Nonlinear dynamics in stock returns: Do risk aversion, investor sentiment and monetary policy shocks matter?

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Abstract

This paper aims to investigate the non-linear effects of the volatility risk, the investor sentiment and the monetary policy on the stock returns for seven international stock market indexes. To this end, we make use of a smooth transition autoregressive methodology. What distinguishes this paper from the previous studies on the non-linear dynamic of equity returns is the use of a set of exogenous transition variables, namely volatility, sentiment indexes and a measure of the the monetary policy stance. Our findings provide a strong evidence for significant non-linear effects. First, we find that stock returns increase with the growth of volatility; whereas; it decreases when the monetary policy rate goes up. These results hold for most stock markets. Second, we find that stock returns become more sensitive to changes in the monetary policy rate in the extreme low-return regime for some markets. Third, our empirical results show that the effect of the sentiment index on the stock market performance diverges in terms of the sign across countries in different regimes.

Keywords: Volatility index, monetary policy shocks, sentiment change, Smooth transition autoregressive (STAR) models.

1. Introduction

One of the most controversial issues in finance concerned the drivers of stock market returns. What might explain the dynamics of returns and what is the best model to predict the dynamics of stock prices has attracted research attention since the pioneer Cootner (1962)′ study. Understanding the fluctuations of the stock returns plays a pivotal role not only in allocation of assets but also in forecasting future dynamics of returns. The general consensus that seems to emerge from the related empirical and theoretical literature is that a set of financial and macroeconomic variables helps to predict stock returns. This conclusion holds for emerging and developed stock markets across countries and through time. Besides, cross-section studies have mainly concerned the US stock markets and have showed that financial variables (i.e. cash-flow yields, book-to-market, size) have a significant predicting power (Fama and French, 1992). Likewise, time series studies have highlighted the predictive power of a more wide range of variables. The research in this field has given rise to two strands.

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One research strand emphasizes the role of the common risk factors such as the market risk, the size and the book-to-market (Fama and French, 1993). Another research strand rather underscores a small set of macroeconomic variables as having a potential predictive power. It is a question interest-rate variables, inflation and output (Fama and French, 1989; Cochrane, 1991; Ferson and Harvey, 1993; Persaran and Timmermann, 2000).

In a nutshell, the research findings on the drivers of the stock market returns are it those related to cross-section or to time series studies. These findings have several theoretical implications. First and foremost, they would cast serious doubts on the market efficiency hypothesis. Indeed, the predictability of the stock returns could be understood as the consequence of the irrational behavior of investors, which ultimately can help setting trading strategies. Furthermore, the predictability can be associated to the conditional asset pricing that seeks to explain returns by using the available information set, which includes among others financial and the macroeconomic variables. In this respect, stock market predictability arises from the predictability of the information set rather than from the efficiency.

Although most of the research dealing with the predictability of the stock returns favors the linear framework, there is a growing strand of empirical research that highlights the relevance of the non-linear framework. It embraces studies using the neuronal network (Leung et al., 2000), those employing switching regimes (Perez-Quiros, 2000) and those having recourse to threshold models (McMillan, 2001, 2005; McMillan, 2007). A variety of non-linear models have been suggested to capture the observed nonlinearity/asymmetry in the return process, including the Markov Switching (MS), the Threshold Autoregressive (TAR) and the Smooth Transition Autoregressive (STAR) models. It is worth noting that the MS and the TAR models allow switching between regimes that occur instantaneously. These non-linear models can be criticized because they ignore the smooth transition process between the upper and lower-return regimes when the financial returns generating process is non-linear.

Since their introduction, the STAR models have appeared as a promising approach for describing the smooth transition regimes. Their explanatory performances in comparison with various nonlinear models such as the TAR and the MS nonlinear models were investigated by (Sarantis, 2001). The author concluded that the STAR models out-performed their competitors and attributed such a result to the fact that the STAR models allowed for the speed of transition between the low and high return regimes to be relatively slow rather than fast for all countries.

More importantly, the threshold variable plays a key role in analyzing the economic forces driving the stock return dynamics in the STAR modeling framework. The choice of an appropriate transition variable is therefore crucial and can affect the reliability of non-linear estimates. For instance, sharp changes at the level of investors' risk aversion may hold information on how the stock prices evolve. Furthermore, the volatility index determines the perception of a risk by option traders in financial markets, thereby shaping the dynamic path of stock returns. In this respect, Giot (2005) demonstrated that an extreme high level of implied volatility might generate higher future returns for long positions.

Some previous researchers also have advocated that the periods of unusual stock market dynamics could be linked to changes in the monetary policy actions. They have found that there is a non-linear dynamic relationship between stock returns and monetary policy shocks (Hsu and Chiang, 2011). Such arguments would imply that monetary policy actions may provide useful information to infer the movements of future stock returns, which might lend support to the view that monetary policy shocks are driving up the stock price process.

In addition, the recent financial literature has stressed the role of the investor sentiment in delivering relevant information about future market dynamics. The investor sentiment can be defined as a measure of their beliefs about future asset prices and investment risks (Baker and Wurgler, 2006, 2007). Consequently, sentiment can be defined as the state of optimism or pessimism regarding the market in general. Although sentiment is unobservable and a hardly measurable concept, the financial literature has nonetheless suggested a wide range of proxies to quantify such a concept. These proxies go from technical indicators, such as the implicit volatility (IV) and the put-call ratio (Simon and Wiggins, 2001; Chen and Chang, 2005) to survey data-based ones (Kurov, 2010; Wang, 2001, 2003; Han et al., 2017). Different degrees of investor sentiment will affect the valuation of asset prices. The noise trader model of (DeLong et al., 1990) motivated some empirical attempts to explore the effect of noise trader's risks on price formation (Baker and Wurgler, 2006). Most significantly, the relationship between equity returns and sentiment changes diverges in terms of sign effect and magnitude (Lee et al., 2002; Brown and Cliff, 2005).

This paper aims to examine the nonlinear dynamics of equity returns when the three variables, namely the risk aversion, the monetary policy shocks and the investor sentiment, are included as switching variables in the STAR model. The two extreme STAR-model regimes induce large negative and positive stock returns that are governed by a nonlinear transition function. That is, the STAR model assumes that there are two regimes, a low-return regime (i.e. turbulent state) and a high-return one (i.e. calm state) in the dynamics of the stock returns. These two regimes have different dynamics depending on the value of the transition variable. Aslanidis and Christiansen (2012) summarized the three following advantages of the STAR model. Basically, the STAR model accounts for the heterogeneity in data since the transition between the regimes is rather smooth, which allows for a continuum of states between extreme-return regimes. Moreover, the threshold value of the transition variables is determined endogenously by the estimation procedure rather than given on an ad hoc basis. Additionally, the STAR model enables most of the economic variables to govern the dynamics of the dependent variable.

The contribution of this paper is threefold. First, unlike the previous studies that accounted for the impacts drivers (i.e. risk aversion, monetary policy shocks and investor sentiment) considered separately, our study suggests a rather unifying modeling framework accounting simultaneously for the potential effects of these stock-return drivers. Second, it goes beyond the linear framework and proposes a nonlinear and flexible framework resting on the SETAR modeling framework. Third, our study provides the rational for using the sentiment as a transition variable. **To the best of our knowledge, no single study has used the sentiment index as a threshold variable in the STAR models so far.**

The remainder of this paper is organized as follows. Section 2 succinctly presents the theoretical background and the related literature. Section 3 outlines the nonlinear models specification, namely the STAR models and suggests a strategy that permits selecting the relevant transition variables. Section 4 presents the data and the empirical results. Finally, section 5 concludes and provides some further research lines.

2. Theoretical background and related literature

The aim of this section is to review the literature on the potential determinants of the non-linear dynamics of the stock returns in order to highlight how our paper is linked to this already growing body of finance literature. The emphasis will be put on the main stock-returns drivers, namely the risk aversion, the monetary policy shocks and the investor sentiment.

