Stock Market Liquidity and Economic Cycles

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ABSTRACT

This paper re-examines the relationship between business cycles and market wide liquidity using a non-linear approach in order to capture the non-linear dynamics of macroeconomic series. Applying both the Markov switching-regime and the STAR models and various proxies for liquidity, this study presents weak evidence that liquidity fundamentals act as leading indicators of future economic conditions. Indeed, the significances of the liquidity measure coefficients are not sufficiently constant and steady under both regimes and both econometric approaches and are even less robust to the inclusion of other explanatory financial variables. Hence, the claim that stock market aggregate liquidity could be exploited to predict the future state of the economy may be premature at best.

JEL codes: G12, G17

Keywords: liquidity, business cycles, regime shifts

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1. Introduction

In financial markets, liquidity is defined as the degree to which a security or an asset can be purchased or sold without affecting significantly its price. Because liquidity is a central aspect of stock markets, empirical research in finance has devoted considerable attention to its role in asset pricing. One recent strand of this research focuses on the predictive power of current liquidity on stock market returns and future economic growth. The underlying motivation of this work relies on a central premise of finance theory: that financial markets are "forward looking." Indeed since news and information about future states of the economy are continuously processed by market participants, their views and expectations about upcoming economic conditions as well as their risk preferences and tolerances are also continually affected. Investors hence reallocate their stock portfolios in response to new information to reflect changes in their beliefs which in turn induce them to trade, which causes relative stock prices and stock market indices to fluctuate. Since trading levels are directly related to liquidity, one might expect that aggregate liquidity should also convey information about future macroeconomic conditions. For instance, the "flight to quality" phenomenon, which reflects the "forward looking" nature of equity markets, usually occurs prior to difficult economic times when investors shift their equity allocation to completely move away from the stock market or invest into safer securities to construct portfolios that are more defensive and more focused on wealth preservation. During a "flight to quality" episode, an unusual amount of asset trading occurs in a short period of time which leads to important price changes, greater stock volatilities and causes aggregate liquidity to worsen (illiquidity increases).

In a recent study that examines the relationship between economic growth and financial market illiquidity, Næs *et al.* (2011) use various measures of stock market liquidity and macroeconomic variables, to proxy for future states of the real economy, to investigate the possible leading indicator property of financial market aggregate liquidity on macroeconomic fundamentals. The authors conclude that economic cycles can be predicted by the levels of aggregate illiquidity *i.e.* financial markets liquidity are good leading indicators of economic cycles. Analyzing data for the United States during the period 1947 to 2008, they provide evidence, even after controlling for many factors associated with financial markets, that market-wide liquidity contains leading information about the future state of the real economy. Næs *et al.* (2011) claim that the predictive power of aggregate stock market liquidity on subsequent economic conditions might indicate that "liquidity measures provide information about the real economy that is not fully captured by stock returns." The authors support the conclusion that "liquidity seems to be a better predictor than stock price changes" by referencing Harvey (1988) who argues that stock prices comprise a more complex mix of information that distort the signals from stock returns.

However, Næs *et al.* (2011)'s results are estimated on a problematic framework: the predictability of aggregate liquidity on future outcomes of the real economy is based on a linear regression framework, this despite increasing evidence that macroeconomic variables (such as the ones employed in Næs *et al.* (2011)'s study *i.e.* real GDP, real Investment, real Consumption) follow nonlinear behaviours. Hence their findings may not be robust to a more appropriate model that links aggregate illiquidity and economic cycles.

This paper looks to re-examine Næs *et al.* (2011)'s analysis by using a non-linear approach for analyzing the connection between market-wide liquidity and business cycles, and providing new evidence on whether liquidity, contains critical information about future economic growth and consequently acts as a leading indicator of subsequent economic conditions. This paper uses two important econometric nonlinear models: the Markov switching regimes and smooth transition autoregressive models which are discussed in greater detail in the following sections.

2. Literature Review

The literature that has analyzed the link between stock market aggregate liquidity and economic fundamentals is relatively scant. Levine and Zervos (1998) find that stock market liquidity -- as measured both by the ratios of the value of stock trading to the size of the stock market and to the size of the economy -- is positively and significantly correlated, after controlling for economic and political factors, with present and subsequent rates of economic growth, capital accumulation, and productivity growth. Gibson and Mougeot (2004) show that over the 1973 to 1997 period, the U.S. stock market liquidity risk premium is linearly associated to an “Experimental Recession Index”. Eisfeldt (2004) presents a model in which liquidity fluctuates with real fundamentals such as economic productivity and investment.

One strand of work that is related to this study has analyzed whether aggregate order flow in financial markets contain valuable information about future macroeconomic conditions.

Beber *et al.* (2011) for instance investigate, over the period 1993 to 2005, the predictive power of financial markets orderflow movements across equity sectors on economic cycles. The authors point out two observations: 1) empirical literature shows that asset prices and returns are good predictors of business cycles and 2) order flow is the process by which stock prices vary. Synthesizing these two observations. Beber *et al*. (2011) thus question how order flow itself is associated with contemporaneous and subsequent economic conditions. Their findings show that an order flow portfolio constructed on cross-sector movements is able to forecast next quarter economic conditions.

Evans and Lyons (2008) present evidence that foreign exchange order flows predict future macroeconomic factors such as money growth, inflation and output growth; and future exchange rates. Finally, Kaul and Kayacetin (2009) provide evidence that market wide order flow on the New York Stock Exchange and order flow differentials (the difference in the order flow between large cap and small cap firms) can forecast variations in industrial production and U.S. real GDP.

3 Liquidity Measures, Macroeconomic and Financial Variables

3.1 Liquidity Measures

In order to construct quarterly aggregate liquidity measures, data on all ordinary common shares traded on the New York Stock Exchange (NYSE) during the period January 1947 through December 2012 is retrieved from the Center for Research in Security Prices (CRSP). The data consists of stock prices, returns, and trading volume for each common share and covers more than 65 years and 10 recessions.

Liquidity is an unobservable factor and has several aspects that cannot be assessed in a single measure; to address these issues numerous studies have developed diverse liquidity proxies. This study focuses on the market wide liquidity proxies, described below, that are analyzed in Næs *et al.* (2011) *i.e.* the Roll (1984) implicit spread estimator, the Amihud (2002) illiquidity ratio, and Lesmond, Ogden, and Trczinka (1999) measure (LOT). The relative spread (RS) measure is dropped from the analysis since the high frequency microstructure data that are needed to measure effective and quoted spreads are not always obtainable for the sample period prescribed for the analysis.

The three liquidity measures are computed on a quarterly basis for each common share. Aggregate liquidity proxies are obtained by taking the equally weighted average of the liquidity measures of the individual securities each quarter.

3.1.1 Roll Liquidity Measure (1984)

The Roll (1984) measure uses a model to estimate the effective spread based on the time series properties of observed market prices *i.e.* the serial covariance of the change in price.

Let V_t denote the unobservable equilibrium value of the stock which evolves as follows on day t:

$$V_t = V_{t-1} + \varepsilon_t \tag{1}$$

where ε_t is the unobservable innovation in the true value of the asset between transaction $t-1$ and t. ε_t is serially uncorrelated with a mean-zero and constant variance σ_ε^2.

Let P_t denote the last observed transaction price of the same given asset on day t, oscillating between bid and ask quotes that depend on the side originating the trade. The observed price can be described as follows:

$$P_t = V_t + \frac{1}{2} S Q_t, \tag{2}$$

where S denote the effective spread, and Q_t is an indicator for the last trade that equals, with equal probabilities, +1 for a transaction initiated by a buyer and −1 for a transaction initiated by a seller. Q_t is serially uncorrelated, and is independent of ε_t.

Taking the first difference of Equation (3.2) and incorporating it in Equation (3.1) yields

$$\Delta P_t = \frac{1}{2} S \, \Delta Qt + e_t \tag{3}$$

where Δ is the change operator.

Using this specification, Roll (1984) demonstrates that the serial covariance is

$$\operatorname{cov}(\Delta P_t, \ \Delta P_{t-1}) = \frac{1}{4} S^2 \tag{4}$$

from which we obtain:

$$S = 2\sqrt{-\operatorname{cov}(\Delta P_t, \, \Delta P_{t-1})} \tag{5}$$

The formula above is only defined when Cov<0. When the sample serial covariance is positive (cov>0), a default numerical value of zero is substitute into the specification. Equation (3.5) specifies the measure of spread proposed by Roll (1984). Roll's estimator is hence calculated by estimating the autocovariance and solving for S. The reasoning behind Equation (3.5) is that the more negative the return autocorrelation is, the lower the liquidity of a given stock will be.

3.1.2 Lesmond, Ogden, and Trzcinka (1999) Liquidity Measure

Using only the time series of daily security returns, Lesmond, Ogden, and Trzcinka (1999) develop a proxy for liquidity (*LOT*). The measure is the proportion of days with zero returns:

$$LOT = (\text{\# of days with zero returns})/\text{T}, \tag{6}$$

where "T" is the number trading days in a month.

The intuition behind the LOT measure is that if the value of the public and private information is lower than to the costs of trading on a particular day, fewer trades (or no trades) will occur, and hence prices will no change from the previous day (zero return). The authors argue that the frequency of zero returns is directly related to both the quoted bid-ask spread and Roll's measure of the effective spread.

3.1.3 Amihud (2002) Liquidity Measure

Amihud (2002) proposes a liquidity measure which estimates the price impact of trading based on the daily price response associated with one dollar of trading volume. The measure is computed as the daily ratio of absolute stock return to dollar volume:

$$Illiq_i = \frac{|r_i|}{DVOL_i} \tag{7}$$

where r_i is a daily stock return of stock *i*, and $DVOL_i$ is daily dollar volume.

Amihud (2002) asserts that there are finer and better measures of illiquidity, such as the bid-ask spread (quoted or effective) or transaction-by-transaction market impact, but these measures necessitate a great deal of microstructure data that are not obtainable in many stock markets and even if available, the data do not cover long lasting periods of time. Hence, Amihud (2002) stresses that this measure allows constructing long time series of illiquidity that are needed to test the effects over time of illiquidity on ex ante and contemporaneous stock excess return.

Figure 1 depicts the relationship between the time series of the three liquidity measures and recession periods (grey bars) according to the National Bureau of Economic Research (NBER). The figure suggests that market wide liquidity deteriorates (liquidity measures increases) ahead of several recessions.

