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Abstract

We investigate the predictability of stock returns in the financial market for a large panel of developed countries using investor sentiment, business-cycle variables and financial indicators within two panel regime-switching models, with threshold and smooth transition between regimes. We find strong evidence of predictability of long-term returns following the business cycles, but much weaker results for the short-run returns. During crisis times, investor sentiment and inflation become key factors in predicting stock returns. Different tests and goodness of fit measures point out that the use of regime-switching models is more appropriate than linear models. To our knowledge, this study is the first to examine the impact of investor sentiment on future returns for a large number of countries, the existing literature being mainly focused on the U.S. stock market.

JEL Classification: C23, C58, G01, G15.

Keywords: Financial stock returns predictability, Investor sentiment, Regime switching, Panel data, Financial crisis.

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1 Introduction

Many studies have found that stock returns contain a predictable component, from macroeconomic and financial indicators, that follows the business cycles.[1] The variability of this predictability with the business cycles suggests the use of models that can take into account such patterns. Stock return predictability has been mainly investigated in the U.S. market, while the extension to other markets has been the research question of a few recent papers. The events in the international financial market since the outset of the subprime crisis, and a new strand of studies have put forward the necessity to include measures of investor behavior among traditional predictors such as inflation, interest rates, dividend yield, liquidity.

Despite the empirical evidence that the returns of risky assets contain a predictable component, there is no theoretical consensus on the reason why they are predictable. Two potential explanations are put forward by the literature (e.g. Fama and French 1989; Pesaran and Timmermann 2000; Lettau and Ludvigson 2001). First, stock returns may be predictable because of market inefficiency triggered by investors' misperception of publicly available information.[2] This noise trading should increase during business-cycle troughs, leading to a higher stock return predictability component from investor sentiment during such periods. A second explanation is related to the rational reactions of investors to time-varying investment opportunities in an efficient market. This hypothesis is more likely to hold at normal times during which macroeconomic factors reflecting the value of the fundamentals should have a greater predictive power.

Financial markets were recently hit by the financial downturn, triggered by the subprime crisis in August 2007 which degenerated in a global crisis. The severe sovereign debt crisis that hit the euro area since the beginning of 2010 had dramatic effects for the financial stock returns. For several economies such as the U.S. and some Asian countries, the collapse of the dot-com bubble around the beginning of the century had severe consequences on financial markets. In such varying business-cycle conditions, our aim is to investigate in an international perspective and a multi-factor regime-switching model how the predictability pattern of long-term financial stock returns has evolved.

Keim and Stambaugh (1986) argue that theoretical models provide limited guidance about specific variables to be used as predictors. In the empirical literature, financial stock return predictability has been investigated by a wide range of variables that can be classified in three groups : (i) business-cycle indicators, (ii) financial variables, and recently (iii) investor sentiment.[3] Among the most used business-cycle indicators we find output and consumption growth (Lettau and Ludvigson 2001), inflation (Erb, Harvey and Viskanta 1995), interest rates (Pesaran and Timmermann 1994), credit and term spreads

[1] See Keim and Stambaugh (1986), Fama and French (1988, 1989), Pesaran and Timmermann (1994, 1995, 2000), Cochrane (1999), Ang and Bekaert (2007), Bollerslev, Tauchen and Zhou (2009), Bollerslev, Marrone, Xu and Zhou (2012), Camponovo, Scaillet and Trojani (2012), Cooper and Priestley (2013).

[2] Daniel, Hirshleifer and Subrahmanyam (1998) argue that the persistence of the return predictability pattern in time and across countries should be explained by a psychological component of the investors' behavior (under- and overreaction to news) and could not be due only to anomalies under market efficiency.

[3] Cochrane (2006) states that "stock returns can be forecastable by other variables such as dividend yields, yet unforecastable by their own past."

(Fama and French 1989, 1993). The most frequently used predictor among the financial variables is dividend yield which is found to have a predictive power on financial returns for different horizons (Ang and Bekaert 2007; Camponovo, Scaillet and Trojani 2012). Other crucial variables are market volatility (Bollerslev, Tauchen and Zhou 2009), market liquidity (Amihud 2002) and indicators related to the profitability of financial firms.

