONEXT market is strictly lower than 1.573% the return depends negatively on its third and fifth lag, while if the CS liquidity is higher than this threshold, the AEX return depends positively on its third, fourth and fifth lag. In other words, in the presence of high liquidity in the EURONEXT market, the AEX return has an opposite sign to past returns. This confirms the findings of Assoil et al. (2021). On the other hand, the use of the HL and ROLL proxies results in a higher threshold with a significantly negative regime 2 on average. From these results, it is clear that the index returns follow autoregressive processes regardless of the liquidity cycle. The coefficients on lagged returns are mostly significant. These results differ from those of Just and Echaust (2020) and

Leirvik et al. (2017) who find no relationship between returns and market liquidity. The coefficients are positive in regime 1 and negative in regime 2. In other words, the returns of European indices are therefore negatively autocorrelated in periods of low market liquidity. This confirms the work of Pástor and Stambaugh (2003), Hameed et al. (2010), and Anthonisz and Putniņš (2016). The negativity of the coefficients of the returns in regime 2 and their positivity in regime 1 is observed for the Roll measure but only for the FTSE, IBX, and AEX indices. This important role of liquidity in the dynamics of returns confirms previous results observed on the US market ((Amihud, 2002), (Goyenko et al., 2006)). The results are consistent with Musneh et al. (2021) who find a significant effect of liquidity risk on the returns of industrial and service sector firms on the Malaysian stock market.

We also obtain the same conclusions, concerning this comparison of proxies for the BFX, CAC40, IBEX stock indices. However, if we use the CS measure as a proxy for liquidity, the above result is valid only for the DAX index. In general, in a period of excess liquidity, which can be attributed largely to the monetary easing policy, investors are increasing their demand for high return assets in order to optimize the risk/return trade-off in their portfolios.

5 Conclusion

The purpose of the study is to analyze the variation of the returns of the main European stock market indices according to the state of market liquidity. Liquidity is measured by three different proxies that are closely related to the bid-ask spread. After having verified the stationarity of the variables, we applied the TAR modeling on index data using a history of 4165 observations, over the period 2005-2020 including four periods of recession: the 2008 subprime crisis, the 2011 debt crisis, the 2016 recession and more recently the market downturn due to the Covid19 pandemic. The main finding of this study is that returns do not vary in the same way in high liquidity and low liquidity regimes. We have used several measures as indicators of liquidity in order to better understand the notion of liquidity. As there is no consensus in the academic world on the measure of liquidity, other dimensions of liquidity could be included (such as resilience, thickness, immediacy). Modeling by STAR processes and Markov changes could provide more explanations on the dynamics of returns and liquidity.

AEX						
	Euro_CS		Euro_HL		Euro_Roll	
	EURO_CS < 0.0157	EURO_CS≥ 0.0157	EURO_HL < 0.0168	EURO_HL ≥ 0.0168	EURO_Roll < 0.0108	EURO_Roll ≥ 0.0108
	3501 obs	659 obs	3290 obs	870 obs	3272 obs	888 obs
AEX(-3)	-0.0405**	0.2837***	0.0193	0.0718***	0.0242	0.0676***
	(0.0168)	(0.0192)	(0.0227)	(0.0210)	(0.0236)	(0.0204)
AEX(-4)	-0.0195	0.3537***	-0.0331	0.0950***	-0.0033	0.0613***
	(0.0160)	(0.0199)	(0.0227)	(0.0210)	(0.0237)	(0.0203)
AEX(-5)	-0.0419**	0.2974***	-0.0030	-0.0647***	0.0143	-0.0733***
	(0.0166)	(0.0195)	(0.0229)	(0.0209)	(0.0240)	(0.0201)
SCR	0.671312		0.668039		0.669527	