Figure 1

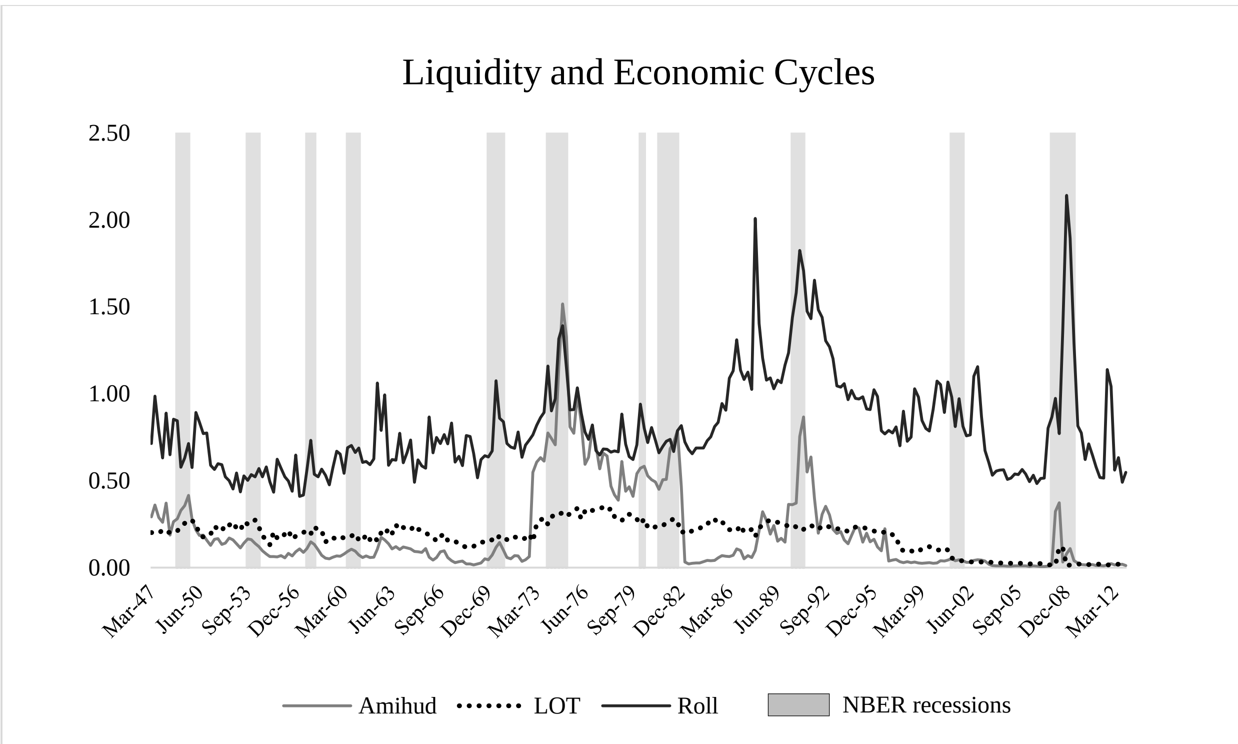

Figure 1. Liquidity and Economic Cycles. The figure depicts time series of the Amihud (2002), LOT (1999) and Roll (1984) illiquidity measures for the United States during the period 1947 to 2012. NBER recession periods are represented by the grey shaded areas. Higher values of the liquidity measures indicates lower levels of aggregate liquidity.

3.2 Macroeconomic and Financial Variables

The following standard set of macroeconomic variables commonly used in the empirical finance and economic research is employed to proxy for the US economic condition during the period

January 1947 through December 2012: real GDP (*RGDP*), unemployment rate (*UE*), real consumption (*RCONS*), and real investment by the private sector (*GPDI*).

Several financial variables that have proven in the literature to be leading indicators of the trend of the state of the economic are also incorporated in the analysis as control variables: The market premium (er_m) which is computed as the return on the value-weighted S&P500 market index in excess of the three-month Treasury bill rate and market volatility (*Vola*) which is computed as the quarterly standard deviation of daily returns in the sample. The Credit spread (*Cred*) factor, calculated as the spread between Moody's Baa credit index1 and the rate on a 30-year U.S. government bond and the term spread variable (*Term*), which corresponds to the spread between the yield on a 10-year Treasury bond and the yield on the three-month Treasury bill are also included in the analysis.

4. The Regime-Switching Models

There is growing evidence that many financial and economic indicators tend to behave differently during high and low economic cycles and that, consequently, the empirical models of these economic time series are characterized by parameter variability. This has generated considerable interest in time-varying parameter models. For instance, GDP growth rates typically stay around a higher level and are more persistent during expansions, but they fluctuate at a relatively lower level and less persistent during contractions. For financial series, bear markets are usually more volatile than bull markets which implies that prices go down faster than they go up. This means that we

[1] The Moody's long-term corporate bond yield index comprises seasoned corporate bonds with maturities close to 30 years.

can expect the variance of bear markets to be higher than the bull markets. For such series data, it would not be realistic to assume a single, linear model to model these distinct dynamics.

Roughly speaking, two main classes of statistical models have been proposed which reinforce the notion of existence of different regimes. The first popular time-varying parameter model is the Markov regime switching framework approach of Hamilton (1989) to modeling macroeconomic and financial data. It has been employed to study the dynamic of GNP growth rates (Hamilton (1989)), real interest rates (Garcia and Perron (1996)), stock returns (Hamilton and Susmel (1994)) and corporate bond default risk (Giesecke et al. (2011)). The second model is the smooth-transition regression model which has been employed to analyze non-linearities in UK consumption and industrial production (Öcal and Osborn (2000)), non-linear relationships between US GNP growth and leading indicators (Granger and Teräsvirta (1993)) and between stock returns and business cycle variables (McMillan (2001)).

4.1 Hamilton's (1989) Regime-Switching Model

The Hamilton (1989) Regime-Switching Model assumes that the behaviour of certain macroeconomic or financial indicators changes as a result of changes in economic activity. However, the state of economic activity, which is unobservable and which determines the process that generates the observable dependent variable (in this study the macroeconomic variables), is inferred through the observed behavior of the dependent variable. In the original Hamilton model (1989), it was assumed, as well as in this study, that there were two possible states of economic phases (regimes), corresponding to the condition of an economy (prosperity vs. recession).

In this study, the two-state Markov-chain regime-switching model is employed to evaluate the effects of different liquidity measures in explaining the growth dynamic in several macroeconomic variables for the United States for the period January 1947 to December 2012.

Let *y* denote the macroeconomic variable for quarter *t* and for which its historical behavior can be described by the following econometric specification:

$$y_t = a_t + \sum_{k=1}^{N} b_k X_{k,t-1} + \varepsilon_t \tag{8}$$

where X_{t-1} is a *k*-vector of explanatory variables and the b_k terms are the corresponding factor loadings. The intercept term a_t follows a two-state Markov chain, taking values a_1 and a_2, with the probability π_{ij} of switching from state *i* to state *j* is given by the matrix:

$$\begin{bmatrix} \pi_{11} & \pi_{21} \\ \pi_{12} & \pi_{22} \end{bmatrix}$$

Moreover let ξ_{it} represent the probability of being in state *i* in quarter *t* conditional on the data and η_{it} the densities under the two regimes which are given by:

$$\eta_{it} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-\left(y_t - a_{jt} - \sum_{k=1}^{N} b_k X_{k,t-1} \right)^2}{2\sigma^2} \right) \tag{9}$$

where σ represents the volatility of the residuals ε_t which are assumed to follow an independent and identically distribution (*iid*) to allow performing standard maximum log likelihood functions.

All *i* and *j* are then sum up to compute the likelihood function f_t,

$$f_t \quad = \sum_{i=1}^{2}\sum_{i=1}^{2}\pi_{ij}\,\xi_{i,t-1}\eta_{it} \tag{10}$$

The state probabilities are then re-estimated by the recursive specification

$$\xi_{i,t} = \frac{\sum_{i=1}^{3}\pi_{ij}\xi_{i,t-1}\eta_{it}}{f_t} \tag{11}$$

The log likelihood function for the data can hence be estimated by summing the log likelihoods for each date by using standard maximum likelihood procedures.

4.2 The Smooth-Transition Regression Model

The other popular model that has been extensively used in the past two decades to modelling nonlinearities in the dynamic properties of many economic time series and for summarizing and explaining cyclical behavior of macroeconomic data and business cycle asymmetries is the Smooth Transition Autoregressive Model (STAR), which was developed by Teräsvirta (1994) and Granger and Teräsvirta (1993).

The smooth transition autoregressive (STAR) model for a univariate time series y_t, is given by:

$$y_t = \alpha_0 + \sum_{i=1}^{p}\alpha_0 y_{t-i} + F(\xi_t,\gamma,c)\left[\beta_0 + \sum_{i=1}^{p}\beta_i y_{t-i}\right] + \varepsilon_t \tag{12}$$

where $F(\xi_t,\gamma,c)$ is a transition function which controls for the switch from one regime to the other and is bounded between 0 and 1. The scale parameter $\gamma > 0$ is the slope coefficient that determines the smoothness of the transition: the higher it is the more abrupt the change from one extreme regime to the other ξ_t. The location or threshold parameter between the two regimes is represented by c and ξ_t is called the transition (threshold) variable, with ξ_t = y_{t-d} (d a delay parameter).

Two popular selections for the transition function are the logistic function (LSTAR) and the exponential function (ESTAR). The LSTAR function is specified as:

$$F = [1 + \exp(-\gamma(\xi_t - c))]^{-1} \tag{13}$$

while the ESTAR function is specified as:

$$F = 1 - \exp(-\gamma(\xi_t - c)^2) \tag{14}$$

The main difference between these two STAR models relies on how they describe macroeconomic series dynamic behaviour. The LSTAR model reflects the asymmetrical adjustment process that usually characterize economic cycles: a sharper transition and sharp recovery following business cycle troughs compare to economic peaks. In contrast, the ESTAR specification suggests symmetrical adjustment dynamic.

To determine the adequate transition function to apply to the data, Terasvirta (1994) suggests a model selection procedure which is explained and applied in the section 3.5 (Empirical Results).

While an exogenous variable could be employed as the transition variable, in this paper as per the majority of research studies using STAR models, the dependent variable (the macroeconomic proxies) plays this role and d equals one, meaning that the first lagged value of the macroeconomic variable investigated acts at the threshold variable.