The impact of investor sentiment on future stock returns has received increasing attention during the last years and was surely motivated by the recent advances in theoretical and empirical behavioral finance (e.g. Baker and Wurgler 2006, 2007; Shefrin 2008). Barone-Adesi, Mancini and Shefrin (2012) document that sentiment decreased dramatically as the systemic risk during the recent financial crisis rose, contributing significantly to the decline of the value of the fundamentals and the value of the financial assets. The impact of investor sentiment in predicting returns should be larger in times of crisis because of an overreaction of investors to bad news, herd behavior and increasing risk aversion.

Given the mounting evidence that the predictability patterns of stock returns is closely linked to variations in business cycles, several studies advise the use of models that allow potential regime changes (Pesaran and Timmermann 1995). We use two panel regime-switching models with threshold (Hansen 1999) and smooth (González, Teräsvirta and van Dijk 2005) transition between regimes and compare from a goodness-of-fit perspective which specification fits better the data. The use of a panel framework, instead of separate time-series at the country level, should result in efficiency gains from the econometric estimation. To the best of our knowledge, this study is the first to examine the predictability of financial stock returns within a panel regime-switching model.

Although we use a panel framework, we are able to uncover the country-specific predictability variations since in the regime-switching models that we employ, the regime changes are driven by an observable transition variable. The spread between 3-month and overnight interbank rates closely tracks the market fluctuations: it is positive and exhibits upward moves during distressed periods and is close to zero or even negative in normal times. This pattern makes this indicator an appropriate transition variable.

Our empirical investigation in 20 developed countries from January 1999 to August 2011 uncovers that there is a substantial predictability component in the long-term financial stock returns. The data suggests that a regime-switching model containing a normal and a crisis regime fits better the data then the linear specification. The rather brusque turning point to a crisis regime is detected at the burst of the dot-com bubble by the beginning of year 2000 and at the inception of the global financial crisis by August 2007. In contrast with this time variation, the predictability pattern of aggregate financial stock returns is almost homogeneous across countries. This evidence is in line with the results in Bollerslev, Marrone, Xu and Zhou (2012) who investigate the predictability of stock returns in six developed countries. The predictability power of most of the factors varies with the business cycles, with investor sentiment and inflation having a larger impact on returns during crisis times. The other factors have a statistically constant impact (output growth), decreasing impact in a crisis regime (short-term rate, volatility, dividend yield, liquidity, market size), or no impact at all (term spread).

Finally, we find that altogether the estimation results are substantially robust. We notably assess the performance of our investor sentiment and liquidity measures by proposing alternative proxies and replace the quarterly real GDP growth by monthly forecasts of this variable, without changing the general conclusions. We also investigate predictability at the one-month horizon, but we find much weaker evidence in line with the current literature. The only robust predictor remains consumer price inflation.

The outline of this paper is as follows. In Section 2 we discuss the set of the predictors considered in this study and how they impact financial markets' performance. In Section 3 we introduce the Panel Threshold Regression (PTR) and the Panel Smooth Transition Regression (PSTR) models. Section 4 presents the data set used and the construction of some variables. The estimation results as well as some robustness analysis are displayed in Section 5. Finally, in Section 6 we conclude on the main findings of this study and suggest directions for future research.

2 Predictive factors of stock returns

In this section we briefly describe variables that are found by an important number of empirical studies to have a significant predictive power on stock returns. We classify them in three groups: (i) investor sentiment indicator (ii) macroeconomic variables related to the business cycles and (iii) variables specific to the financial markets. We do not claim that our set of predictors captures all aspects of financial return predictability, but we strongly believe that it captures the most persistent aspects of it.