BFX						
	Euro_CS		Euro_HL		Euro_Roll	
	EURO_CS < 0,0162	EURO_CS≥ 0,0162	EURO_HL < 0,0164	EURO_HL ≥0,0164	EURO_Roll < 0,0108	EURO_Roll ≥ 0,0108
	3535 obs	627 obs	3246 obs	916 obs	3274 obs	888 obs
BFX(-1)	-0,0748***	0,2406***	0,0023	0,0624***	0,0325	0,0428**
	(0,0191)	(0,0258)	(0,0234)	(0,0207)	(0,0224)	(0,0214)
BFX(-3)	-0,0216	-0,0841***	0,0021	-0,0739***	0,0254	-0,0877***
	(0,0192)	(0,0256)	(0,0224)	(0,0215)	(0,0232)	(0,0208)
SCR	0,637412		0,651069		0,650489	

CAC40						
	Euro_CS		Euro_HL		Euro_Roll	
	EURO_CS < 0.0159	EURO_CS ≥ 0.0159	EURO_HL < 0.0168	EURO_HL ≥ 0.0168	EURO_Roll < 0.0114	EURO_Roll ≥ 0.0114
	3515 obs	645 obs	3290 obs	870 obs	1624 obs	2536 obs
CAC40(-1)	-0,1321***	0,1582***	0,0285	-0,0274	-0,0495	-0,0230
	(0,0192)	(0,0258)	(0,0228)	(0,0213)	(0,0371)	(0,0170)
CAC40(-3)	-0,0205	-0,0626	0,0039	-0,0720***	0,0611*	-0,0538***
	(0,0193)	(0,0254)	(0,0219)	(0,0220)	(0,0382)	(0,0169)
CAC40(-5)	-0,0365*	-0,0711***	-0,0008	-0,0748***	0,0110	-0,0475***
	(0,0189)	(0,0265)	(0,0219)	(0,0220)	(0,0389)	(0,0169)
SCR	0,7677		0,7810		0,7813	

DAX						
	Euro_CS		Euro_HL		Euro_Roll	
	EURO_CS< 0.0160	EURO_CS≥ 0.0160	EURO_HL< 0.0192	EURO_HL≥ 0.0192	EURO_Roll< 0.0127	EURO_Roll≥ 0.0127
	3518 obs	643 obs	3536 obs	625 obs	3536 obs	625 obs
DAX(-1)	0,1047***	0,1776***	0,0192	0,0214	0,0008	-0,0026
	(0,0193)	(0,0254)	(0,0207)	(0,0233)	(0,0203)	(0,0241)
DAX(-4)	0,0032	0,0606**	-0,0372*	0,0955***	-0,0104	0,0570*
	(0,0190)	(0,0264)	(0,0204)	(0,0238)	(0,0206)	(0,0235)
SCR	0,7413		0,7521		0,7548	

IBEX						
	Euro_CS		Euro_HL		Euro_Roll	
	EURO_CS< 0.0107	EURO_CS ≥ 0.0107	EURO_HL < 0.01680356	EURO_HL ≥ 0.0168	EURO_ROLL 0.0091	EURO_ROLL ≥ 0.0091
	3074 obs	1088 obs	3292 obs	870 obs	2904 obs	1258 obs
IBEX(-1)	-0,0648***	0,0930***	0,0183	-0,0056	0,0569**	-0,0256
	(0,0209)	(0,0230)	(0,0224)	(0,0216)	(0,0243)	(0,0201)
IBEX(-3)	-0,0239	-0,0504**	-0,0180	-0,0558**	0,0191	-0,0680***
	(0,0210)	(0,0229)	(0,0212)	(0,0228)	(0,0247)	(0,0199)
SCR	0,8747		0,8799		0,8773	