2.1. Volatility

The linkage between stock returns and their volatility has been intensely researched in the finance literature. Such a linkage finds its roots in several finance theories or approaches. On the one hand, '*the feedback hypothesis*' ('*or time-varying risk premium theory*') introduced by Poterba and Summers (1986) and developed by Campbell and Hentschek (1992) and Bekaert and Wu (2000) stipulates that changes in conditional volatility puts in motion asymmetric dynamics in stock returns. According to this theory, a negative shock (i.e. the arrival of bad news) generates an upward increase in the current volatility, which brings about upward revisions of the conditional volatility. Such revisions have to be counterbalanced by a higher expected return, resulting in an instantaneous downward bend in the current market value. Furthermore, the volatility feedback effect tends to amplify the initial fall in stock market prices. Conversely, subsequent to a positive shock (good news arrival), the volatility goes up and the stock prices decline, which generates higher expected returns. As a consequence, the volatility feedback effect counterbalances the initial price rise. In this set-up, stock price dynamics are governed, partly, by the potential revisions in the measured conditional volatility which is closely associated to expected loss measures.

On the other hand, *'the leverage hypothesis'*, which conjectures that there is a well established relationship between volatility and equity returns, provides a different explanation to the stock returns and their volatility. According to this approach, a reduction in the firm value brings about a decrease in the the associated stock price, which manifests in a high debt-to-equity ratio amplifying therefore the firm exposure to the total risk and its associated volatility. The term *'leverage'* refers to the economic interpretation that when asset prices go down, firms will be endowed with a higher debt-to-equity ratio, hence becoming more leveraged. As a result, market operators expect their stock to become more risky, and so more volatile. The leverage effect hypothesis, which was invoked to rationalize such a risk-return relationship, was first suggested by Black (1976) who demonstrated that negative shocks to returns would increase the financial leverage, thus making stocks riskier and subsequently driving up volatility.

The related literature (Bates, 2000; Wu and Xiao, 2002; Eraker, 1995) has documented that the stock returns and their volatility is generally asymmetric, implying that negative returns are associated with an increase in volatility whose magnitude is higher than that of the volatility decrease, which is linked to negative returns of the same scale. The degree of asymmetry depends on the volatility proxy employed in the estimation, with options′ Implied Volatility (IV) generally exhibiting much more pronounced asymmetry.

The IV is a reliable indicator of investor sentiment since it reflects the expectations of the market operators regarding returns and risks, which are far from being accounted for by fundamentals. The IV is a forward looking indicator: It indicates how volatile the market might be in the future. Blatantly, it mirrors the market′s expectation regarding the future volatility of an asset and it is implied by the price of the stock′s options. In fact, IV is unobservable but it can be proxied based on an option price. The first implied volatility index for the US market *–the so-called VIX–*, which was introduced by Whaley (1993), has had a great success for several reasons. Fundamentally, a number of papers document the predictive performance of the VIX when it comes to forecasting future realized volatility (i.e. (Poon and Granger, 2003; Giot, 2005; Whaley, 2000)). Besides, many markets throughout the world have adopted the Chicago Board Options Exchange (CBOE) methodology and developed their own IV. Additionally, unlike the historical (conditional) volatility metrics, the IV index is not a statistical variance, which makes it immune against model-related misspecification error. Therefore, the IV index has been deemed reliable and has been considered a robust metric of the expected market volatility (Siriopoulos and Fassas, 2012; Busch et al., 2011). The findings of Park and Sears (1985) lent support to the usage of the IV as a measure of what rational operators would actually perceive regarding the future volatility rather than historical volatility.

Previous research has considered the link between the implied VIX and the stock market returns, where the volatility index would play an important role in the price discovery. For instance, Whaley (2000) pointed out that if the expected market volatility grew then investors would demand higher rates of returns on stocks, which ultimately could bring down stock prices. More interestingly, the author showed that the volatility index, namely the VIX in the US market, was regarded as an investor-fear gauge since a high level of volatility index concurred with a potential drop in the stock market. Likewise, Fleming et al. (1995), Whaley (2000) and Giot (2005) found a statistically significant negative and an asymmetric contemporaneous relationship between stock returns and changes in the implied volatility as measured by the VIX index. Likewise, Boollen and Whaley (2004) and Whaley (2009) argued that the IV index would reflects the price of portfolio insurance, and therefore the demand for put options would be the key driver in volatility measures such as the VIX. Siriopoulos and Fassas (2009) came to the same conclusion using a range of international implied volatility indexes and their corresponding underlying equity indexes.

In the same vein, some empirical studies focused on the predictive performance of the volatility index in forecasting future stock returns. For example, Fleming et al. (1995) provided strong evidence for the negative contemporaneous relationship between the volatility index and the stock returns. This finding was corroborated by Sarwar (2012) who documented a negative and statistically significant (contemporaneous) relation between the stock returns and the change in the volatility index during high volatile periods, suggesting that returns would fall (resp. would rise) when the expected market volatility went up (resp. declined). Again, Giot (2005) showed that high levels of the VIX indicated oversold stock markets, which led to positive future returns inducing thereby profitable trading opportunities for long-run positions.

In a similar context, but considering different markets, many researchers have attempted to check whether the non-linear linkage holds or not. In a couple of well done papers, Smales (2016, 2017) indicated that the same relationship held between the VIX and the returns in the bond and currency markets. Similarly, Low (2004) found that the relationship was rather non-linear and exhibited a '*house-money effect*' [1].

2.2. Monetary policy

Another potential source that affects stock price dynamics is monetary policy shocks. Indeed, a large number of studies have empirically investigated the relationship between the monetary policy shocks and the equity returns. One view asserts that an increase in the money supply would raise stock prices. Using the growth rate of the aggregate monetary M1 as a measure of monetary shocks, Homa and Blinder (1971) came to the conclusion that monetary policy would significantly impact stock prices. Another view suggested that monetary policy might influence stock prices via the interest rate. Even since the seminal work of Bernanke and Blinder (1992) who found that federal fund rate was a good measure of the monetary policy stance, the relation has been re-estimated by using the change in the short-term interest rate. In particular, Thorbecke (1997) examined the response of stock returns to policy monetary shocks utilizing a vector autoregressive (VAR) model and suggested that monetary policy tightening was negatively related to stock returns. Rigobon and Sack (2004) provided empirical evidence of the negative relationship between stock prices and the short-term interest rate using an event study approach. Furthermore, Bernanke and Kuttner (2005) pointed out that an unexpected 25-basis-point cut in the Federal Fund rate result in a 1% growth in stock prices.

More interestingly, Basistha and Kurov (2008) showed that the Central Bank transparency (especially, the policy communication) and the different phases of the business cycle might shape the effects of the monetary policy actions on the stock returns. It was well documented that financial constraints could be an important source of the effects of the asymmetric monetary shocks on the financial market (Bernanke, 1983) in the sense that if firms were typically constrained financially, the monetary policy would be more likely to have stronger effects on stock returns, especially under bear-markets conditions.

Another set of empirical studies have investigated how monetary policy has asymmetric effects on the value of firms with asymmetry related to their financial constraints. For instance, Ehraman and Fratzscher (2004) gave evidence for an asymmetric relationship between the stock market performance and the monetary policy by demonstrating that financially constrained firms were more strongly affected by monetary policy. In the same vein, using MS models, Chen (2007) argued that the asymmetric effect of the monetary policy on the financial market in bear markets could be explained by the agency costs that led to information asymmetry between firms and financial institutions. Similarly, Hsu and Chiang (2011) examined the potential nonlinear effects of the monetary policy on the stock returns using the

[1] The *house money effect* is the tendency for investors to take more and greater risks when investing with profits.

STAR model and they showed that the relation between the monetary policy shocks and the equity returns was positive and nonlinear in the US as well.