2.1 Investor sentiment

A new strand of literature attributes the predictability component of returns (at least partially) to factors other than business-cycle proxies and financial indicators, such as noise trading or psychological factors that influence investment decisions (Pesaran and Timmermann 2000). Very recent papers call these behavioral aspects of trading under the notion of *investor sentiment*. Shefrin (2008) defines investor sentiment as excessive optimism or pessimism regarding stocks' performance in general. Put differently, sentiment reflects the misperception of noise investors concerning future prices. Lee, Jiang and Indro (2002) verify empirically the significant and persistent effect of investor sentiment on stock returns and volatility, putting forward that asset prices are not only determined by fundamentals, but most importantly by noise traders. The extent to which financial markets are affected by investor sentiment should depend on the business cycles with a larger influence during troughs characterized by a higher degree of information asymmetry and risk aversion. De Long, Shleifer, Summers and Waldmann (1990) show within a theoretical model how noise trader risk (persistence of over- or underreaction of noise trading) can make asset prices diverge from the value of the fundamentals. The unpredictability of the noise traders' behavior discourages rational and risk averse arbitrageurs to bet against them.

Given the unavailability of a direct measure of investor sentiment for reasonably long time periods and for a large number of countries, many studies have attempted to use accurate proxies of it.[4] Consumer Confidence Indices (CCI) are found to be highly adequate measures of investor sentiment (e.g. Fisher and Statman 2003; Qiu and Welch 2006). An advantage of this proxy is that it covers the sentiment of investors at the aggregate level and not exclusively of financial markets. For robustness checks we also use as a proxy for investor sentiment an Economic Sentiment Index (ESI) which is a leading indicator of general economic conditions. Lemmon and Portniaguina (2006) and Baker and Wurgler (2007) argue that indirect investor sentiment measures such as the consumer confidence may also reflect expectations about future economic outlook. Therefore, in these studies it is proposed to regress these proxies on a set of macroeconomic variables such as output growth, inflation, unemployment, and consider the residuals as an investor sentiment unrelated to economic fundamentals.

2.2 Business-cycle variables

Very early studies relate stock return predictability with business-cycles indicator. In Clay (1925) one can find the following statement: "So it is that the stock market is a creature of every day economic forces." Pesaran and Timmermann (1995) write that future stock returns not only vary with the business cycles, but they also depend on the magnitude of the real shocks. Variables having an important business-cycle component and frequently used predictors of stock and bond returns are real activity measures, such as real output growth or industrial production growth, inflation, short-term interest rates and term spreads.

Real output growth. The empirical evidence has found that the correlation between the financial returns and different measures of real economic activity is positive, suggesting that stock returns are pro-cyclical (Fama 1981; Chen, Roll and Ross 1986; Fama and French 1989; Boyd, Levine and Smith 1997).

Inflation. Empirical evidence in various studies vigorously suggests that stock returns react negatively to inflation (Chen, Roll and Ross 1986; Amihud 1996). This finding appears to go against the classical view that higher future stock returns should compensate for higher inflation. Erb, Harvey and Viskanta (1995) confirm that even in the long horizon, stock returns do not appear to hedge against inflation. Indeed, higher inflation rates are a feature of economies with less developed financial markets. From a theoretical standpoint Boyd, Levine and Smith (1997) write that high levels of inflation aggravate the efficiency of financial systems through more intense market frictions, leading to lower returns.

Short-term interest rate. Ang and Bekaert (2007) and many other studies find that short rates are a robust predictor of stock returns. Variations in the short interest rates may reflect variability in the real rate of return (Pesaran and Timmermann 1994) or monetary policy decisions (Rosa 2011), both associated positively to future returns.

Term spread. There is extensive empirical evidence that the term spread between

[4] Several surveys are conducted to quantify investor sentiment, but they are mainly concerned with the U.S. market and generally involve quite short time spans (e.g. UBS/Gallup, Investor Intelligence, American Association of Individual Investors surveys). Baker and Wurgler (2006, 2007) construct a composite investor sentiment for the U.S. market, which is extended to (only) six developed countries in Baker, Wurgler and Yuan (2012).

long- and short-term government bond yields is a leading indicator of business cycles, and as such it should have significant power in predicting stock returns. Fama and French (1989, 1993), Fama (1990) and Amihud (2002) find a positive impact of the term spread on expected returns. In contrast with the previous results, the estimated impact of term spread in Chen, Roll and Ross (1986) is negative.