In the Smooth Transition Autoregression (STAR) all predetermined variables are lags of the dependent variable. An extension to the STAR model is the smooth transition regression (STR) model which is an amendment to the STAR model that allows for exogenous variables $x_{1t},\ldots, x_{kt}$ as additional regressors. In this study, the applied STR model includes other exogenous factors the *i.e.* the liquidity measures and the factors *Term*, *Cred*, *Vola*, er_m. The standard method of estimation of STR (STAR) models is nonlinear least squares (NLS), which is equivalent to the quasi-maximum likelihood approach.

Two interpretations of a STR (STAR) model are possible. First, the STR model may be thought of as a regime-switching model that allows for two regimes, associated with the extreme values of the transition function, $F(\xi_t; y, c) = 0$ and $F(\xi_t; y, c) = 1$, where the transition from one regime to the other is smooth. The regime that occurs at time t is determined by the observable variable ξ. Second, the STR model can be said to enable a continuum of states between the two extremes. The key advantage in favour of STR models is that changes in some economic and financial aggregates are influenced by changes in the behaviour of many diverse agents and it is highly improbable that all agents respond instantaneously to a given economic signal. For instance, in financial markets, with a considerable number of investors, each switching at different times (probably caused by heterogeneous objectives), a smooth transition or a continuum of states between the extremes seems more realistic.

Both the Hamilton's (1989) Markov switching regime model and the smooth transition autoregressive model assume that the series under examination are stationary. Indeed these specifications investigate time series by distinguishing non-stationary or stationarity linear systems from stationary nonlinear ones.

Note that while the empirical literature shows that all studies related to economic regimes employ the first difference of the variables under consideration to make them stationary, some studies investigate, in addition, the levels of macroeconomic time series for robustness purposes. Implementing this approach in this essay, the results question the conclusion that stock market liquidity may act as a leading indicator to economic cycles.

5. Empirical Results

In order to investigate the link between stock market liquidity and business cycles in a non-linear specification, the dependent variables, *i.e.* the macroeconomic proxies *dRGDP*, *dCONS*, *dGPDI* and *dUE,* need to be tested to verify whether linearity should be rejected or not. Terasvirta (1994)'s model allows to perform this test by doing a Lagrange multiplier test for linearity versus an alternative of LSTAR or ESTAR in a univariate autoregression:

$$y_t = \beta_0 + \sum_{j=1}^{p} \beta_{1j} y_{t-j} + \sum_{j=1}^{p} \beta_{2j} y_{t-j} y_{t-d} + \sum_{j=1}^{p} \beta_{3j} y_{t-j} y_{t-d}^2 + \sum_{j=1}^{p} \beta_{4j} y_{t-j} y_{t-d}^3 + e_t \tag{15}$$

As mentioned previously, in this study both the lags value p and the delay parameter d equals 1[2]. The null hypothesis of linearity is therefore $\beta_2 = \beta_3 = \beta_4 = 0$. If the null hypothesis is rejected, the next step is to choose between LSTAR and ESTAR models by a sequence of nested tests:

H_{01} is a test of the first order interaction terms only: $\beta_2 = 0$

H_{02} is a test of the second order interaction terms only: $\beta_3 = 0$

H_{03} is a test of the third order interaction terms only: $\beta_4 = 0$

[2] There exists no econometric specification that allows to precisely determine the value of the delay parameter *p*. Most of the literature related to non-linear STAR models uses *p* = 1.

H_{12} is a test of the first and second order interactions terms only: $\beta_2 = \beta_3 = 0$

The decision rules of choosing between LSTAR and ESTAR models are suggested by Teräsvirta (1994): Either an LSTAR or ESTAR will cause rejection of linearity. If the null of linearity is rejected H_{12} and H_{03} become the appropriate statistic if ESTAR is the main hypothesis of interest: If both H_{12} is rejected and H_{03} is accepted, this may be interpreted as a favor of the ESTAR model, as opposed to an LSTAR.

Table 1 presents the results of the Teräsvirta (1994) linearity test performed on the macroeconomic proxies of interest which show that the specification rejects the hypothesis of linearity for three variables: *dRGDP*, *dGPDI* and *dCONSR*. However, the hypothesis of linearity cannot be rejected for the unemployment rate (*dUE*) proxy triggering the exclusion of this variable from the analysis. These findings are important since they provide evidence that Næs *et al.* (2010), by using a linear framework, improperly analyzed the link between stock market liquidity and the variables *dRGDP*, *dGPDI* and *dCONSR* since these macroeconomic proxies behave according to non-linear behaviours. Moreover, hypothesis H_{12} is rejected and hypothesis H_{03} is not rejected simultaneously only for the variable *dGPDI* which implies that the LSTAR model is the appropriate specification for the variables *dRGDP* and *dCONSR* and that the ESTAR model will be applied to investigate the variable *dGPDI*.

Table 1. – Tests of Linearity and LSTAR vs ESTAR Models

This table shows the results of the Teräsvirta (1994)'s approach to first test for linearity of the dependent variable. If the hypothesis of linearity is rejected and H_{03} is accepted while H_{12} is rejected then the specification will point toward an ESTAR instead of a LSTAR model.

	dRGDP		*dUE*		*dGPDI*		*dCONSR*	
	F-Value	Significance	F-Value	Significance	F-Value	Significance	F-Value	Significance
Linearity	6.733	0.0002	0.073	0.9742	2.607	0.0522	18.258	0.0000
H_{01}	8.236	0.0045	0.005	0.9418	3.746	0.0540	16.619	0.0001
H_{02}	7.944	0.0052	0.159	0.3897	4.051	0.0452	17.966	0.0000
H_{03}	3.625	0.0580	0.056	0.8128	0.011	0.9162	16.808	0.0001
H_{12}	8.202	0.0004	0.107	0.8978	3.921	0.0210	17.955	0.0000

Table 2 provides descriptive statistics for the liquidity measures of interest as well as for the macroeconomic variables. Panel A shows that the mean of the liquidity measures *Amihud*, *LOT* and *Roll* investigated in this study are over the period 1947 through 2012 are 1.040, 0.188 and 0.768 respectively. Sub-period averages reveal that all three liquidity measures were the lowest for the last time span of the period covered *i.e.* 2000 to 2012. This implies that stocks are more liquid in the most recent era.

Correlations between the liquidity measures (Panel B) present evidence of a strong positive correlation between *Amihud* and *LOT* (0.63). The *Roll* liquidity is more highly correlated with the *Amihud* liquidity proxy (0.30) than with the *LOT* measure (0.10).

Panel C and D of Table 2 presents the corresponding statistics for the macroeconomic proxies. The sub-period 2000-2012 has generated the lowest economic growth according to all three economic variables. This relative underperformance of the U.S. economy during that time period comparatively to previous ones may be explained by the severe economic recession that has hit the nation in 2008 and 2009 and which was not followed by a usually observed sharp economic recovery.

Finally, Panel D shows that the three macroeconomic proxies during the period analyzed are highly and positively correlated since 70% of U.S. GDP is due to consumer spending[3] and that private fixed investment represents 15% of the U.S. economy.[4]

[3] http://research.stlouisfed.org/fred2/graph/?g=hh3

[4] http://data.worldbank.org/indicator/NE.GDI.FTOT.ZS

Table 2
Descriptive Statistics

Panels A and B exhibit descriptive statistics for the U.S. liquidity measures for the period 1947 through 2012. The liquidity measures analyzed are the Lesmond, Ogden, and Trzcinka (1999) (*LOT)*, the Amihud (2002) *(Amihud)* and the Roll (1984) implicit spread estimator (*Roll*). Panel A present the mean and median of the liquidity measures, and average liquidity measures for different subperiods. Panel B shows correlation coefficients between the liquidity measures. Panels C and D show equivalent statistics for U.S. macroeconomic proxies *i.e.* real GDP growth (*dRGDP*), growth in private investment (*dGPDI*), and real consumption growth (*dCONSR*).

Panel A: Descriptive Statistics, Liquidity Measures

	Mean	Median	Means, Subperiods					
			1947–59	1960–69	1970–79	1980–89	1990–99	2000–12
Amihud	1.040	0.919	1.465	0.762	1.246	1.397	1.132	0.252
LOT	0.188	0.200	0.209	0.176	0.263	0.239	0.192	0.030
Roll	0.768	0.733	0.592	0.378	0.822	0.929	1.081	0.792

Panel B: Correlation Coefficients, Liquidity Measures

	LOT	*Amihud*
Amihud	0.63	
Roll	0.10	0.30

Panel C: Descriptive Statistics, Macroeconomic Variables

	Mean	Median	Means, Subperiods					
			1947–59	1960–69	1970–79	1980–89	1990–99	2000–12
dRGDP	0.811	0.777	0.939	1.025	0.861	0.789	0.811	0.444
dGPDI	0.842	1.009	0.880	1.073	0.834	0.851	0.886	0.533
dCONSR	0.895	0.832	0.865	0.973	1.206	0.721	1.471	0.147

Panel D: Correlation Coefficients, Macroeconomic Variables

	dCONSR	*dRGDP*
dRGDP	0.59	
dGPDI	0.24	0.79

The main results of this study are presented in Tables 3 through 8 for the Markov switching-regime model and Tables 9 through 14 for the STAR framework. The models applied allow to determine whether changes in the macro proxy y_{t+1} (*dRGDP*, *dCONSR* and *dGPDI*) over quarter $t + 1$ can be estimated by changes in the independent variables in quarter *t*. LIQ_t is the liquidity measure (*Amihud*, *Roll* and *LOT*) and the variables *Term*, *Cred*, *Vola*, er_m, and the lag of the dependent variable y_t represent the control variables included in the models. Three different specifications are investigated. In the first, y_t is regressed on its lag and the liquidity measure; in the second, y_t is regressed on the previous two explanatory variables and the variables *Term* and *Cred*; in the third, the variables *Vola and* er_m are added to the previous four.

The findings, using the Markov switching-regime model, for the relationship between the dependent variable and the Amihud (2002) liquidity measure as well as the other explanatory variables under the economic expansion regime and the economic contraction regime are presented in Tables 3 and 4 respectively. Results show that the coefficients for the Amihud (2002) measure are not significant for all three macroeconomic variables when the economy is going toward an expansion phase (Table 3). When the economy is moving towards a recession the coefficient of the Amihud (2002) measure becomes significant and negative for the variables *rGDP* and *rCONSR* when the dependent variable is regressed on this liquidity measure and the lag of the explained variable: this means that when aggregate liquidity worsens (liquidity measures increase) growth in the macroeconomic proxies decline which explain the negative coefficients. However, these coefficients remain robust to the inclusion of the bond variables *Term* and *Cred* but not to the adding of the equity variables *Vola* and er_m (3rd specification).