2.3. Investor sentiment

Investor sentiment could reasonably influence asset prices, since behavioral finance theories suggest that times of overlay optimistic or pessimistic expectations can significantly persist and affect stock prices for significant periods of time (DeLong et al., 1990). Generally, *the investor sentiment index measures the expectations of market participants with respect to a norm. Put simply, a bullish (resp. bearish) investor expects the returns to be above (resp. below) average, whatever average may be* (Brown and Cliff, 2004). There exists a substantial amount of evidence showing that a significant tie exists between the equity returns and the sentiment index. For example, (Brown and Cliff, 2004, 2005) argued that there was a significant negative link between the two variables. According to these authors, an extreme level of investor sentiment is based on both a mispricing brought about by irrationalities among market participants and a limit of arbitrage, which would imply that every mispricing had to be corrected. When the level of investor sentiment increases, the future stock returns will tend to decrease and vice versa. It is worth noting that the investor sentiment–stock returns nexus may be positive in the short-run. This argument was revealed by Brown and Cliff (2004) who pointed out that the high investors′ optimism might be associated with over-evaluation.

There is an increased interest in investigating the asymmetric effects of the investor sentiment on the stock returns. Dridi and Germain (2004) explained that the stock market response to investor sentiment was highly asymmetric in the sense that bullish market sentiment would predict higher future returns while the extremely bearish sentiment would predict lower returns. Furthermore, several studies (Ding et al., 2004; Zhang and Semmler, 2009) indicated that the impact of pessimism on stock returns would be much smaller than the impact of optimism. Using a threshold model, Chen et al. (2013) investigated the potential non-linear effects of both local and global sentiments on stock returns for 11 Asian countries. The authors found that the high extreme level of global investor sentiment (optimism) would make returns overvalued while the low level of global sentiment (pessimism) would make them undervalued. This finding was corroborated by Ni et al. (2015) who examined the relationship between investor sentiment and monthly stock returns in the Chinese A-share stock markets, suggesting a positive relationship for large stocks with high returns in the short term and a negative relationship for small stocks with lower returns in the long term.

In sum, risk aversion, monetary policy shocks and investor sentiment measures play an important role in influencing financial markets. They are not considered only as leading variables to discover the process of prices, but also economic variables that can describe the nonlinear dynamic of stock returns. Thus, this paper focuses on these as threshold variables in the STAR model

3. Empirical methodology

The main objective of this section is to present the empirical methodology that will be used in this paper in order to assess the potential effects of the volatility risk, the sentiment index and the the measure of the monetary policy stance on the stock market returns in a sample of seven industrialized countries. Three main issues will be highlighted, namely the model specification search strategy and the selection procedure of the transition variables.

3.1. STAR model: A basic non-linear approach

The STAR model, developed by (Lukkonen et al., 1988; Terasvirta and Andersen, 1992; Terasvirta, 1994), is a general form of the TAR models that enables non-discrete switching points between two extreme regimes. A basic STAR model with two extreme return regimes is given by:

$$y_t = a_0 + \alpha(L)x_t + [a_1 + \beta(L)x_t]F(z_{t-d}, c, \gamma) + \epsilon_t \tag{1}$$

where y_t is the dependent variable,x_t is a vector of exogenous variables including past values of dependent variable, $F(z_{t-d})$ is the smooth transition function, which depends on the transition variable z_{t-d}, and d denotes the delay parameter of the transition variable. There are two variants of STAR models. The first one is the Logistic Smooth Transition Autoregressive (LSTAR) model and the second one is the Exponential Smooth Transition Autoregressive (ESTAR) model. The LSTAR model characterizes different dynamics of equity returns for either large or small values of the transition function. In the ESTAR model, the transition function is given by:

$$F(z_{t-d}, c, \gamma) = [1 + e^{-\gamma(z_{t-d}-c)}]^{-1}, \gamma > 0 \tag{2}$$

where c is the threshold critical value. The parameter γ measures the speed of the transition from one extreme regime to another. An increase in the value of the transition variable z_{t-d} will lead the logistic function to change smoothly from zero to one.

Unlike the STAR models, the ESTAR model suggests that the upper and lower regimes have similar dynamics, and its the transition function is given by:

$$F(z_{t-d}, c, \gamma) = [1 + e^{-\gamma(z_{t-d}-c)^2}], \gamma > 0 \tag{3}$$

It is worth noting that when the transition variable z_{t-d} approaches the threshold value, the exponential transition function tends to zero. It approaches one when z_{t-d} deviates further from the half-way point between the two extreme regimes.

3.2. Model specification search

The conventional modeling strategy for building STAR models involves a number of steps ((Granger and Terasvirta, 1993; Terasvirta, 1994)). The first step consists in specifying a base linear AR model with an optimal lag order (p). Such a lag length can be identified by carrying out a search over different combinations of the explanatory' lags using either information criteria and/or white noise tests such as the Ljung-box (LB) statistic for serial correlation. The second step is to perform linearity test against STAR models for a varying delay parameter d of the transition variables z_{t-d}, while considering the linear AR model as a null hypothesis. To this purpose, Terasvirta and Andersen (1992) proposed replace the transition function $F(z_{t-d})$ in Eq.(1) by its first Taylor approximation around $\gamma = 0$, which permits getting the following auxiliary regression model:

$$y_t = c_0 + \phi_0(L)x_t + \phi_1(L)x_t z_{t-d} + \phi_2(L)x_t z_{t-d}^2 + \phi_3(L)x_t z_{t-d}^3 + \mu_t \quad (4)$$

The linearity test is therefore performed for a given transition variable z and a delay parameter d based on the following null hypothesis of linearity $H_0 : \phi_1(L) = \phi_2(L) = \phi_3(L) = 0$. The Lukkonen et al. (1988)'s Lagrange multiplier LM = $(\mathrm{SSR}_0 - \mathrm{SSR})/\hat{\sigma}^2$ with $\hat{\sigma}^2 = (1/T)\sum_{t=1}^{T}\hat{\mu}_t^2$ is run to test the null hypothesis of the linear assumption. It is worth mentioning that SSR is the sum of squared estimated errors from the unconstrained regression model, Eq.(4). Whereas SSR_0 is the squared estimated errors from the regression model under the null hypothesis, under which the LM statistic follows a χ^2 with 3p degree of freedom. When the null hypothesis of Eq.(4) is rejected for different values of d, we have linear STAR models. The non-linear model that should be selected is the one with the delay parameter of the transition variable having the lowest p-linearity test p-value.

Once the linearity hypothesis is rejected in favor of a STAR model, the third step will consist in choosing between the LSTAR and the ESTAR. To this end, a sequence of nested tests are run in order to determine the specification of the STAR model based on Eq.(4) given by:

$$H_{0,1} : \phi_3(L) = 0 \quad (5)$$

$$H_{0,2} : \phi_2(L)|\phi_3(L) = 0 \quad (6)$$

$$H_{0,3} : \phi_1(L)|\phi_2(L) = \phi_3(L) = 0 \quad (7)$$

If $H_{0,1}$ is rejected, an LSTAR model will be chosen. If $H_{0,1}$ is not rejected while $H_{0,2}$ is rejected, we choose an ESTAR model. Failing to reject $H_{0,1}$ and $H_{0,2}$ while rejecting $H_{0,3}$ leads to select a LSTAR model. Finally, we estimate STAR models using non-linear least squares.

It goes without saying that before estimating the parameters of STAR models, we have to select the transition variable that imparts non-linear dynamics in equity returns. Following Terasvirta (1994), we estimate Eq.(1) according to the following steps. We estimate a linear AR model combined with explanatory variables and determine the lag length of the AR process using the AIC information criteria. We also conduct the linearity test of Lukkonen et al. (1988). Once the linearity assumption is rejected, the second step will consist in bringing to light all possible transition variables candidates. Then a sequence of hypotheses and decision rules is conducted to identify among STAR models (i.e LSTAR or ESTAR) the most relevant. Finally, we carry out the nonlinear least squares to estimate the parameters of the selected models.