SMI						
	Euro_CS		Euro_HL		Euro_Roll	
	EURO_CS < 0.0101	EURO_CS ≥ 0.0101	EURO_HL < 0.0192	EURO_HL ≥ 0.0192	EURO_Roll < 0.0110	EURO_Roll≥ 0.0110
	2970 obs	1190 obs	3535 obs	625 obs	3299 obs	861 obs
SMI(-2)	0,0100	-0,1283***	-0,0381*	-0,0887***	-0,0496**	-0,0753***
	(0,0227)	(0,0211)	(0,0204)	(0,0237)	(0,0221)	(0,0216)
SMI(-4)	0,0347*	0,0366*	-0,0341*	0,1331***	-0,0253	0,0935***
	(0,0222)	(0,0216)	(0,0202)	(0,0239)	(0,0221)	(0,0216)
SMI(-5)	-0,0294	-0,0946***	-0,0194	-0,1213***	-0,0077	-0,1090***
	(0,0224)	(0,0213)	(0,0203)	(0,0235)	(0,0224)	(0,0212)
SCR	0,4824		0,4803		0,4821	

FTSE						
	Euro_CS		Euro_HL		Euro_Roll	
	EURO< 0.0145	EURO_CS ≥ 0.0145 EURO_S	EURO_HL < 0.0170	EURO_HL ≥ 0.0170	EURO_ROLL < 0.0086	EURO_OLL≥ 0.0086
	3429 obs	731 obs	3325 obs	835 obs	2795 obs	1365 obs
FTSE(-1)	-0,1090***	0,0966***	-0,0460**	-0,0168	0,0064	-0,0629***
	(0,0193)	(0,0256)	(0,0219)	(0,0220)	(0,0243)	(0,0201)
FTSE(-5)	-0,0353**	-0,0667**	0,0109	-0,1080**	0,0041	-0,0710***
	(0,0192)	(0,0260)	(0,0209)	(0,0230)	(0,0250)	(0,0197)
SCR	0,9994		1,0056		1,0068	

Table 8: Estimation of TAR models.
*** 1% **5% *10% (standard error)

References

Abdi, F. and Ranaldo, A. (2017). A simple estimation of bid-ask spreads from daily close, high, and low prices. *The Review of Financial Studies*, **30**(12):4437–4480.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, **5**(1):31–56.

Amihud, Y. and Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of financial Economics*, **17**(2):223–249.

Amihud, Y. and Mendelson, H. (1991). Liquidity, maturity, and the yields on us treasury securities. *The Journal of Finance*, **46**(4):1411–1425.

Amihud, Y., Mendelson, H., and Lauterbach, B. (1997). Market microstructure and securities values: Evidence from the tel aviv stock exchange. *Journal of Financial Economics*, **45**(3):365–390.

Amihud, Y., Mendelson, H., Pedersen, L. H., et al. (2006). Liquidity and asset prices. *Foundations and Trends® in Finance*, **1**(4):269–364.

Anthonisz, S. A. and Putniņš, T. J. (2016). Asset pricing with downside liquidity risks. *Management Science*, **63**(8):2549–2572.

Assoil, A., Ka, N., and Sadefo-Kamdem, J. (2021). Analysis of the dynamic relationship between liquidity proxies and returns on the french cac 40 index. *SN Business & Economics*, **1**(10):1–23.

Bekaert, G., Harvey, C. R., and Lundblad, C. (2007). Liquidity and expected returns: Lessons from emerging markets. *The Review of Financial Studies*, **20**(6):1783–1831.

Brennan, M. J. and Subrahmanyam, A. (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of financial economics*, **41**(3):441–464.

Chan, H. W. and Faff, R. W. (2003). An investigation into the role of liquidity in asset pricing: Australian evidence. *Pacific-Basin Finance Journal*, **11**(5):555–572.

Chiang, T. C. and Zheng, D. (2015). Liquidity and stock returns: Evidence from international markets. *Global Finance Journal*, **27**:73–97.

Chung, K. H. and Zhang, H. (2014). A simple approximation of intraday spreads using daily data. *Journal of Financial Markets*, **17**:94–120.

Constantinides, G. M. (1986). Capital market equilibrium with transaction costs. *Journal of political Economy*, **94**(4):842–862.

Corwin, S. A. and Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, **67**(2):719–760.