2.3 Factors related to the financial market

The variables described below are directly linked to the financial index that we use in this study, that is why they are classified in this group. The empirical literature shows strong evidence of the predictive power of these factors.

Volatility. Periods of economic and financial distress are characterized by high levels of volatility. Bacchetta and van Wincoop (2013) document that the unprecedented high levels of volatility during the recent financial crisis were a general phenomenon affecting a large number of countries. Future stock returns are in general positively related to measures of volatility. Bollerslev, Tauchen and Zhou (2009) explain the association of higher variation in returns with higher future returns by the fact that high volatility includes a discount premium into prices. Furthermore, empirical investigations uncover that the predictive power of volatility on stock returns is not constant over time. An accurate measure of market return variation is the realized volatility, as asserted by a large number of studies (see French, Schwert and Stambaugh 1987; Amihud 2002; Adrian and Rosenberg 2008).

Dividend yield. The dividend yield is undoubtedly the most frequently used predictor with vast empirical evidence of its predictive power on asset returns. There is nevertheless no unanimous conclusion about the sign of this relation (Ang and Bekaert 2007). Black and Scholes (1974) write that dividend-paying stocks may increase in value because of investors' preference to receive dividends rather than capital gains, and thus accept lower returns. This negative dividend-return linkage could hold if the dividend yield is a characteristic of less risky assets, or dividend-paying assets are perceived as being more liquid (Amihud 2002). On the other hand, Brennan, Chordia and Subrahmanyam (1998) and Amihud (2002) suggest that the heavier taxation on dividends in comparison with capital gains may lead investors to require higher returns for dividend-paying stocks.

Liquidity. Seminal empirical studies (Amihud and Mendelson 1986; Brennan and Subrahmanyam 1996; Amihud 2002; Pástor and Stambaugh 2003; Acharya and Pedersen 2005; Bekaert, Harvey and Lundblad 2007, Gibson and Wang 2011) have found that expected equity returns contain a premium for systematic illiquidity: more illiquid stocks should offer larger returns. Besides, this risk premium should rise during deep economic or financial slowdowns when market liquidity dries out. We require a global indicator of liquidity prevailing in national financial markets.[5] Chordia, Roll, Subrahmanyam (2001) and Li,

[5]We could not use the Amihud (2002) proxy for market-wide illiquidity because in our panel framework endogeneity issues could arise. Indeed, Fasnacht (2008) estimates that not only the Amihud illiquidity measure explains stock market returns, but the inverse relation is also true. Concerning the Pástor and Stambaugh (2003) liquidity measure, in theory the coefficient associated with the signed volume can be interpreted as a liquidity cost and should be negative. In practice, there is no guarantee that its estimated value is negative and significantly different from zero. Our estimation results support this view.

Wang, Wu and He (2009) argue that higher trading volume is a feature of active markets and consequently an indicator of liquid markets.

Market size. Fama and French (1993) and Pesaran and Timmermann (2000) argue that market size reflects economic fundamentals and profitability. In our international perspective the average market capitalization per firm should capture variations in the development degree of countries. Indeed, in advanced economies the average firm size should be larger and the financial system well-developed, yielding a positive correlation between average market capitalization per firm and financial returns.

3 Predictive regressions

In this section we specify the Panel Threshold Regression (PTR) model of Hansen (1999) and the Panel Smooth Transition Regression (PSTR) model of González, Teräsvirta and van Dijk (2005), and show that the PTR is a special case of the PSTR when the smoothness parameter tends to infinity. We briefly describe the estimation method, some testing procedures to check the models' goodness of fit and the transition variable selection.