4. Empirical results

4.1. Data description and preliminary analysis

As previously noted, we are interested in measuring the nonlinear effect of risk aversion, investor sentiment and monetary policy shocks on stock returns. This paper employs monthly data of an implied volatility index and closing prices for seven major stock indexes, namely Paris CAC40, Frankfurt DAX30, London FTSE 100, Amsterdam AEX, SWISSSMI, Tokyo's

NIKKEI 225 and US S& P500, covering the sample period from February 2000 to March 2015. All closing prices and volatility indexes are sourced from the Thomsen Reuters Eikon Database. The continuously compounded monthly returns are calculated as the logarithmic difference of monthly closing stock prices. Following Chen et al. (2017), we use change in implied volatility indexes (hereafter ΔIV) for each market to measure risk aversion. We utilize also the first difference of the monthly short interest rates as a proxy variable for monetary policy shocks (hereafter ΔMPS). However, there is no wide consensus on the proxy to use when it comes to measuring investor sentiment. The problem is further complicated when it comes to propose a unique indicator for all countries included in our sample. A solution was suggested by Lemmon and Portniaguina (2006) and Schmeling (2009) who uses the Consumer Confidence Index (CCI) as an investor sentiment proxy. Unlike other sentiment measures, the CCI is available for multiple countries as a benchmark indicator for investor sentiment [2]. All interest rates and consumer confidence indexes are extracted from the Federal Reserve economic data.

Summary statistics and various tests on monthly returns and on each transition variable are reported in Table (1). These statistics include results on skewness, kurtosis and the Jarque-Bera normality test, which provide evidence against normality in stock returns, sentiment, volatility change and monetary policy shocks variables for the seven countries considered in our study. The stationarity characteristics of each variable are investigated using the ADF test. The results of the ADF test show that null hypothesis of non-stationarity is rejected at the conventional risk levels for all variables (i.e. R, ΔIV, MPS, and ΔCCI). In fact , we find that policy monetary shocks (PS) and the change in implied volatility are stationary at the observed level whereas CCIs indexes are taken in their first differences to obtain stationary series.

[2] It is worth noting that for US there are several monthly sentiment measures, namely the American Association of Individual Investors (AAII) sentiment index, the Investors Intelligence Advisors′ (IIA) sentiment index and the Baker and Wurgler (2007) (BW) sentiment index. We have not used these indexes in our study since we aim to utilize a sentiment proxy that is comparable across countries. Furthermore, Fisher and Statman (2003) provided evidence for a strong correlation between the CCI and other sentiment proxies, such as the American Association Investor Index (AAII).

Table 1: Descriptive statistics

		Mean	S.D.	Min	Max	Skew	Kurt	JB	ADF	PP
France	R	-0.001	0.050	-0.624	0.445	-0.185	0.131	0.009	0.001	0.001
	IV	23.465	8.676	11.46	57.200	1.441	5.172	0.001	0.138	0.138
	ΔIV	-0.007	1.000	0.345	2.383	-3.523	3.635	0.001	0.001	0.001
	MPS	-0.107	1.000	-1.649	5.165	-4.244	2.358	0.001	0.001	0.001
	CCI	99.765	0.802	98.036	101.643	0.306	2.755	0.129	0.452	0.452
	ΔCCI	-0.050	1.000	0.015	-0.284	-2.328	2.466	0.500	0.001	0.001
Germany	R	0.000	0.060	-0.221	0.137	-0.370	0.284	0.079	0.001	0.001
	IV	22.257	8.6155	10.990	53.67	1.493	5.044	0.001	0.135	0.135
	ΔIV	-0.001	1.000	-3.216	7.214	2.033	15.067	0.001	0.001	0.001
	MPS	0.009	1.000	-6.154	5.029	-0.304	18.016	0.001	0.001	0.001
	CCI	100.114	1.423	96.149	102.526	-0.456	2.654	0.03	0.626	0.626
	ΔCCI	-0.005	1.000	-3.085	3.138	0.089	0.806	0.079	0.001	0.001
Japan	R	0.000	0.060	-0.221	0.137	-0.370	0.284	0.079	0.001	0.001
	IV	25.641	8.635	12.66	101.879	2.533	14.033	0.001	0.134	0.134
	ΔIV	-0.001	1.000	-3.216	7.214	2.033	15.067	0.001	0.001	0.001
	MPS	0.009	1.000	-6.154	5.029	-0.304	18.016	0.001	0.001	0.001
	CCI	99.443	1.371	95.757	81.210	-0.334	2.901	0.126	0.616	0.616
	ΔCCI	-0.005	1.000	-3.085	3.138	0.089	0.806	0.079	0.001	0.001
Netherlands	R	-0.002	0.061	-0.249	0.131	-1.087	2.206	0.001	0.001	0.001
	IV	23.368	10.259	11.653	63.41	1.647	1.653	0.001	0.124	0.124
	ΔIV	-0.008	1.000	-3.365	4.353	0.551	3.832	0.001	0.001	0.001
	MPS	-0.065	1.000	-3.041	2.199	-0.378	-0.124	0.082	0.001	0.001
	CCI	100.101	1.1550	97.906	102.780	0.1916	2.491	0.155	0.395	0.395
	ΔCCI	-0.107	1.000	-4.256	2.364	-1.654	5.210	0.001	0.001	0.001
Switzerland	R	0.001	0.044	-0.161	0.122	-0.831	1.426	0.001	0.001	0.001
	IV	19.189	7.887	9.676	53.255	1.7700	6.318	0.001	0.106	0.106
	ΔIV	-0.004	0.994	-2.858	3.992	1.036	4.280	0.001	0.001	0.001
	MPS	-0.116	1.000	-4.274	2.374	-1.680	5.301	0.001	0.001	0.001
	CCI	100.539	1.501	95.888	103.126	-0.508	3.465	0.0132	0.375	0.375
	ΔCCI	-0.059	1.003	-3.311	3.112	0.248	1.341	0.007	0.003	0.002
UK	R	0.001	0.044	-0.147	0.116	-0.636	0.950	0.001	0.001	0.001
	IV	20.274	8.256	9.870	50.491	1.418	5.048	0.001	0.001	0.088
	ΔIV	-0.013	1.000	-2.769	3.974	0.708	2.738	0.001	0.001	0.001
	MPS	-0.133	1.000	-7.392	3.892	-2.881	18.789	0.001	0.001	0.001
	CCI	100.152	1.132	97.906	102.780	0.111	2.558	0.303	0.417	0.417
	ΔCCI	-0.072	1.000	-3.045	2.202	-0.372	-0.114	0.089	0.001	0.001
US	R	0.002	0.050	-0.184	0.146	-0.682	2.129	0.001	0.001	0.001
	IV	20.821	8.725	10.31	68.51	1.935	2.661	0.001	0.094	0.094
	ΔIV	-0.009	1.000	-5.887	3.578	-0.454	7.426	0.001	0.001	0.001
	MPS	-0.166	1.000	-4.873	1.489	-2.037	5.649	0.001	0.001	0.001
	CCI	99.701	1.415	96.70	102.803	-0.182	8.668	0.302	0.415	0.415
	ΔCCI	-0.045	1.000	-3.026	2.429	-0.130	0.049	0.500	0.001	0.001

Notes: Descriptive statistics (mean, standard deviation, minimum, maximum, skewness, and kurtosis) are calculated for daily returns, the change in implied volatility (ΔIV), the monetary policy shocks (MPS) and the sentiment change (ΔCCI) series. The JB, ADF, PP tests denote the P-value of Jarque Bera normality , the ADF and the Phillips Perean tests, respectively.

4.2. Results for linearity test and suggested non-linear models

When modeling stock-returns series, we first consider the ARX model while including the potential switching variables separately in the AR model. Whereas there are many financial and economic variables that may affect stock returns, this simple linear specification allows considering one regime change in stock returns. The ARX linear model can be written as follows:

$$y_t = a_0 + \alpha(L)y_t + \theta(L)x_t + \eta_t \tag{8}$$

where x_t is one among the candidate transition variables such as changes of volatility indexes (ΔIV),sentiment changes (ΔCCI) or monetary shocks (MPS).