The corresponding results for the Amihud (2002) liquidity measure using the LSTAR model (Tables 9 and 10) indicate that this measure has even less predictive power for the subsequent quarter of the state of the economy. Indeed, the coefficients are again all not significant for the growth phase of the economy but the findings related to the economic contraction phase show that only the specification using the liquidity measure and the lag of the dependent variable provides a significant coefficient that however doesn't stay robust to the inclusion of other explanatory variables.

Using the Markov switching-regime, the Roll (1984) liquidity measure also has no forecasting power for the subsequent quarter when the state of the economy is heading toward a recession (Table 5): the coefficients of this liquidity measure are all insignificant at the 5% level except for *dRGDP* in the third specification. In the expansion phase of the business cycle (Table 6), the *Roll* variable presents a more forecasting prowess as the coefficients on this liquidity measure become significant for all three macroeconomic proxies under the first and second specifications. However, using all control variables (third specification) only the coefficient for *dGDPR* remains distinguishable from zero.

The LSTAR model (Tables 11 and 12) estimates demonstrate that *Roll* possesses a strong ability to predict future growth of the *dGPDI* variable as represented by the significant coefficients of this liquidity measure for all three specifications and for both the expansion and contraction regimes. Coefficients are also different from zero under the recession phase (Table 6) for *dRGDP* and *dCONSR* in the second regime but both these significances disappear when including the control variables related to the stock market *i.e. Vola* and er_m.

Finally, when the Markov switching-regime is applied to investigate the relationship between the *LOT* measure and upcoming economic conditions, only one coefficient of this liquidity measure is significant for forecasting an expansion phase (Table 7) *viz*. when *dGPDI* is the forecasted variable under the second specification. However, this coefficient turns out insignificant when adding the explanatory variables *Vola* and er_m. For predicting the recession phase (Table 8), *LOT* liquidity measure is able to forecast the future growth of the *dCONSR* variable under the third specification. Using the STAR models (Tables 13 and 14), similar results are observed for both regimes: *LOT* liquidity measure has the ability to predict the growth of *dGDPR* even when including some or all control variables (second and third specification).

All in all, while some coefficients of the three liquidity measures are significant in the prediction of the future growth of macroeconomic proxies, only few remain distinguishable from zero after including the control variables. This critical fact implies that the findings are not strong and reliable enough to affirm with confidence that aggregate liquidity is a strong leading indicator and contains significant additional information about future economic growth as claimed by Næs *et al.* (2010).

Finally, it is important to mention that the analysis in this study was also performed using the levels of the macroeconomic variables as well as the liquidity measures instead of their log differences. This alternative approach permitted analysis of three other relationships: levels of the macroeconomic proxies versus levels and versus log differences of the liquidity measures as well as the log differences of the economic variables versus levels of liquidity measures. The results obtained are even less significant and robust to the ones presented previously.

Table 3
Amihud (2002) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the economic expansion regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory and erm. Significant coefficients for the liquidity measure are in bold font. variables are the Amihud (2002) liquidity measure (LIQ), the lag of the dependent variable (yt), Term, dCred, Vola, and erm. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
			Amihud Liquidity Measure – Economic Expansion Regime				
dGDPR	0.718	-0.131	0.207				
	(7.43)	(-0.86)	(2.73)				
dCONSR	0.782	-1.671	-0.412				
	(1.47)	(-0.68)	(-1.57)				
dGPDI	0.977	-0.420	0.161				
	(3.71)	(-0.57)	(1.85)				
dGDPR	2.809	2.151	-0.486	0.045	0.232		
	(4.72)	(0.80)	(-1.17)	(0.08)	(0.37)		
dCONSR	1.085	-2.101	-0.506	0.484	0.177		
	(1.81)	(-0.81)	(-1.75)	(0.90)	(0.61)		
dGPDI	0.988	-0.482	0.200	0.480	0.284		
	(3.86)	(-0.71)	(2.32)	(3.42)	(3.33)		
dGDPR	3.804	1.668	-0.847	-0.322	0.108	-0.485	0.207
	(2.61)	(0.68)	(-1.96)	(-0.806	(0.34)	(-0.78)	(1.75)
dCONSR	4.245	-1.208	-0.581	0.462	0.174	-1.453	-0.034
	(1.18)	(-0.45)	(-1.92)	(0.66)	(0.55)	(-0.83)	(-0.18)
dGPDI	2.295	-1.993	0.122	0.274	-0.024	-0.659	0.494
	(0.94)	(-1.00)	(0.992)	(1.11)	(-0.21)	(-0.70)	(2.49)

Table 4.
Amihud (2002) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the economic contraction regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Amihud (2002) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
	Amihud Liquidity Measure – Economic Contraction Regime						
dGDPR	-0.431	**-1.079**	0.999				
	(-1.63)	**(-2.03)**	(4.76)				
dCONSR	0.583	**-0.222**	0.307				
	(7.76)	**(-2.13)**	(4.49)				
dGPDI	0.044	-3.093	0.147				
	(0.143)	(-1.35)	(1.17)				
dGDPR	0.388	**-0.312**	0.427	0.075	0.025		
	(5.44)	**(-2.31)**	(7.66)	(2.48)	(1.35)		
dCONSR	0.585	**-0.224**	0.306	0.006	0.004		
	(7.83)	**(-2.11)**	(4.48)	(0.25)	(0.26)		
dGPDI	0.151	-2.615	0.226	0.441	0.022		
	(0.32)	(-1.23)	(7.66)	(1.95)	(0.29)		
dGDPR	0.556	-0.258	3.78	0.064	0.199	-0.043	0.038
	(2.63)	(-1.91)	(6.36)	(2.17)	(1.04)	(-0.585)	(2.75)
dCONSR	0.796	-0.198	0.261	0.004	0.000	-0.065	0.017
	(4.39)	(-1.81)	(3.49)	(0.24)	(0.05)	(-1.11)	(1.33)
dGPDI	1.726	-0.099	0.188	0.474	0.275	-0.264	0.191
	(1.89)	(-0.21)	(2.13)	(3.28)	(2.99)	(-0.79)	(3.08)

Table 5.
Roll (1984) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Roll (1984) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
			Roll Liquidity Measure – First Regime				
dGDPR	0.552	0.126	0.265				
	(5.82)	(0.44)	(2.39)				
dCONSR	0.844	2.859	-0.398				
	(1.42)	(0.85)	(-1.48)				
dGPDI	0.280	-1.627	0.982				
	(0.75)	(-1.23)	(2.85)				
dGDPR	0.699	0.478	0.145	-0.020	0.001		
	(6.43)	(1.53)	(1.23)	(-0.86)	(0.10)		
dCONSR	1.885	1.013	-0.943	1.224	0.138		
	(2.83)	(0.452)	(-3.98)	(1.84)	(0.43)		
dGPDI	0.266	-0.961	1.086	0.469	0.272		
	(0.70)	(-0.68)	(3.17)	(3.22)	(2.85)		
dGDPR	0.836	**-0.993**	0.315	0.070	0.009	-0.096	0.064
	(2.36)	**(-2.11)**	(3.93)	(1.43)	(0.24)	(-0.68)	(2.62)
dCONSR	0.950	-0.201	0.250	-.002	-0.003	-0.108	0.026
	(4.88)	(-0.76)	(3.27)	(-0.12)	(0-0.21)	(-1.70)	(2.07)
dGPDI	0.850	0.299	0.959	0.483	0.283	-0.158	0.183
	(0.80)	(-0.21)	(2.76)	(3.10)	(2.65)	(-.044)	(2.93)

Table 6.
Roll (1984) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the second regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Roll (1984) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
			Roll Liquidity Measure – Second Regime				
dGDPR	0.533	**-1.305**	0.355				
	(4.82)	**(-2.72)**	(4.63)				
dCONSR	0.568	**-0.541**	0.321				
	(8.08)	**(-2.45)**	(4.99)				
dGPDI	-0.533	**-8.567**	1.277				
	(-0.61)	**(-2.04)**	(2.12)				
dGDPR	0.500	**-1.284**	0.404	0.091	0.016		
	(4.67)	**(-2.77)**	(5.39)	(1.93)	(0.48)		
dCONSR	0.599	**-0.588**	0.282	-0.001	-0.004		
	(8.20)	**(-2.39)**	(4.19)	(-0.06)	(-0.20)		
dGPDI	-0.696	**-8.405**	1.556	0.361	-0.015		
	(-0.78)	**(-1.95)**	(2.52)	(1.57)	(-0.16)		
dGDPR	0.822	**-0.651**	0.072	-0.28	-0.009	-0.248	0.015
	(4.04)	**(-2.31)**	(0.674)	(-0.91)	(-0.56)	(-2.13)	(1.17)
dCONSR	-0.859	-2.631	-0.719	0.534	0.197	0.288	-0.066
	(-0.80)	(-1.66)	(-6.52)	(2.93)	(1.97)	(0.77)	(-1.42)
dGPDI	0.816	-6.490	1.019	0.229	-0.052	-0.332	0.376
	(0.31)	(-1.49)	(1.51)	(0.65)	(-0.23)	(-0.35)	(1.79)

Table 7
Lesmond, Ogden, and Trczinka (1999) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Lesmond *et al*. (1999) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
			LOT Liquidity Measure - First Regime				
dGDPR	0.540	0.287	0.289				
	(5.45)	(0.62)	(2.30)				
dCONSR	0.816	0.890	-0.369				
	(1.43)	(0.21)	(-1.44)				
dGPDI	0.969	2.504	0.172				
	(3.69)	(1.26)	(1.91)				
dGDPR	3.008	-0.683	-1.202	0.044	-0.065		
	(0.69)	(-0.04)	(-2.88)	(0.04)	(-0.07)		
dCONSR	-0.196	-4.526	-0.829	0.083	-0.343		
	(-0.39)	(-1.44)	(-6.64)	(0.22)	(-1.24)		
dGPDI	2.407	**-4.345**	-0.640	0.595	0.319		
	(1.51)	**(-2.34)**	(-2.37)	(1.06)	(0.83)		
dGDPR	1.038	-0.982	0.294	0.080	0.017	-0.172	0.076
	(2.65)	(-1.33)	(3.40)	(1.57)	(0.45)	(-1.07)	(2.96)
dCONSR	1.079	-0.251	0.182	0.012	0.008	-0.129	0.021
	(5.64)	(-0.71)	(2.45)	(0.44)	(0.48)	(-2.07)	(1.66)
dGPDI	1.729	-0.156	0.198	0.475	0.278	-0.272	0.190
	(1.95)	(-0.12)	(2.24)	(3.29)	(3.09)	(-0.84)	(3.02)