3.1 PTR and PSTR specifications

The PTR model for the prediction of the financial market return series $r_{i,t}$ of a panel of developed countries can be written as follows:

$$r_{i,t} = \mu_i + \boldsymbol{\lambda}_1' \boldsymbol{x}_{i,t-1} \mathbb{1}_{(q_{i,t-1} \le c)} + \boldsymbol{\lambda}_2' \boldsymbol{x}_{i,t-1} \mathbb{1}_{(q_{i,t-1} > c)} + \varepsilon_{i,t} \qquad i = 1, \ldots, N, \quad t = 1, \ldots, T \quad (1)$$

where $\mathbb{1}_{(\cdot)}$ is an indicator function, $\boldsymbol{x}_{i,t-1}$ is the 1-month lag of a set of k predictors described in Section 2, μ_i is an individual fixed effect and $\varepsilon_{i,t}$ is an error term which is assumed to be *i.i.d.* $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_2$ are two sets of k coefficients indicating the marginal effect of $\boldsymbol{x}_{i,t-1}$ on expected financial returns during the first and the second regimes, respectively. The non-constancy of the marginal effect is the outstanding feature of the threshold models. The transition between regimes is driven by an observable variable $q_{i,t-1}$ with the parameter c designing their threshold. We follow the notation of Hansen (1999) and rewrite the two-regime[6] threshold model in Equation 1 in a compact representation.

$$r_{i,t} = \mu_i + \boldsymbol{\lambda}' \boldsymbol{x}_{i,t-1}(c) + \varepsilon_{i,t} \quad (2)$$

with $\boldsymbol{\lambda} = \left(\boldsymbol{\lambda}_1' \ \ \boldsymbol{\lambda}_2'\right)'$ and $\boldsymbol{x}_{i,t-1}(c) = \left(\boldsymbol{x}_{i,t-1}' \mathbb{1}_{(q_{i,t-1} \le c)} \ \ \boldsymbol{x}_{i,t-1}' \mathbb{1}_{(q_{i,t-1} > c)}\right)'$.

Hansen's (1999) specification constrains the transition between regimes to be abrupt, splitting the observations in two according to the value of $q_{i,t-1}$ with respect to c. The more flexible nonlinear specification of González, Teräsvirta and van Dijk (2005) allows

[6]The PTR model can be generalized in a straightforward manner to involve more than two regimes. For instance the three-regime model can be written as follows:

$$r_{i,t} = \mu_i + \boldsymbol{\lambda}_1' \boldsymbol{x}_{i,t-1} \mathbb{1}_{\left(q_{i,t-1} \le c_1\right)} + \boldsymbol{\lambda}_2' \boldsymbol{x}_{i,t-1} \mathbb{1}_{\left(c_1 < q_{i,t-1} \le c_2\right)} + \boldsymbol{\lambda}_1' \boldsymbol{x}_{i,t-1} \mathbb{1}_{\left(q_{i,t-1} > c_2\right)} + \varepsilon_{i,t}.$$

for a smooth turning point, the parameter of smoothness being jointly estimated with the other coefficients of the model. The model can be written as follows:

$$r_{i,t} = \mu_i + \boldsymbol{\beta}_0' \boldsymbol{x}_{i,t-1} + \boldsymbol{\beta}_1' \boldsymbol{x}_{i,t-1} G\left(q_{i,t-1}; \gamma, c\right) + \varepsilon_{i,t}. \tag{3}$$

For the purposes of the estimation procedure described below we write Equation 3 in a more compact form.

$$r_{i,t} = \mu_i + \boldsymbol{\beta}' \boldsymbol{x}_{i,t-1}(\gamma, c) + \varepsilon_{i,t} \tag{4}$$

with $\boldsymbol{\beta} = \left(\boldsymbol{\beta}_0' \ \ \boldsymbol{\beta}_1'\right)'$ and $\boldsymbol{x}_{i,t-1}(\gamma, c) = \left(\boldsymbol{x}_{i,t-1}' \ \ \boldsymbol{x}_{i,t-1}' G(q_{i,t-1}; \gamma, c)\right)'$.