Once the linearity hypothesis is rejected, we consider several STAR specifications including the selected transition variable in the transition function as a regressor. The associated underlying STAR model is as follows:

$$y_t = a_0 + \sum_{i=1}^{p1} \alpha_{1i} y_{t-i} + \sum_{i=1}^{p2} \alpha_{2i} x_{t-i} + [a_1 + \sum_{i=1}^{p1} \beta_{1i} y_{t-i} + \sum_{i=1}^{p2} \beta_{2i} x_{t-i}] F(z_{t-d}) + \epsilon_t \quad (9)$$

where z_{t-d} is the transition function.

To assess the relevance of STAR models, we present on Table (2) the results of linearity tests along with the maximum lag order of the baseline AR(p) model and the delay parameter d of the transition variable. To determine the optimal lag, we estimate a fully parameterized linear model permitting a maximum of ten-lag length for all return series. The proper lags of AR models are reported in the first column of Table (2), having the smallest AIC[3].

Most of return series are best fitted with AR(1) or AR(2) linear models. Better, lagged MPS, ΔIV, and ΔCCI are used to identify the parameters of the transition function. It stands out from Table (4) that stock returns depict a non-linear path as the p-values of linearity test are lower than the 5% critical value. It goes without saying that we have a minimum p-value for all countries, except for Switzerland and Netherlands. Such finding holds only when ΔCCI and MPS are added as threshold variables. More interestingly, the results tend to show that ΔIV, MPS, and ΔCCI could be potential threshold variables. Furthermore, the optimal delay lags turn out to be either one or two in most cases. The results of the nested null hypotheses in Eq.(4) are provided in Table (3). Based on the decision rules discussed in Section 2.2., we conclude that returns series are better fitted with an ESTAR or a LSTAR model depending on the choice of the threshold variable.

Table 2: Linearity tests

	Linear $AR(p)$	Transition variable							
	p	R_{t-d}		ΔIV_{t-d}		MPS_{t-d}		ΔCCI_{t-d}	
		d	p-value	d	p-value	d	p-value	d	p-value
France	2	2	0.017**	1	0.004***	1	0.008***	1	0.026**
Germany	2	1	0.011**	1	0.000***	1	0.001***	2	0.001***
Japan	1	1	0.006***	1	0.001***	2	0.019**	4	0.014**
Netherlands	2	2	0.000***	1	0.000***	5	0.123	1	0.000***
Switzerland	1	1	0.007***	1	0.000***	1	0.030**	5	0.151
UK	2	2	0.010**	1	0.000***	1	0.007***	1	0.004***
USA	1	1	0.000***	1	0.000***	1	0.000***	1	0.012**

Note: The parameter p denotes the optimal lag order of the linear AR model that minimizes the AIC statistic and d denotes the selected delayed parameter which has the minimum p-value of the linearity LM test.
* Significance at 10 % level.
**Significance at 5% level.
*** Significance at 1% level.

[3] According to Liew and Venus (2005), the AIC is found to be the best performing information criteria when it comes to determine the optimal lag order of an AR model as it minimizes the chance of underestimating the true lag length while maximizing the chance of recovering it. To save space, the results of the optimal lag of the AR model are not reported. They are available upon request.

Table 3: Specifications of nonlinear models

	d	$H_{0,1}: \phi_3 = 0$	$H_{0,2}: \phi_2 = 0/\phi_3 = 0$	$H_{0,3}: \phi_1 = 0/\phi_2 = \phi_3 = 0$	Selected model
Transition variable (R_{t-d})					
France	2	0.891	0.037	0.000*	LSTAR
Germany	1	0.300	0.019*	0.052	ESTAR
Japan	1	0.059	0.143	0.020*	LSTAR
Netherlands	2	0.000*	0.031	0.219	LSTAR
Switzerland	1	0.003*	0.202	0.275	LSTAR
UK	2	0.525	0.015*	0.028	ESTAR
US	1	0.000*	0.000*	0.000*	LSTAR
Transition variable (ΔIV_{t-d})					
	d	$H_{0,1}: \phi_3 = 0$	$H_{0,2}: \phi_2 = 0/\phi_3 = 0$	$H_{0,3}: \phi_1 = 0/\phi_2 = \phi_3 = 0$	Selected model
France	1	0.352	0.033	0.007*	LSTAR
Germany	1	0.416	0.000*	0.097	ESTAR
Japan	1	0.125	0.138	0.001*	LSTAR
Netherlands	1	0.011	0.000*	0.271	ESTAR
Switzerland	1	0.007	0.005*	0.181	ESTAR
UK	1	0.043	0.001*	0.002	ESTAR
US	1	0.035	0.000*	0.000*	LSTAR
Transition variable (MPS_{t-d})					
	d	$H_{0,1}: \phi_3 = 0$	$H_{0,2}: \phi_2 = 0/\phi_3 = 0$	$H_{0,3}: \phi_1 = 0/\phi_2 = \phi_3 = 0$	Selected model
France	1	0.819	0.037	0.000*	LSTAR
Germany	1	0.002*	0.023	0.459	LSTAR
Japan	1	0.260	0.298	0.007*	LSTAR
Netherlands	5	0.0566	0.1132	0.8928	Linear
Switzerland	1	0.300	0.056*	0.067	ESTAR
UK	1	0.051	0.897	0.002*	LSTAR
US	1	0.221	0.000*	0.000*	LSTAR
Transition variable (ΔCCI_{t-d})					
	d	$H_{0,1}: \phi_3 = 0$	$H_{0,2}: \phi_2 = 0/\phi_3 = 0$	$H_{0,3}: \phi_1 = 0/\phi_2 = \phi_3 = 0$	Selected model
France	1	0.138	0.056*	0.146	ESTAR
Germany	2	0.152	0.001*	0.201	ESTAR
Japan	4	0.178	0.012	0.007*	ESTAR
Netherlands	1	0.001*	0.014	0.481	LSTAR
Switzerland	5	0.052*	0.520	0.405	Linear
UK	1	0.256	0.006*	0.063	ESTAR
US	1	0.079	0.039*	0.199	ESTAR

Notes: The p-values of the nested tests $H_{0,1}$, $H_{0,2}$ and $H_{0,3}$ serve to identify whether the STAR model is either an ESTAR or an LSTAR model. Asterisks indicate the lowest p-value among the three tests.

4.3. Estimates of linear models

Before estimating the smooth transition the non-linear models, it is useful to unveil whether a linear relationship between stock returns and various threshold variables exists. To this purpose, we fit an AR model with and without exogenous regressors (see Table 4). The main findings are the following: Firstly, the results are homogenous in terms of log likelihood and AIC. Indeed, it stands our from Table (4) that models including exogenous variables appear with a higher value of log likelihood and a lower value of AIC when compared to models without exogenous variables, implying that the former outperform the latter.

Secondly, it is noticeable from Table 4 that ΔIV has a negative, albeit not statistically significant, effect on returns in five out of seven stocks markets. This implies that international equity returns are highly affected by the information content of the implied volatility indexes. Such findings lend support to Campbell (1993)$'$s theoretical asset pricing models in which an unexpected change in market volatility will deteriorate the investment opportunity, bringing about a decrease in future stock returns. The only exception is Netherlands where the coefficient of ΔIV is rather positive and statistically significant.

Thirdly, the estimates of AR models with MPS as exogenous regressors are depicted in the third column of Table (4), which vary from one country to another. The coefficients of the lagged monetary shocks are positive and statistically significant for four out of seven market equities, except for Netherlands and Switzerland. Such findings indicate that prices fall in response to an unexpected decrease in the interest rate where the coefficient bears a negative sign. This raises the possibility that policy monetary actions may be counterproductive. Indeed, the positive relationship between MPS and the stock returns are consistent with the empirical results obtained by Kurov (2010).