Table 8

Lesmond, Ogden, and Trczinka (1999) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

This table shows the parameter estimates under the second regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Lesmond *et al*. (1999) liquidity measure (*LIQ*), the lag of the dependent variable (*yt*), *Term*, *dCred*, *Vola*, and e*rm*. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
			LOT Liquidity Measure - Regime 2				
dGDPR	0.506	-0.769	0.374				
	(4.37)	(-1.02)	(4.64)				
dCONSR	0.560	0.116	0.335				
	(7.65)	(0.35)	(5.06)				
dGPDI	0.210	-6.093	0.198				
	(0.29)	(-1.01)	(1.72)				
dGDPR	0.820	-0.605	0.359	0.065	0.030		
	(3.89)	(-1.51)	(5.92)	(2.11)	(1.50)		
dCONSR	0.617	-0.110	0.310	0.014	0.013		
	(8.53)	(-0.33)	(4.76)	(0.57)	(0.82)		
dGPDI	0.309	-1.682	0.476	0.604	0.284		
	(0.839)	(-0.53)	(4.96)	(2.94)	(2.28)		
dGDPR	0.667	0.242	0.247	-0.022	-0.009	-0.032	0.013
	(2.92)	(0.44)	(1.99)	(-0.63)	(-0.45)	(-0.49)	(0.99)
dCONSR	1.230	**-7.753**	-0.733	-0.470	-0.608	-0.901	0.122
	(0.75)	**(-2.80)**	(-5.24)	(-2.04)	(-3.11)	(-1.33)	(-1.72)
dGPDI	2.624	-4.981	0.129	0.250	-0.026	-0.754	0.536
	(0.94)	(-0.79)	(-1.04)	(-0.60)	(-0.08)	(-0.68)	(2.65)

Table 9.
Amihud (2002) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Amihud (2002) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	***F***	***Gamma***	***c***
				Amihud Liquidity Measure – Economic Expansion Regime						
dGDPR	0.354	0.944	-0.444					8.388	191.47	-0.562
	(1.45)	(1.74)	(-2.18)					(0.00)	(0.11)	(-11.4)
dCONSR	1.050	-0.080	-0.514					6.381	32.609	1.414
	(0.21)	(-0.01)	(0.10)					(0.03)	(0.63)	(23.1)
dGPDI	3.519	0.572	-0.387					4.143	0.688	4.762
	(1.87)	(0.14)	(-1.85)					(0.02)	(0.91)	(2.04)
dGDPR	0.003	0.732	-0.075	-0.133	-0.021			5.91	4.197	0.382
	(0.01)	(-1.35)	(-0.46)	(-1.63)	(-0.42)			(0.00)	(0.18)	(1.19)
dCONSR	0.720	-0.093	-0.801	-0.174	-0.139			4.227	54.935	1.542
	(3.14)	(-0.29)	(-5.14)	(-1.96)	(-2.03)			(0.00)	(0.25)	(23.5)
dGPDI	4.291	2.132	-0.492	-0.614	0.076			4.508	0.585	5.268
	(1.94)	(0.45)	(-2.03)	(-0.96)	(0.15)			(0.00)	(1.24)	(2.43)
dGDPR	-0.379	0.439	0.244	-0.049	-0.006	0.007	-0.153	6.264	32.722	-0.416
	(-0.84)	(1.39)	(1.67)	(-0.76)	(-0.15)	(0.05)	(-3.86)	(0.00)	(0.60)	(-7.22)
dCONSR	-76.46	3.570	-21.74	-12.36	-7.028	48.680	2.397	3.683	1.259	5.547
	(-0.08)	(0.06)	(-0.08)	(-0.08)	(-0.08)	(0.08)	(0.07)	(0.00)	(1.37)	(0.49)
dGPDI	10.00	-4.273	-0.443	-0.879	-0.135	-3.155	0.514	5.097	308.90	7.394
	(1.37)	(-0.67)	(-2.47)	(-1.46)	(-0.25)	(-0.94)	(-1.60)	(0.00)	(0.00)	(0.00)

Table 10.
Amihud (2002) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the second regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Amihud (2002) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	***F***	***Gamma***	***c***
				Amihud Liquidity Measure – Economic Recession Regime						
dGDPR	0.217	**-1.106**	0.737					8.388	191.47	-0.562
	(0.93)	**(-2.12)**	(3.80)					(0.00)	(0.11)	(-11.4)
dCONSR	0.530	-0.181	0.230					6.381	32.609	1.414
	(6.51)	(-1.21)	(3.01)					(0.03)	(0.63)	(23.1)
dGPDI	0.063	-1.569	0.235					4.143	0.688	4.762
	(0.12)	(-1.59)	(3.05)					(0.02)	(0.91)	(2.04)
dGDPR	0.523	-0.679	0.402	0.148	0.036			5.91	4.197	0.382
	(3.87)	(-1.77)	(3.32)	(2.75)	(1.10)			(0.00)	(0.18)	(1.19)
dCONSR	0.603	-0.233	0.309	0.031	0.017			4.227	54.935	1.542
	(7.80)	(-1.41)	(4.08)	(1.01)	(0.91)			(0.00)	(0.25)	(23.5)
dGPDI	-0.094	-1.877	0.293	0.667	0.228			4.508	0.585	5.268
	(-0.18)	(-1.87)	(3.72)	(3.33)	(1.91)			(0.00)	(1.24)	(2.43)
dGDPR	1.330	-0.491	0.089	0.073	0.010	-0.184	0.174	6.264	32.722	-0.416
	(3.83)	(-1.88)	(0.69)	(1.40)	(0.31)	(-1.72)	(4.78)	(0.00)	(0.60)	(-7.22)
dCONSR	1.272	-0.212	0.111	0.048	0.021	-0.225	0.028	3.683	1.259	5.547
	(4.86)	(-0.99)	(1.04)	(1.10)	(0.80)	(-2.04)	(1.39)	(0.00)	(1.37)	(0.49)
dGPDI	1.200	-0.966	0.216	0.530	0.204	-0.229	0.329	5.097	308.90	7.394
	(1.19)	(-1.29)	(3.28)	(3.18)	(1.94)	(-0.60)	(4.41)	(0.00)	(0.00)	(0.00)

Table 11.
Roll (1984) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Roll (1984) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	***F***	***Gamma***	***c***
					Roll Liquidity Measure – First Regime					
dGDPR	0.330	0.878	0.833					8.893	227.41	-0.446
	(1.71)	(0.96)	(5.31)					(0.00)	(0.00)	(0.00)
dCONSR	17.812	2.656	-1.092					8.304	0.676	1.220
	(0.621)	(1.06)	-0.77)					(0.00)	(1.26)	(1.25)
dGPDI	-7.490	**13.435**	-0.501					5.054	0.936	-4.187
	(-2.36)	**(2.81)**	(-1.62)					(0.02)	(0.93)	(-4.17)
dGDPR	0.622	1.590	0.658	0.061	0.129			6.501	1518	-.0286
	(3.96)	(1.58)	(4.54)	(1.65)	(2.31)			(0.00)	(0.30)	(0.00)
dCONSR	1.074	**1.844**	-0.523	0.004	0.019			4.662	183.10	1.407
	(0.17)	**(2.46)**	(-4.22)	(0.05)	(0.31)			(0.00)	(0.08)	(0.00)
dGPDI	-7.063	**14.268**	-0.567	-0.072	0.235			4.950	2.646	-3.438
	(-2.93)	**(3.28)**	(-2.08)	(-0.13)	(0.96)			(0.00)	(0.85)	(-5.88)
dGDPR	1.503	1.300	0.939	-0.143	-0.176	-0.541	-0.189	6.511	40.891	-0.417
	(1.97)	(0.99)	(2.19)	(-2.16)	(-1.71)	(-2.28)	(-3.20)	(0.00)	(0.50)	(-8.29)
dCONSR	8.281	3.028	-1.216	-0.348	-0.134	-0.319	-0.070	4.695	1.158	1.461
	(1.61)	(1.58)	(-1.79)	(-1.60)	(-1.01)	(-0.74)	(-0.79)	(0.00)	(2.19)	(2.77)
dGPDI	-8.493	**10.429**	-0.499	-0.138	0.193	0.648	-0.155	5.00	2.840	-3.181
	(-2.73)	**(2.15)**	(-1.91)	(-0.34)	(0.82)	(-0.75)	(-0.77)	(0.00)	(0.89)	(-6.72)

Table 12.
Roll (1984) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the second regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Roll (1984) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	***F***	***Gamma***	***c***
					Roll Liquidity Measure - Second Regime					
dGDPR	0.254	-1.803	-0.558					8.893	227.41	-0.446
	(1.71)	(-1.87)	(-3.31)					(0.00)	(0.00)	(0.00)
dCONSR	-4.943	-1.498	-1.854					8.304	0.676	1.220
	(-0.43)	(-1.43)	(-0.74)					(0.00)	(1.26)	(1.25)
dGPDI	7.796	**-16.204**	0.780					5.054	0.936	-4.187
	(2.52)	**(-3.71)**	(2.59)					(0.02)	(0.93)	(-4.17)
dGDPR	-0.167	**-.2653**	-0.328	-0.063	-0.100			6.501	151.8	-.0286
	(-0.90)	**(-2.50)**	(-2.07)	(-1.39)	(-1.46)			(0.00)	(0.30)	(0.00)
dCONSR	0.534	**-0.627**	0.215	0.012	-0.001			4.662	183.10	1.407
	(6.65)	**(-1.97)**	(2.82)	(0.38)	(-0.09)			(0.00)	(0.08)	(0.00)
dGPDI	7.350	**-16.510**	0.890	0.545	0.004			4.950	2.646	-3.438
	(3.13)	**(-4.24)**	(3.43)	(1.49)	(0.02)			(0.00)	(0.85)	(-5.88)
dGDPR	-0.673	-1.816	-0.580	0.154	0.217	0.412	0.221	6.511	40.891	-0.417
	(-0.94)	(-1.44)	(-1.36)	(2.50)	(2.25)	(1.88)	(3.93)	(0.00)	(0.50)	(-8.29)
dCONSR	-0.540	-1.222	-0.771	0.120	0.041	-0.025	0.036	4.695	1.158	1.461
	(-0.32)	(-1.64)	(-1.46)	(1.43)	(0.90)	(-0.16)	(1.30)	(0.00)	(2.19)	(2.77)
dGPDI	9.037	**-11.536**	0.797	0.545	0.024	-0.695	0.432	5.00	2.840	-3.181
	(3.29)	**(-2.60)**	(3.22)	(1.59)	(0.13)	(-1.03)	(2.40)	(0.00)	(0.89)	(-6.72)