$G(q_{i,t-1}; \gamma, c)$ is the transition function, continuous and bounded between 0 and 1, given by Equation 5. We follow the literature[7] and choose as a transition function the logistic distribution.

$$G\left(q_{i,t-1}; \gamma, c\right) = \left(1 + \exp\left\{-\gamma\left(q_{i,t-1} - c\right)\right\}\right)^{-1}, \quad \gamma > 0. \tag{5}$$

The degree of smoothness of the transition from one regime to the other is determined by the scale parameter γ. Upon the value of this coefficient two limiting models can be distinguished. First, when γ tends to 0, the logistic function becomes constant (equal to 0.5) leading to the standard linear panel model with fixed effects. Given the positiveness constraint on γ, the second limiting case is when it converges to infinity. The transition function tends to an indicator function for $q_{i,t-1}$ greater than c and 0 otherwise. Consequently, the PSTR model converges to the PTR model.

As for the PTR, the principal advantage of the PSTR modeling upon the standard fixed-effects linear panel specification is that the marginal effect ($e_{i,t}$) of $\boldsymbol{x}_{i,t-1}$ on the dependent variable is time-varying and heterogeneous across individuals. It depends on the value of the transition variable $q_{i,t-1}$ pointing out its crucial role, and is given by the following formula:

$$e_{i,t} = \frac{\partial r_{i,t}}{\partial \boldsymbol{x}_{i,t-1}} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 G\left(q_{i,t-1}; \gamma, c\right). \tag{6}$$

With an increasing $q_{i,t-1}$, the marginal effect $e_{i,t}$ is increasing if $\boldsymbol{\beta}_1 > 0$ and decreasing if $\boldsymbol{\beta}_1 < 0$. Given that $G\left(q_{i,t-1}; \gamma, c\right)$ is bounded between 0 and 1, the extreme regimes are associated with the values $\boldsymbol{\beta}_0$ and $\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1$.

In a generalized setting, the PSTR approach can account for more than two regimes. In Equation 7 there are L transition functions and therefore $L + 1$ distinct regimes.

$$r_{i,t} = \mu_i + \boldsymbol{\beta}_0' \boldsymbol{x}_{i,t-1} + \sum_{l=1}^{L} \boldsymbol{\beta}_l' \boldsymbol{x}_{i,t-1} G_l\left(q_{i,t-1}^{(l)}; \gamma_l, \boldsymbol{c}_l\right) + \varepsilon_{i,t} \tag{7}$$

The transition variable $q_{i,t-1}^{(l)}$ can be different, or the same among the L transition func-

[7] See van Dijk, Teräsvirta and Franses (2002) and González, Teräsvirta and van Dijk (2005). In the first paper it is argued that regime-switching models using the logistic distribution are suitable to examine the business-cycle asymmetry relating the distinct regimes to the upward and downward moves.

tions. For $q^{(l)}_{i,t-1} = q_{i,t-1}$ and $\gamma_l \to \infty$ with $l = 1, \ldots, L$ the model in 7 converges to the PTR specification with $L+1$ distinct regimes.

3.2 Estimation

We estimate the parameters of the PTR and the PSTR specifications by nonlinear least squares method.[8] The standard estimation procedure requires a demeaned model in order to eliminate the individual fixed effects. Applying this transformation to Equations 2 (PTR) and 4 (PSTR) yields the following model:

$$r^*_{i,t} = \boldsymbol{\Psi}' \boldsymbol{x}^*_{i,t-1}(\boldsymbol{\theta}) + \varepsilon^*_{i,t} \tag{8}$$

where $\boldsymbol{\theta} = c$ and $\boldsymbol{\Psi} = \boldsymbol{\lambda}$ in the PTR, or $\boldsymbol{\theta} = (\gamma\ \ c)'$ and $\boldsymbol{\Psi} = \boldsymbol{\beta}$ in the PSTR. $r^*_{i,t} = r_{i,t} - \bar{r}_{i,t}$ with $\bar{r}_{i,t} = \frac{1}{T}\sum_{t=1}^{T} r_{i,t}$, $\varepsilon^*_{i,t} = \varepsilon_{i,t} - \bar{\varepsilon}_{i,t}$ with $\bar{\varepsilon}_{i,t} = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{i,t}$, $\boldsymbol{x}^*_{i,t-1}(\boldsymbol{\theta}) = \boldsymbol{x}_{i,t-1}(\boldsymbol{\theta}) - \bar{\boldsymbol{x}}_{i,t-1}(\boldsymbol{\theta})$ with $\boldsymbol{x}_{i,t-1}(\boldsymbol{\theta})$ defined above for both models and $\bar{\boldsymbol{x}}_{i,t-1}(\boldsymbol{\theta})$ given by Equations 9 for the PTR model and 10 for the PSTR model.