Fourthly, for the linear AR-ΔCCI model, as expected, the estimated coefficient of ΔCCI that measures the sensitivity of aggregated stock returns to the change in investor sentiment is positive and statistically significant for siw out of seven stock indexes, except for Switzerland. Our findings corroborated those of Kurov (2010) who came to the same conclusion. Consistently with our empirical findings, Brown and Cliff (2004, 2005) concluded that there was a positive relationship between the stock market performance and the sentiment index. The most likely explanation for the results was that when investors were optimistic, the market would be overvalued. Therefore, optimistic investors had to drive up prices, which would lead to positive returns. This was also consistent with the Lee et al. (2002)$'$s finding that when investor sentiment became more optimistic, they would hold more risky assets, which would raise market prices and increases expected returns. In other words, the positive association between the change in investor sentiment and the expected returns for most of indexes was driven by the hold-more effect (Lee et al. (2002)). In contrast, the relationship between returns and lagged sentiment changes was negative and statistically significant at 10% level for the SMI returns series, thereby indicating that every mispricing had to be instantaneously corrected by declining future returns. These findings show that the negative impact of sentiment changes on expected returns was associated with the price-pressure effect on expected returns. Indeed, when investors overreacted, this would induces price pressure, which depicted future returns (Lee et al. (2002) for more explanation).

Finally, when comparing all the linear models with the designed exogenous regressors among others, the linear AR-ΔCCI model generally performes far better than the other augmented AR models regarding the Likelihood Ratio (LR).

Table 4: Estimates of linear models

	Linear		Linear + ΔIV		Linear + MPS		Linear + ΔCCI	
	coeff	p-value	coeff	p-value	coeff	p-value	coeff	p-value
France								
c	-0.001	0.845	-0.001	0.829	0.000	0.925	0.000	0.980
α_1	0.095	0.205	0.036	0.764	0.093	0.212	0.014	0.854
α_2	-0.044	0.561	-0.024	0.766	-0.061	0.416	-0.098	0.188
θ_1			-0.004	0.525	0.011	0.004***	0.017	0.000***
LL	263.94		264.14		267.96		272.44	
AIC	-519.87		-518.28		-525.91		-534.88	
LR			0.4		8.04***		17***	
Germany								
c	0.003	0.558	0.003	0.675	0.004	0.415	0.003	0.505
α_1	0.104	0.161	0.071	0.518	0.097	0.190	0.029	0.698
α_2	-0.056	0.452	-0.052	0.485	-0.062	0.406	-0.134	0.071*
$\theta 1$			-0.003	0.675	0.010	0.004***	0.018	0.000***
LL	239.78		239.87		241.81		246.85	
AIC	-471.56		-469.74		-473.62		-483.71	
LR			0.18		4.06**		14.14***	
Japan								
c	0.000	0.988	0.000	0.987	0.001	0.855	-0.259	0.995
$\alpha 1$	0.126	0.085*	0.117	0.149	0.136	0.067	0.046	0.534
θ_1			-0.001	0.771	0.009	0.054*	0.016	0.000***
LL	256.16		256.21		258.05		261.68	
AIC	-506.33		-504.41		-506.1		-515.36	
LR			0.1		3.68**		11.04***	
Netherlands								
c	-0.002	0.731	-0.002	0.793	-0.002	0.697	-0.001	0.850
α_1	0.104	0.158	0.103	0.159	0.112	0.140	0.038	0.607
α_2	-0.012	0.733	0.155	0.114	-0.011	0.881	-0.099	0.194
θ_1			0.013	0.036**	-0.002	0.621	0.014	0.003***
LL	250.82		252.65		250.94		254.52	
AIC	-493.63		-495.29		-491.88		-499.29	
LR			3.66		0.24		7.4***	
Switzerland								
c	0.001	0.714	0.000	0.708	0.003	0.453	0.002	0.498
α_1	0.180	0.013**	0.112	0.189	0.189	0.011	0.122	0.097*
θ_1			-0.006	0.104	-0.077	0.304	-0.133	0.077*
LL	312.54		313.88		319.08		319	
AIC	-619.08		-619.76		-628.17		-628	
LR			2.68		13.08***		12.92***	
UK								
c	0.001	0.863	0.000	0.886	0.001	0.675	-0.001	0.559
α_1	-0.004	0.558	-0.189	0.054*	-0.045	0.546	-0.141	0.056*
α_2	-0.022	0.771	-0.011	0.878	-0.080	0.327	-0.103	0.152
θ_1			-0.009	0.003***	0.005	0.120	0.013	0.000***
LL	309.79		311.96		310.95		320.24	
AIC	-611.57		-613.93		-611.89		-630.48	
LR			4.34**		2.32		20.9***	
US								
c	0.002	0.532	0.002	0.570	0.004	0.333	0.003	0.398
α_1	0.051	0.484	0.028	0.777	0.004	0.959	-0.043	0.558
θ_1			-0.001	0.797	0.009	0.016**	0.015	0.000***
LL	296.08		294.63		297.35		303	
AIC	-555.16		-581.27		-586.69		-598.6	
LR			-2.9		2.54		13.84***	

Note: This table presents the estimation results of simple linear AR and the ARX models. The constant term c stands for a_0 when it comes to an AR(p)model and it stands for $a_0 + \theta_0$ for an ARX model. The log likelihood ratio (LR) denotes the log likelihood ratio of $H_0 : y_t = \alpha_0 + \alpha(L)y_t + \eta_t$ versus $H_1 : y_t = \alpha_0 + \alpha(L)y_t + \theta(L)x_t + \eta_t$.
* Significance at 10 % level.
**Significance at 5% level.
*** Significance at 1% level.

4.4. Estimates of nonlinear models

Table 5 reports the estimated results of STAR models formed by different specifications of transition variables, namely,R_{t-d}, ΔIV_{t-d}, MPS_{t-d}, ΔCCI_{t-d}. As far as STAR-R_{t-d} is concerned, our results indicate that lagged returns can act as observable economic variables that govern the transition of stock returns from one regime to another. The estimates of γ that can be interpreted as the speed of transition between the two extreme regimes range from 1.42 to 27.46 for the seven indexes, they are statistically significant at 5% only for two indexes. At the extremes, the coefficients of lagged returns appear with the opposite sign and statistically at 1% level for France, Japan and Netherlands, Switzerland, and the USA implying a nonlinear return process. For the UK and Germany, the coefficients estimates of lagged returns are not statistically significant. Indeed, for most value of returns above or below the threshold parameter, the returns appear to follow a random walk, indicating that there is no predictability in security prices.

As for the STAR-ΔIV_{t-d} model, the transition parameter γ estimates have the expected positive sign for all countries while being strongly important only for Japan and the UK. It is worth noting that the estimates of γ are far from being statistically significant for the remaining countries which would indicate that the model switches between the regimes very fast. This is in favor of using TAR models that assume a sharp switch between lower and upper regimes of stock returns. c_1 and c_2 stand for the threshold parameters that indicate the half-way point between the two regimes.

More specifically, non-linear models that have one threshold parameter $c1$ are referred to as LSTAR models. This parameter turns to be statistically significant at 1% level for France and Switzerland, while those who have two threshold constants c_1 and c_2 are specified as ESTAR models. According to the results, the fitted models happen to be LSTAR for five out of seven stock markets, which lend support to the hypothesis of an asymmetric behavior of stock returns in these countries.

When stock returns are modeled by STAR models with lagged volatility risk changes as transition variable, we find some evidence that the change in volatility indexes affects the dynamics of the stock returns. In the low stock-return regime, the innovation in the implied volatility indexes ΔIV has a large negative impact on the stock index returns for France, Germany, Switzerland and the UK. That is to say, if ΔIV increases up to the threshold parameter, stock returns decrease. In the extreme high stock-return regime and when ΔIV is above the threshold, the stock returns are positive for France, Germany, Japan, Netherlands and the UK, implying that an extreme high level of investor fear gauge makes profitable trading opportunities for long positions. This supports the results in Giot (2005), who pointed out that very high levels of the volatility index would indicate an oversold stock market, leading to positive future returns. This means that an extremely high level of volatility risk show profitable buying opportunities. Further, The test for no remaining non-linearity reveals that a model with two regimes governed by the volatility risk change adequately explains the nonlinear dynamic of stock returns in five out of seven market indexes.