Table 13
Lesmond, Ogden, and Trczinka (1999) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Lesmond *et al*. (1999) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	*F*	*Gamma*	*c*
				LOT Liquidity Measure – First Regime						
dGDPR	0.147	1.384	-0.477					0.054	215.7	-0.394
	(0.70)	(1.13)	(-2.76)					(0.98)	(0.00)	(0.00)
dCONSR	-39.812	1.476	-7.609					0.962	0.373	-0.222
	(-0.16)	(0.30)	(-0.24)					(0.38)	(0.52)	(-0.04)
dGPDI	0.022	1.861	0.276					4.020	0.722	4.104
	(0.04)	(0.63)	(3.57)					(0.00)	(0.99)	(2.30)
dGDPR	-0.084	**3.556**	-0.052	-0.197	-0.112			4.662	510.64	0.123
	(-0.505)	**(3.02)**	(-0.39)	(-2.94)	(-2.48)			(0.00)	(0.14)	(5.18)
dCONSR	3.955	5.496	-3.974	-1.151	-0.986			3.266	1.038	3.702
	(0.92)	(0.51)	(-1.10)	(-0.83)	(-0.91)			(0.00)	(1.29)	(1.62)
dGPDI	-0.084	2.142	0.342	0.675	0.233			4.483	0.609	4.813
	(-0.172)	(0.71)	(4.21)	(3.35)	(1.88)			(0.00)	(1.28)	(2.35)
dGDPR	-0.564	**3.657**	0.195	-1.08	-0.076	0.073	-0.156	6.920	14.09	0.109
	(-1.19)	**(3.11)**	(1.33)	(-1.61)	(-1.71)	(0.47)	(-3.64)	(0.00)	(0.176)	(5.39)
dCONSR	16.526	-1.439	-2.089	-0.502	-0.242	-0.260	-0.148	4.501	0.771	1.868
	(0.75)	(-0.99)	(-1.27)	(-1.04)	(-0.42)	(-1.04)	(1.42)	(0.00)	(1.42)	(1.65)
dGPDI	1.408	-1.184	0.230	0.541	0.222	-0.299	0.353	5.079	19.306	6.309
	(1.36)	(-0.53)	(3.51)	(3.20)	(2.06)	(-0.76)	(4.69)	(0.00)	(0.09)	(29.94)

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Table 14.
Lesmond, Ogden, and Trczinka (1999) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the second regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Lesmond *et al*. (1999) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	***F***	***Gamma***	***c***
					LOT Liquidity Measure – Second Regime					
dGDPR	0.409	-1.474	0.779					0.054	215.7	-0.394
	(2.12)	(-1.30)	(4.84)					(0.98)	(0.00)	(0.00)
dCONSR	77.370	-2.521	1.645					0.962	0.373	-0.222
	(0.19)	(-0.34)	(0.10)					(0.38)	(0.52)	(-0.04)
dGPDI	3.196	-10.783	-0.423					4.020	0.722	4.104
	(2.30)	(-1.45)	(-2.08)					(0.00)	(0.99)	(2.30)
dGDPR	0.591	**-3.346**	0.408	0.223	0.119			4.662	510.64	0.123
	(4.08)	**(-3.10)**	(3.54)	(4.15)	(3.21)			(0.00)	(0.14)	(5.18)
dCONSR	0.542	-0.348	0.352	0.069	0.052			3.266	1.038	3.702
	(3.08)	(-0.50)	(2.20)	(1.11)	(1.22)			(0.00)	(1.29)	(1.62)
dGPDI	3.846	-14.862	-0.593	-0.473	0.244			4.483	0.609	4.813
	(2.13)	(-1.60)	(-2.31)	(-0.79)	(0.52)			(0.00)	(1.28)	(2.35)
dGDPR	1.493	**-3.642**	0.114	0.133	0.08	-0.022	0.181	6.920	14.096	0.109
	(3.96)	**(-3.36)**	(0.88)	(2.43)	(2.20)	(-2.04)	(4.54)	(0.00)	(0.176)	(5.39)
dCONSR	-2.339	0.163	-1.273	0.167	0.078	-0.046	0.064	4.501	0.771	1.868
	(-0.38)	(0.14)	(0.86)	(1.19)	(1.02)	(-0.24)	(1.83)	(0.00)	(1.42)	(1.65)
dGPDI	2.212	-10.483	0.558	-0.533	0.249	0.219	-0.592	5.079	19.306	6.309
	(0.59)	(-1.31)	(-3.28)	(-1.04)	(0.58)	(0.14)	(-2.21)	(0.00)	(0.09)	(29.94)

6. Robustness Tests: Cointegration Analysis

Cointegration analysis has been widely used over the past three decades since its introduction by Engle and Granger (1987). Basically the approach tests for a long run equilibrium relationship between two or more non-stationary random time series based on the existence (or non-existence) of a linear combination of such variables that divulges the property of stationarity. Equivalently if two or more data time series are individually integrated (*i.e.* presence of unit roots) and if there exists a linear combination of them which displays a lesser order of integration, then the time series are said to be cointegrated. For instance, an equity market index and its corresponding futures contract price may follow individual random walks while an equilibrium relationship exists between the two variables because a linear combination of the two time series presents a lesser order of integration, especially if it is I(0), and which would imply that the two time series are cointegrated.

This study employs two popular methods for testing whether the time series of macroeconomic proxies and liquidity measures are cointegrated: The Johansen (1988) (including a recursive Cointegration test) and Gregory and Hansen (1996) cointegration tests.

However before tests of cointegration can be performed on the data series it is critical to test for the presence of unit roots or the property of non-stationarity and in the affirmative whether they are integrated of the same order. By applying the Augmented Dickey-Fuller unit root test it is found that all macrovariables and liquidity measures previously investigated in this study present the characteristic of nonstationarity except the *Roll* liquidity measure which is consequently removed from the following cointegration analysis. Moreover the variables presenting evidence of units roots (*i.e. RGDP*, *GPDI*, *RPCE*, *Amihud*, *LOT*) are all integrated of order 1 meaning that if they are differenced once the series become stationary and which also implies that they can be jointly tested for cointegration with the two previously mentioned models.

In practice, cointegration is often used and is more generally applicable for two series, but it can be used to analyse additional relationships: Multicointegration or multivariate cointegration tests, which are also performed in this essay, extend the cointegration methodology beyond two variables.

6.1 Johansen's (1988) Cointegration Test

The Johansen's methodology (1988) takes its starting point in the vector autoregression (VAR) of order *p* given by:

$$z_t = c + A_1 z_{t-1} + \dots + A_p z_{t-p} + \mu_t \tag{16}$$

where z_t is a n×1 vector of variables that are integrated of order one — commonly denoted $I(1)$ — and μ_t is a zero mean white noise vector process. This VAR can be re-written as:

$$\Delta z_t = c + \Pi z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta_i + \mu_t \tag{17}$$

where $\Pi = \sum_{i=1}^{p} A_i - I$ and $\Gamma_i = -\sum_{j=i+1}^{p} A_j$. If the coefficient matrix has reduced rank $r < n$, then there exist $n \times r$ matrices α and β each with rank r such that = $\alpha\beta'$ and $\beta' z_t$ is stationary. r is the number of cointegration relationships, the elements of α are known as the adjustment parameters in the vector error correction model and each column of β is a cointegrating vector. It can be shown that for a given r, the maximu likelihood estimator of β defines the combination of z_{t-1} that yields the r largest canonical correlations of z_t with z_{t-1} after correcting for lagged differences and deterministic variables when present. Johansen proposed two different likelihood ratio tests of the significance of these canonical correlations and thereby the reduced rank of the matrix, that is the trace (λ_{trace}) and maximum eigenvalue (λ_{max}) test,which are computed by using the following formulas:

$$\lambda_{trace} = -T\sum_{j=r+1}^{k}\ln(1-\hat{\lambda}_j) \tag{18}$$

$$\lambda_{max} = -T\ln(1-\hat{\lambda}_{r+1}) \tag{19}$$

where T is the sample size, $\hat{\lambda}_j$ and $\hat{\lambda}_{r+1}$ are the estimated values of the characteristic roots obtained from the matrix. The trace test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors, while the maximum eigenvalue tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of r+1 cointegrating vectors.

To reflect the potential time-varying co-movement, the recursive cointegration methodology is also employed in the section. This dynamic approach examines whether a group of variables becomes progressively cointegrated by visually evaluating the cointegration over time.

In the recursive analyse Johansen's (1988) trace statistic is estimated over the initial observations which are kept fixed and then recursively recomputed as additional observations are added to the base sample. This approach allows to plot and graphically evaluate the trace statistics.

If a cointegration property between the variables is significantly present, it should be revealed by an increasing number of cointegrating vectors emerging over time as the data generating process is being gradually governed by the same shocks with a permanent effect.

6.2 Gregory & Hansen's (1996) Cointegration Test

Gregory and Hansen (1996) propose a test that allows for a possible structural break in the cointegration relationship. More specifically the Gregory and Hansen (1996) methodology tests the null hypothesis that the series are not cointegrated against the alternative hypothesis of cointegration with a single structural break at a single unknown time during the sample period. The timing of the structural change is estimated endogeneously rather than arbitrarily selected or assumed on the basis of market history.

According to Gregory and Hansen (1996) cointegration with the existence of a structural change can be thought of a relationship occuring over some prolonged period of time and then shifting to a new long-run equilibrium relationship.

Structural changes can manifest themselves through changes in the long-term relationship either in the form of a change in the intercept, or a change in the cointegrating vector. Gregory and Hansen (1996) propose three alternative models that accommodate variation in parameters of the cointegration vector.