Czauderna, K., Riedel, C., and Wagner, N. (2015). Liquidity and conditional market returns: Evidence from german exchange traded funds. *Economic Modelling*, **51**:454–459.

Datar, V. T., Naik, N. Y., and Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of financial markets*, **1**(2):203–219.

Dinh, M. T. H. (2017). The returns, risk and liquidity relationship in high frequency trading: Evidence from the oslo stock market. *Research in International Business and Finance*, **39**:30–40.

Fong, K. Y., Holden, C. W., and Trzcinka, C. A. (2017). What are the best liquidity proxies for global research? *Review of Finance*, **21**(4):1355–1401.

Foucault, T., Pagano, M., Roell, A., and Röell, A. (2013). *Market liquidity: theory, evidence, and policy*. Oxford University Press.

Goyenko, R., Holden, C., and Ukhov, A. (2006). Do stock splits improve liquidity?

Goyenko, R. Y., Holden, C. W., and Trzcinka, C. A. (2009). Do liquidity measures measure liquidity? *Journal of financial Economics*, **92**(2):153–181.

Hameed, A., Kang, W., and Viswanathan, S. (2010). Stock market declines and liquidity. *The Journal of Finance*, **65**(1):257–293.

Harris, L. (2003). *Trading and exchanges: Market microstructure for practitioners*. OUP USA.

Hasbrouck, J. (2005). Trading costs and returns for us equities: The evidence from daily data.

Hiemstra, C. and Jones, J. D. (1994). Testing for linear and nonlinear granger causality in the stock price-volume relation. *The Journal of Finance*, **49**(5):1639–1664.

Just, M. and Echaust, K. (2020). Stock market returns, volatility, correlation and liquidity during the covid-19 crisis: Evidence from the markov switching approach. *Finance Research Letters*, **37**:101775.

Leirvik, T., Fiskerstrand, S. R., and Fjellvikås, A. B. (2017). Market liquidity and stock returns in the norwegian stock market. *Finance Research Letters*, **21**:272–276.

Lesmond, D. A. (2005). Liquidity of emerging markets. *Journal of financial economics*, **77**(2):411–452.

Lesmond, D. A., Ogden, J. P., and Trzcinka, C. A. (1999). A new estimate of transaction costs. *The Review of Financial Studies*, **12**(5):1113–1141.

Martens, M., Kofman, P., and Vorst, T. C. (1998). A threshold error-correction model for intraday futures and index returns. *Journal of Applied Econometrics*, **13**(3):245–263.

Musneh, R., Karim, A., Rahimie, M., Baburaw, A., Geetha, C., et al. (2021). Liquidity risk and stock returns: empirical evidence from industrial products and services sector in bursa malaysia. *Future Business Journal*, **7**(1):1–10.

Pástor, L. and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political economy*, **111**(3):642–685.

Phillips, P. C. and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, **75**(2):335–346.

Ramsey, J. B. (1969). Tests for specification errors in classical linear least[U+2010]squares regression analysis. *Journal of the royal statistical society series b-methodological*, **31**:350–371.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of finance*, **39**(4):1127–1139.

Smimou, K. (2017). Does gold liquidity learn from the greenback or the equity? *Research in International Business and Finance*, **41**:461–479.

Spiegel, M. (2008). Patterns in cross market liquidity. *Finance Research Letters*, **5**(1):2–10.

Tong, H. (1990). *Non-linear time series: a dynamical system approach*. Oxford University Press.

Tong, H. and Lim, K. S. (2009). Threshold autoregression, limit cycles and cyclical data. In *Exploration Of A Nonlinear World: An Appreciation of Howell Tong's Contributions to Statistics*, pages 9–56. World Scientific.

Van Den End, J. W. and Tabbae, M. (2012). When liquidity risk becomes a systemic issue: Empirical evidence of bank behaviour. *Journal of Financial Stability*, **8**(2):107–120.

Zheng, X. and Su, D. (2017). Impacts of oil price shocks on chinese stock market liquidity. *International Review of Economics & Finance*, **50**:136–174.