The estimation results of the STAR-MPS model have also some crucial findings. Blatantly, the estimated stock returns are again time varying and characterized by both expansion and contraction phases of stock markets. As expected, the rate transition γ is positive and statistically significant for four out of six indexes, revealing that the model shifts between two regimes smoothly. Moreover, the estimated threshold $c1$ value is negative and significant at 10% level for most countries.

Besides, the signs of all coefficients appear consistent with the empirical monetary policy literature. The coefficient for the threshold variable (MPS) bears a positive sign in low-return regime, albeit such coefficient appears statistically significant only for the US. However, it bears a negative and statistically significant for the high-return regime, except for the US. Such a finding implies that the response of the stock market to monetary shocks switches signs from positive to negative, suggesting that unexpected cuts in the policy interest rate over the threshold value would affects negatively the performance of stock market. Again, this phenomenon is more pronounced when it comes to the STAR-MPS model.

In addition, the lagged returns have a significant effect on monetary policy decision in the low extreme regime of stock returns for France, Switzerland and the UK. This indicates that when the stock returns are very low, a decrease in lagged returns should positively affects monetary authority response by decreasing the short interest rate, which can significantly increase future returns. Conversely, when the equity returns are large, the impact of lagged returns on policy monetary action is much smaller than the impact when returns are in the extreme low regime. In other words, stock returns became more sensitive to a change in the short interest rate in the low regime. The probable reason is that when the given market is declined and returns are extremely low, the impacts is stronger for agents that are more financially constrained. This finding is broadly consistent with that of Hsu and Chiang (2011) who find that monetary policy might have asymmetric effects on stock returns.

More interestingly, our results show that the null hypothesis of no-remaining non-linearity cannot be rejected at the conventional risk levels for the STAR models with the lagged MPS for five countries. This implies that the suggested nonlinear models with lagged MPS capture the non-linear dynamics in stock returns.

Regarding the STAR-ΔCCI_{t-d} model, the transition parameters are significant for four countries and take small value for most indexes, which suggests a slow transition between the two regimes. Regime 1 is when the ΔCCI is low. In this case, the stock returns are negative for Netherlands and the US. On the other hand, regime 2 is when the ΔCCI is high and the stock returns now become positive for these indexes. These effects are consistent with Dridi and Germain (2004) and Chen et al. (2013) who documented positive and negative effects of investor sentiment on return in the regimes of high and low extreme returns, respectively. Nevertheless, the picture is completely different for Japan and the UK. In particular, regime 1 applies when sentiment indexes are low and stock returns are positive. In contrast, regime 2 takes effects when the sentiment change is high and the stock return is now negative. This result is quite different from the findings of Chen et al. (2013). A high level of optimism will increase future returns while low level of investor sentiment will decrease stock returns. However, but it appears to be consistent with those provided by Lee et al. (2002) who stated that higher (resp. lower) returns wee associated with a large increase (resp. decrease) in sentiment shift. These findings lend support to the basic implication of the Friedman effect, which implies that asset prices tend to be negatively affected when the noise traders$'$

misperceptions become more severe. The results of the of no-remaining non-linearity show that STAR models augmented with a sentiment change indicator as transition variable can adequately describe the dynamic characteristics of stock returns.

Table 5: Non linear models estimates

	Transition functions							
	Lagged returns		ΔIV		MS		ΔCCI	
	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value
France								
a0	0.2018	0.0030	3.6375	0.3297	0.1470	0.0142	0.0588	0.0021
α_{11}	0.3690	0.4092	0.6948	0.7222	0.0346	0.8609	1.0828	0.0009
α_{12}	1.1680	0.0042	0.9072	0.4090	0.5848	0.0096	0.0804	0.0561
α_{21}			0.3764	0.0052	0.0709	0.0020	0.5318	0.0931
a1	0.2063	0.0025	6.7357	0.3502	0.1489	0.0138	0.0780	0.0011
β_{11}	0.0081	0.9660	1.3818	0.7033	0.0637	0.7675	1.4269	0.0015
β_{12}	1.1158	0.0082	1.5243	0.4603	0.6319	0.0092	0.5213	0.1877
β_{21}			0.2098	0.3128	0.0605	0.0104	0.0510	0.1087
γ	27.4600	0.4904	0.1571	0.3570	11.0471	0.3433	1.5755	0.0075
c1	0.0800	0.0000	1.0154	0.0000	1.1071	0.0000	0.2637	0.8048
c2							0.2598	0.8077
R2	0.0837		0.0601		0.1718		0.2022	
auto	0.0431		0.1884		0.7059		0.1011	
nonlin	0.1017***		0.0689		0.7050		0.2936	
LM	0.0058		0.0035		0.1250		0.0021	
JB	0.0000		0.1167		0.0475		0.0761	
Germany								
a0	0.1937	0.1708	0.0052	0.2788	0.1105	0.0093	0.0026	0.5920
α_{11}	1.0623	0.1804	0.0392	0.7562	0.1872	0.2670	0.1027	0.2024
α_{21}			0.0046	0.5546	0.0471	0.0026	0.0214	0.0006
a1	0.2011	0.1580	0.1417	0.0002	0.1088	0.0109	0.0311	0.2155
β_{11}	0.9984	0.2132	1.5381	0.0654	0.1660	0.3831	0.7753	0.0010
β_{21}			0.0586	0.1000	0.0417	0.0242	0.0059	0.6259
γ	2.7929	0.0505	27.8100	0.9493	11.4180	0.4156	21.6192	0.8612
c1	0.1010	0.0048	2.3910	0.0000	1.0220	0.0000	2.0276	0.0000
c2			3.1589	0.7206			1.7605	0.0000
R2	0.0501		0.1064		0.0902		0.1601	
auto	0.2291		0.6690		0.0172		0.1249	
nonlin	0.2652		0.3640		0.0129		0.2369	
LM	0.0030		0.0132		0.2600		0.0988	
JB	0		0		0		0	
Japan								

Continued on next page

Table 5 – *Continued from previous page*

	Transition functions							
	Lagged returns		ΔIV		MS		ΔCCI	
	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value
a0	0.0413	0.0097	0.5557	0.4785	0.2992	0.0476	0.0001	0.8076
α_{11}	0.6803	0.0013	1.6503	0.1643	0.6457	0.2056	0.1343	0.0761
α_{21}			0.0919	0.3610	0.0741	0.0093	0.0042	0.4080
a1	0.0439	0.0169	1.2528	0.1111	0.3100	0.0419	0.5099	0.0777
β_{11}	0.6068	0.0250	3.8962	0.0016	0.5965	0.2644	0.7207	0.3819
β_{21}			0.0387	0.0000	0.0729	0.0108	0.1909	0.0649
γ	20.9100	0.4967	0.3519	0.0000	1.2742	0.0352	6.0895	0.6147
c1	0.0151	0.0738	0.7133	0.6738	2.4064	0.0099	1.8127	0.0000
c2							3.1996	0.0000
R2	0.0641		0.1213		0.0997		0.1079	
auto	0.1266		0.3924		0.5611		0.3688	
nonlin	0.9143		0.0462		0.0712**		0.3914	
LM	0.2708		0.1456		0.6589		0.0759	
JB	0.4739		0.7043		0.4910		0.1118	
Netherlands								
a0	3.5228	0.0004	0.0014	0.7578			0.3757	0.0354
α_{11}	2.1914	0.0052	0.0935	0.2162			0.1155	0.6454
α_{12}	15.3791	0.0003	0.0097	0.4467			0.3813	0.2269
α_{21}			0.0180	0.0464			0.1671	0.0297
a1	3.5236	0.0004	0.2350	0.2733			0.3892	0.0332
β_{11}	2.0968	0.0072	0.0539	0.9291			0.2124	0.4718
β_{12}	15.4657	0.0003	10.3422	0.1912			0.5703	0.0986
$\beta 21$			0.4029	0.1916			0.1688	0.0247
γ	14.5633	0.5056	2.5857	0.8684			3.0740	0.0363
c1	0.1905	0.0000	2.2456	0.0134			1.5953	0.0000
c2			3.2194	0.0000				
R2	0.1162		0.1641				0.1409	
auto	0.0017		0.1450				0.0474	
nonlin	0.2883		0.1972				0.1043	
LM	0.0117		0.0402				0.0000	
JB	0.0000		0.0000				0.0000	
Switzerland								
a0	0.2616	0.0264	0.0004	0.9191	0.1955	0.0523		
α_{11}	2.0605	0.0205	0.1622	0.1164	0.9540	0.0670		
α_{21}			0.0018	0.7712	0.0810	0.0128		
a1	0.2641	0.0260	0.0435	0.0365	0.1924	0.0598		
β_{11}	2.2326	0.0110	0.2778	0.3942	1.1825	0.0260		
β_{21}			0.0310	0.0228	0.0818	0.0089		
γ	4.8059	0.3478	14.8334	0.5344	2.3015	0.0849		
c1	0.0845	0.0000	0.7755	0.0002	2.2732	0.0016		