The first one is the so-called level shift model (or C model) that allows for the change only in the intercept.

$$y_t = \mu_1 + \mu_2\, \varphi_{t\tau} + \alpha' x_t + e_t \quad t = 1,...,n. \tag{20}$$

The second model accommodates a trend in the data, while also restricting the changes to shifts in the level (C/T model).

$$y_{1t} = \mu_1 + \mu_2\, \varphi_{t\tau} + \beta_t + \alpha' x_t + e_t \quad t = 1,...,n. \tag{21}$$

The last model allows for changes both in the intercept and in the slope of the cointegration vector (C/S model).

$$y_{1t} = \mu_1 + \mu_2\, \varphi_{t\tau} + \alpha'_1\, x_t + \alpha'_2\, x_t\, \varphi_{t\tau} + e_t \quad t = 1,...,n. \tag{22}$$

where: y_1 is the dependent variable, x is the independent variable, t is time subscript, e is the error term τ is the break date.

The dummy variable φ_t which captures the structural change is defined as follows:

$$\varphi_{t\tau} = \begin{cases} 0, & t \leq [n\tau] \\ 1, & t > [n\tau] \end{cases} \tag{23}$$

where $\tau \in (0,1)$ is a relative timing of the change point. Equations (20)–(22) are estimated sequentially with the break point changing over the interval $\tau \in (0,1)$. The nonstationarity of the obtained residuals, expected under the null hypothesis, is verified by the ADF test.

6.3 Results of Johansen (1988), Gregory and Hansen (1996) and the Recursive Analysis Cointegration Tests

The findings of the Johansen's (1988) cointegration test under a bivariate setting are presented in Panel A of Table 16 and provide no evidence that a long-run relationship exists between the macroeconomic variables and the liquidity proxies.

The results of the Gregory and Hansen (1996)'s bivariate cointegration test over the extended period analyzed show that one equilibrium relationship is present between the *Real Investment in the Private Sector* (*GPDI*) variable and the *Amihud* liquidity measure under the C/S model. Moreover this model indicates that a structural break occured in the first quarter of the year 1990 which corresponds to the period preceding by 2 quarters the July 1990-March 1991 recession in the United States.

Models C/T and C/S also reveal some co-movements between the *LOT* and *GPDI* variables with a structural break taking place on the fourth quarter of 1996, a time period that corresponds to no major economic event in the United States.

Table 17 exhibits the findings of the Johansen's (1988) cointegration under a multivariate setting and present some evidence of cointegration between the variables *RGDP - Amihud & LOT* and *RPCE - Amihud & LOT* since at least one cointegration equation exists for each of these two sets of variables.

The Gregory and Hansen (1996) multivariate test results (Table 18) show that the null hypothesis of no cointegration is not rejected under all model specifications (C, C/T, and C/S) considered except for the set of variables *GPDI - Amihud & LOT* (Model C/S) with a structural break once more occuring in the first quarter of the year 1990.

Finally, Figures 2 to 4 depict the results from the recursive cointegration analysis. For ease of interpretation the test statistics in these figures have been scaled by their critical values such that the number of lines above 1.0 indicates the number of cointegrating relationships. These graphs indicate one cointegrating vector between the macroeconomic variable *RGDP* and the *Amihud* and *Roll* liquidity measures. Note that during the period analyzed no other cointegrating vector is appearing at any point in time. The same conclusion is also observed between the macroeconomic proxy *RPCE* and both liquidity measures.

The dynamic Trace Test Statistic involving the relationship between the macroeconomic variable *GPDI* and the *Amihud* and *Roll* liquidity measures only rise above one for some time intervals and not in the entirity of the sample period indicating a quasi-non-existent cointegration association between these three variables.

These visual findings corroborate the static Johansen's (1988) multivariate cointegration test results (Table 17) for all three relationships.

All in all, while some evidence of cointegration may exist between some of the macroeconomic fundamentals and some liquidity measures under the Johansen (1988), the Gregory and Hansen (1996) and the recursive cointegration tests, these findings are not overall convincing since the majority of the results do not allow to assert with certitude that liquidity measures are cointegrated with economic cycles.

Table 16 Johansen (1988) and Gregory & Hansen (1996) Cointegration Tests (Bivariate Setting)

Panel A: Johansen's (1988) Cointegration Test (Bivariate Setting)

	RGDP	*GPDI*	*RPCE*
Amihud	12.228	8.320	14.233
LOT	10.487	7.303	10.514

The null is that the hypothesized number of cointegration equations between the variables amounts to none. The test statistics are based on the Trace approach. Results obtained with the Eigenvalue methodology are quivalent. 5% Critical Value: 15.494.

Panel B: Gregory & Hansen (1996) Cointegration Test (Bivariate Setting)

Variables	Test Statistic	Date of Structural Shift
Model C (5% Critical Value: -4.61)		
Amihud - RGDP	-4.341	1971:02
Amihud - GPDI	-4.240	1971:03
Amihud - RPCE	-4.440	1971:02
LOT- RGDP	-3.234	1973:03
LOT - GPDI	-3.655	1973:03
LOT - RPCE	-3.320	1971:04
Model C/T (5% Critical Value: -4.99)		
Amihud - RGDP	-3.445	1963:04
Amihud - GPDI	-4.652	1966:02
Amihud - RPCE	-3.249	1966:03
LOT- RGDP	-3.803	1963:04
LOT - GPDI	**-5.090***	1996:04
LOT - RPCE	-3.181	1966:01
Model C/S (5% Critical Value: -5.50)		
Amihud - RGDP	-3.741	2003:01
Amihud - GPDI	**-6.420***	1990:01
Amihud - RPCE	-3.269	1990:01
LOT- RGDP	-4.905	2000:02
LOT - GPDI	**-5.986***	1996:04
LOT - RPCE	-3.270	1993:03

The null hypothesis states that there is cointegration between the two variables. Critical values are obtained from Gregory and Hansen (1996). The model specifications are denoted by C—level shift, C/T—level shift with a trend, C/S—regime shift (see Section 6.2).

Table 17 Johansen's (1988) Cointegration Test (Multivariate Setting)

Panel A — Variables: *RGDP - Amihud & LOT*

Hypothesized Number of Cointegration Equations	Trace Statistic	5% Critical Value	Significance at 5% Level
None	**44.84026**	42.91525	*Yes*
At most 1	16.63970	25.87211	*No*
At most 2	6.358762	12.51798	*No*

Panel B — Variables: *GPDI - Amihud & LOT*

Hypothesized Number of Cointegration Equations	Trace Statistic	5% Critical Value	Significance at 5% Level
None	37.49708	42.91525	*No*
At most 1	14.02273	25.87211	*No*
At most 2	4.529922	12.51798	*No*

Panel C — Variables: *RPCE - Amihud & LOT*

Hypothesized Number of Cointegration Equations	Trace Statistic	5% Critical Value	Significance at 5% Level
None	**43.46440**	42.91525	*Yes*
At most 1	18.39456	25.87211	*No*
At most 2	5.609697	12.51798	*No*

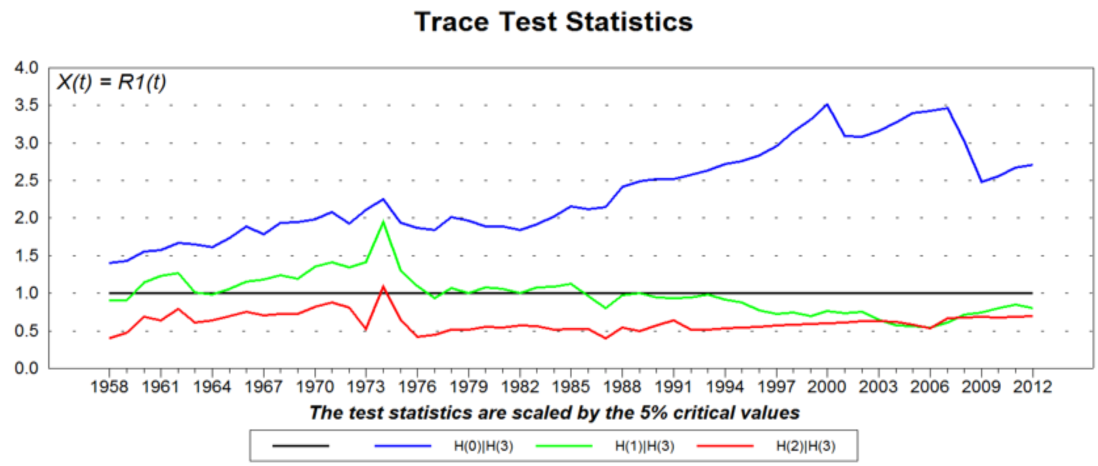
The null is that the hypothesized number of cointegration equations between the variables amounts to none. The test statistics are based on the Trace approach. Results obtained with the Eigenvalue methodology are quivalent. 5% Critical Value: 15.494.

Table 18 Gregory & Hansen (1996) Cointegration Test (Multivariate Setting)

Variables	Test Statistic	Date of Structural Shift
Model C - (5% Critical Value: -4.92)		
RGDP - Amihud & LOT	-3.816	1971:02
GPDI - Amihud & LOT	-4.017	1971:04
RPCE - Amihud & LOT	-3.900	1971:02
Model C/T - (5% Critical Value: -5.29)		
RGDP - Amihud & LOT	-3.702	1963:03
GPDI - Amihud & LOT	-4.949	1998:02
RPCE - Amihud & LOT	-3.065	1966:03
Model C/S - (5% Critical Value: -5.96)		
RGDP - Amihud & LOT	-3.992	1993:01
GPDI - Amihud & LOT	**-6.412***	1990:01
RPCE - Amihud & LOT	-3.584	1993:01

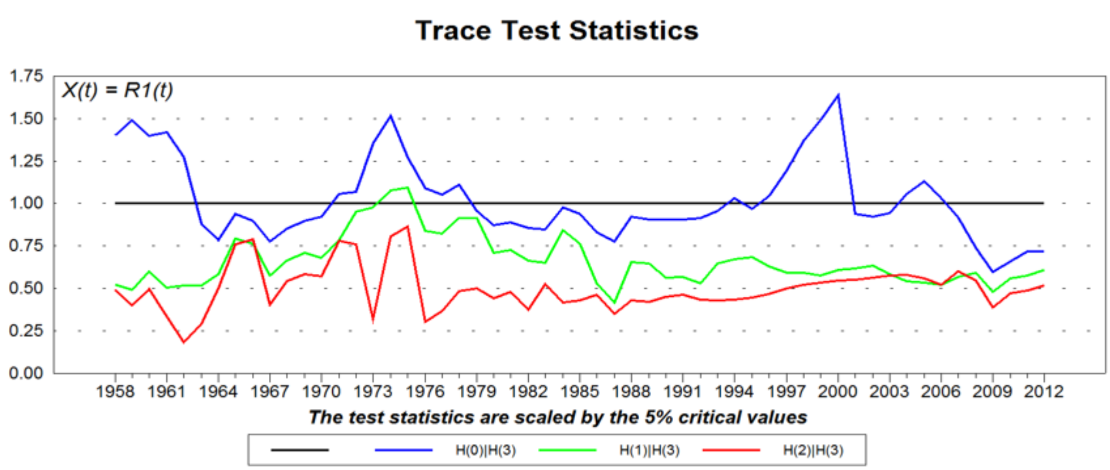
The null hypothesis states that there is cointegration between the two variables. Critical values are obtained from Gregory and Hansen (1996). The model specifications are denoted by C—level shift, C/T—level shift with a trend, C/S—regime shift (see Section 6.2).

Figure 2 – Recursive Cointegration Analysis - Variables: *RGDP ROLL AMIHUD*



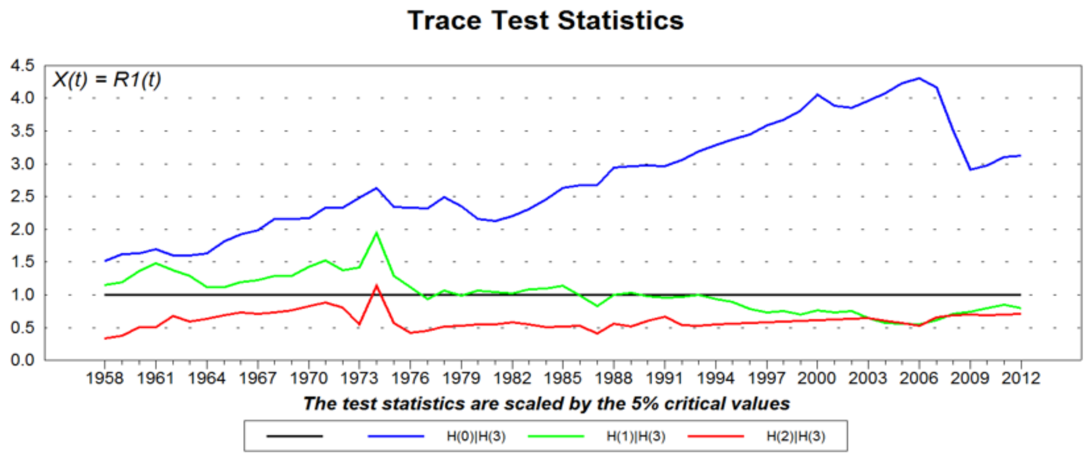
The test statistics in this figure has been scaled by their critical values such that the number of lines above 1.0 indicates the number of cointegrating relationships.

Figure 3 – Recursive Cointegration Analysis - Variables: *GPDI ROLL AMIHUD*



The test statistics in this figure has been scaled by their critical values such that the number of lines above 1.0 indicates the number of cointegrating relationships.

Figure 4. – Recursive Cointegration Analysis - Variables: *RPCE ROLL AMIHUD*



The test statistics in this figure has been scaled by their critical values such that the number of lines above 1.0 indicates the number of cointegrating relationships.

7. Conclusion

In a provocative recent paper, Næs *et al.* (2011) suggest that stock market aggregate liquidity is a leading indicator of subsequent economic cycles. Using several macroeconomic variables to proxy for the state of the economy, they show that different liquidity measures possess a predictive power of the future state of the real economy even after controlling for the present economic conditions and several bond and stock market factors. This forecasting power leads the authors of the paper to assert that "stock market liquidity contains useful information for estimating the future state of the economy" since equity market investors rebalance their portfolio into more secure securities before economic downturns causing greater variations in aggregate liquidity. While this idea is intuitively appealing, the analysis suffers from an important shortcoming since this predictability ability is established upon a linear functional form even though the empirical research has documented over the years that macroeconomic series follow non-linear behaviour.

This paper examines the relationship between business cycles and market wide liquidity using a non-linear approach in order to capture the non-linear dynamics of macroeconomic series. Applying two popular econometric frameworks i.e. the Markov switching-regime and the STAR models, the findings present weak evidence that liquidity fundamentals act as leading indicators of future economic conditions. Indeed, the significance of the liquidity measure coefficients are not sufficiently constant and steady under both regimes and both econometric approaches and are not robust to the inclusion of other explanatory financial variables. Hence, the claim that stock market aggregate liquidity could be exploited to predict the future state of the economy may be premature at best.

References

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Aslanidis, N., Osborn, D., and Sensier, M. 2002, Smooth Transition Regression Models in UK Stock Returns, *Royal Economic Society Annual Conference*, Paper: No. 11.

Beber, A., Brandt, M. W., Kavajecz, K.A., 2010. What does equity sector orderflow tell us about the economy? Working paper, University of Amsterdam.

Bencivenga, V. R., Smith, B.D. and Starr, R.M., 1995. Transactions costs, technological choice, and endogenous growth, *Journal of Economic Theory* 67, 153–177.

Brunnermeier, M.K., Pedersen,L. 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Chordia, T., Roll, R., Subrahmanyam, A. 2000. Commonality in liquidity, *Journal of Financial Economics* 56, 3–28.

Coughenour, Jay F., and Mohsen M. Saad, 2004, Common market makers and commonality in liquidity, *Journal of Financial Economics* 73, 37–69.

Evans, M. D.D., and Lyons, R.K., 2008. How is macro news transmitted to exchange rates? *Journal of Financial Economics* 88, 26–50.

Fujimoto, A., 2003. Macroeconomic sources of systematic liquidity, Working paper, Yale University.

Garcia R., Perron P., 1996. An analysis of the real interest rate under regime shifts. *Review of Economics and Statistics* 78, 111–125.

Gibson, R., Mougeot, N., 2004. The pricing of systematic liquidity risk: Empirical evidence from the U.S. stock market, *Journal of Banking and Finance* 28, 157–178.

Giesecke, K., Longstaff, F., Schaefer, S., Strebulaev, I., 2011. Corporate bond default risk: A 150-Year Perspective. *Journal of Financial Economics* 102, 232–50.

Gilchrist, S., Yankov, V., Zakrajsek, E., 2009. Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets, *Journal of Monetary Economics* 56, 471–493.

Goyenko, R.Y., Holden, C.W., Trzcinka, C.A., 2009. Do liquidity measures measure liquidity? *Journal of Financial Economics* 92, 153–181.

Goyenko, R. Y., Ukhov, A.D., 2009. Stock and bond market liquidity: A long-run empirical analysis, *Journal of Financial and Quantitative Analysis* 44, 189–212.

Granger, C.W.J. and T. Terasvirta 1993. Modelling Nonlinear Economic Relationships, *Oxford: Oxford University Press*.

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

Harris, L., 1990. Statistical properties of the Roll serial covariance bid/ask spread estimator, *Journal of Finance* 45, 579–590.

Harvey, C.R., 1988. The real term structure and consumption growth, *Journal of Financial Economics* 22, 305–333.

Harvey, C. R., 1989. Forecasts of economic growth from the bond and stock markets, *Financial Analysts Journal*, 38–45, September–October 1989.

Harvey, D. I., Leybourne, S.J., Newbold, P., 1998. Tests for forecast encompassing, *Journal of Business and Economic Statistics* 16, 254–259.

Hasbrouck, J., and Seppi, D., 2001. Common factors in prices, order flows, and liquidity, *Journal of Financial Economics* 59, 383–411.

Huberman, G., and Halka, D. 2001. Systematic liquidity, *Journal of Financial Research* 24, 161–178.

Kaul, A., Kayacetin, V. 2009. Forecasting economic fundamentals and stock returns with equity market order flows: Macro information in a micro measure? Working paper, University of Alberta.

Kyle, A., 1985. Continous auctions and insider trading, *Econometrica* 53, 1315–1335.

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

Levine, R., 1991, Stock markets, growth, and tax policy, *Journal of Finance* 46, 1445–1465.

Levine, R., Zervos, S., 1998. Stock markets, banks, and economic growth, *American Economic Review* 88, 537–558.

Longstaff, F.A., 2004, The flight-to-quality premium in U.S. Treasury bond prices, *Journal of Business* 77, 511–525.

Hamilton, J. D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica* 57, 357-384.

Hamilton, J. D., Susmel, R., 1994. Autoregressive conditional heteroskedasticity and changes in regime, *Journal of Econometrics*, 64, 307–333.

McMillan, D. G., 2001. Non-linear predictability of stock market returns: *Evidence* from non-parametric and threshold models. *International Review of Economics and Finance*, 10, 353–368.

Mills T.C., 1999. The econometric modelling of financial time series, Cambridge: *Cambridge University Press*.

Næs, Randi, Johannes Skjeltorp, and Bernt Arne Ødegaard, 2008, Liquidity at the Oslo Stock Exchange, Working paper series, Norges Bank, ANO 2008/9.

Næs, R., Skjeltorp, J.A., Ødegaard, B.A., 2011. Stock Market Liquidity and the Business Cycle. *Journal of Finance* 66, 139-176.

Öcal, N., Osborn, D.R., 2000. Business cycle nonlinearities in UK consumption and production, *Journal of Applied Econometrics* 15, 27-43.

O'Hara, Maureen, 2003. Presidential address: Liquidity and price discovery, *Journal of Finance* 58, 1335–1354.

Pástor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Pedrosa, M., Roll, R., 1998. Systematic risk in corporate bond credit spreads, *Journal of Fixed Income* 8, 7–26.

Roll, R.,, 1984. A simple implicit measure of the effective bid–ask spread in an efficient market, *Journal of Finance* 39, 1127–1139.

Skalin, J., Terasvirta, T., 1999. Another look at Swedish business cycles, *Journal of Applied Econometrics* 14, 359-378.

Söderberg, J., 2008. Do macroeconomic variables forecast changes in liquidity? An out-of sample study on the order driven stock markets in Scandinavia, Working paper 10/2009, University of Växjö.

Stock, J.H., Watson, M.W., 2003. Forecasting output and inflation: The role of asset prices, *Journal of Economic Literature* 41, 788–829.

Teräsvirta, T., 1994. Specification, estimation, and evaluation of smooth transition autoregressive models, *Journal of the American Statistical Association*, 89, 208-218.

Van Dijk, D., Franses, P.H., 1999. Modelling multiple regimes in the business cycle. *Macroeconomic Dynamics* 3, 311-340.

Van Dijk, D., Franses, P.H. 2000, Non-linear time series models in empirical finance. Cambridge: *Cambridge University Press*.