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Table 5 – *Continued from previous page*

	Transition functions							
	Lagged returns		ΔIV		MS		ΔCCI	
	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value
c2								
R2	0.1069		0.1482		0.1399			
auto	0.0910		0.5820		0.0061			
nonlin	0.1049		0.0039		0.1480			
LM	0.0002		0.0000		0.0000			
JB	0.1592		0.0055		0.0000			
UK								
a0	0.0643	0.4635	0.0051	0.9598	0.0116	0.6866	0.3107	0.0184
α_{11}	1.0997	0.0167	1.5455	0.2102	0.5923	0.0036	0.5144	0.0310
α_{12}	1.7340	0.1413	0.1654	0.5032	0.6926	0.0045	0.0956	0.7693
α_{21}			0.0050	0.2442	0.0288	0.0019	0.1147	0.0002
α_{22}							0.2233	0.0012
a1	0.0592	0.5114	0.0018	0.9329	0.0083	0.7748	0.3177	0.0175
β_{11}	1.2575	0.0119	2.8112	0.0098	0.5458	0.0127	0.3254	0.2296
β_{12}	1.9179	0.0980	0.4601	0.4653	0.6519	0.0655	0.1762	0.6188
β_{21}			0.0806	0.0045	0.0420	0.0002	0.0915	0.0016
β_{22}							0.2069	0.0023
γ	1.4289	0.0212	0.5904	0.0033	36.2074	0.7302	3.8055	0.0753
c1	0.0745	0.0720	0.2723	0.7288	1.4466	0.0000	1.6574	0.0000
c2	0.0860	0.0336						
R2	0.0848		0.1028		0.1346		0.2595	
auto	0.6742		0.3024		0.6970		0.3024	
nonlin	0.0003		0.0069		0.1247		0.0069	
LM	0.0004		0.0000		0.0244		0.0000	
JB	0.0001		0.0000		0.0000		0.0000	
US								
a0	0.1926	0.0000	0.0170	0.0181	0.0523	0.6114	2.1906	0.1832
α_{11}	1.8354	0.0000	0.0805	0.6843	0.1044	0.5526	1.6404	0.2048
α_{21}			0.0158	0.0614	0.0212	0.3277	0.2787	0.0566
α_{22}					0.0176	0.4429		
a1	0.1999	0.0000	0.0278	0.0010	0.1072	0.0644	4.2370	0.0593
β_{11}	1.8515	0.0000	0.3134	0.3657	0.1153	0.6379	3.3430	0.1864
β_{21}			0.0298	0.0945	0.0313	0.5465	0.0788	0.1380
β_{22}					0.0028	0.9493		
γ	17.8706	0.5771	2.7293	0.3901	0.6671	0.4413	0.2483	0.0857
c1	0.1752	0.0000	0.2784	0.7577	0.2223	0.8957	0.2875	0.7095
c2	0.0587	0.0000						
R2	0.1131		0.0444		0.0495		0.1419	
auto	0.0289		0.0338		0.1922		0.5189	

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Table 5 – *Continued from previous page*

Transition functions								
	Lagged returns		ΔIV		MS		ΔCCI	
	Coeff	P-value	Coeff	P-value	Coeff	P-value	Coeff	P-value
nonlin	0.0065		0.0110		0.0001		0.5062	
LM	0.0000		0.0000		0.0000		0.0000	
JB	0.0000		0.0000		0.0000		0.0000	

The table shows the parameter estimates and their P -value from the nonlinear least squares estimation of the LSTAR and ESTAR models when we use three proxies of volatility risk(δIV), monetary shocks (MS) and investor sentiment (δCCI). The last five lines for each stock market show the adjusted R2, the p-value of autocorrelation , non lineartiy tests and The ARCH LM tests. N.B. Non linear estimates are not reported in the case of STAR- PMS and STAR-CCI for Netherland and Switzerland, respectively since linearity is accepted for a high delayed parameter of the transition variable.

5. Main findings, concluding remarks and policy implications

This study contributes to the growing literature on behavioral finance related to modeling and forecasting stock return dynamics by suggesting a new modeling framework that has the appeal to investigate the dynamics of the stock market returns. Particularly, in line with McMillan (2005), we find that equity returns relative to G5 countries are well described by smooth transition AR models with two extreme regimes corresponding to large positive and large negative returns related to movements in financial and economic variables. Three major proxies of risk aversion, policy monetary shocks, and investor sentiment are therefore employed simultaneously to appraise how their threshold levels may shape their linkage with stock returns.

Our study′s main findings are as follows: We find that stock returns display a nonlinear pattern that it is contingent on the transition variable. More interestingly, we show that stock returns increase as the change in volatility risk becomes large, which predicts higher trading profits for long positions. This result corroborates Giot (2005)′s findings who provided evidence of an asymmetric relationship between the implied volatility index and the stock returns. Likewise, our results indicate that the stock returns tend to decrease subsequent to a monetary policy contraction, which would indicate that the stock prices are more responsive to an increase in the interest rates. Such findings are consistent with those of Thorbecke (1997) who came to the same conclusion. In like manner, the monetary policy response to the stock market decline is found to be more pronounced in the extreme low return regime in three stock markets; i.e. the monetary policy decisions become more sensitive to a change in their targets which affects significantly the stock market, especially in a low-return regime (Hsu and Chiang, 2011). Lastly, our estimates demonstrate that the stock returns rise when the sentiment index level exceeds the threshold level, whereas they decline when the sentiment index is below the threshold value. This finding, which is particularly pronounced for Netherlands and the US, can be explained by the high level of optimism, which leads to over-evaluated stocks with high potential returns. Conversely, when investors are pessimistic about the prospect for stocks, they will perceive them as under-evaluated with low potential returns.

On the other hand, we note a negative linkage between the sentiment change and the stock returns in both low and high return regimes for Japan and the UK. This indicates that the decrease in the risk premium, associated with the price-pressure effect is relatively more important than the positive impacts of the hold-more effect expected in the DeLong et al. (1990)′s DSSW model (Lee et al., 2002).

This study also serves as a basis for future research that seeks to analyze the non-linear effects of volatility risk, investor sentiment and monetary policy shocks on stock returns and suggests several promising directions of further research. For instance, one may conduct an empirical study that considers the heterogeneity among cross-sectional units and allows for smooth rather than discrete switching between regimes using panel smooth transition AR models. Another propitious research line would consist in conducting an empirical study using firm level data to find out whether or not monetary policy actions have larger effects on small firms. Finally, one may also appraise the forecasting performances of these smooth-transition nonlinear models that include risk aversion, monetary policy shocks and sentiment indexes as transition variables in terms of trading rules.

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