$$\bar{\boldsymbol{x}}_{i,t-1}(\boldsymbol{\theta}) = \begin{pmatrix} \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{x}_{i,t-1} \mathbb{1}_{(q_{i,t-1} \leq c)} \\ \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{x}_{i,t-1} \mathbb{1}_{(q_{i,t-1} > c)} \end{pmatrix} \tag{9}$$

$$\bar{\boldsymbol{x}}_{i,t-1}(\boldsymbol{\theta}) = \begin{pmatrix} \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{x}_{i,t-1} \\ \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{x}_{i,t-1} G(q_{i,t-1}; \boldsymbol{\theta}) \end{pmatrix}. \tag{10}$$

Under the assumptions of exogeneity of the explanatory variables and of an *i.i.d.* error term, the estimation procedure is performed combining Equations 11 and 12. Conditioned upon the value of the vector $\boldsymbol{\theta}$, both PTR and PSTR specifications are linear on the slope parameters $\boldsymbol{\Psi}$ which can be estimated by an ordinary least squares method. The location parameter (and the smoothness parameter for the PSTR) are numerically estimated in a second step by the minimization of the residuals sum of squares.

$$\hat{\boldsymbol{\Psi}}(\boldsymbol{\theta}) = \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \boldsymbol{x}^*_{i,t-1}(\boldsymbol{\theta}) \boldsymbol{x}^*_{i,t-1}(\boldsymbol{\theta})' \right\}^{-1} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \boldsymbol{x}^*_{i,t-1}(\boldsymbol{\theta}) r^*_{i,t} \right\} \tag{11}$$

$$\min_{\boldsymbol{\theta}}\ S(\boldsymbol{\theta}) = \sum_{i=1}^{N} \sum_{t=1}^{T} \left\{ r^*_{i,t} - \hat{\boldsymbol{\Psi}}(\boldsymbol{\theta})' \boldsymbol{x}^*_{i,t-1}(\boldsymbol{\theta}) \right\}^2. \tag{12}$$

The distribution of $\hat{\boldsymbol{\Psi}}(\hat{\boldsymbol{\theta}})$ depends on the estimates $\hat{\boldsymbol{\theta}}$. For the PTR model, Hansen (1999) argues that the asymptotic distribution of the slope parameters is normal since it is shown (see Chan 1993 and Hansen 2000) that the estimates of the threshold function which follow a nonstandard distribution, are not of *first-order asymptotic importance*. Under standard assumptions, the asymptotic distribution of all the parameters in the PSTR model is normal.

[8] The coefficients of these models are estimated in Matlab using algorithms provided by C. Hurlin.

3.3 Hypothesis testing

The adequacy of the predictive regressions for financial stock returns with regime-switching patterns should be tested against the null hypothesis of a linear model. Nonetheless, the testing procedure in both models proposed above faces a nuisance parameter issue under the null hypothesis, rendering the distribution of the tests nonstandard (see Davies 1977, 1987; Hansen 1996).

For the PTR model in Equation 1 the null hypothesis of linearity is formulated as $H_0 : \boldsymbol{\lambda}_1 = \boldsymbol{\lambda}_2$ against the alternative that they are different. Under the null hypothesis the value of the threshold parameter c cannot be defined. The identification issue is overcome by means of a bootstrap procedure (see Hansen 1999) to simulate the asymptotic distribution of the likelihood ratio test given by the following formula:

$$F_{1(PTR)} = \left(S_0 - S_1\left(\hat{c}\right)\right)/\hat{\sigma}^2 \tag{13}$$

S_0 and $S_1(\hat{c})$ are the residuals sum of squares for the linear and the single threshold models, respectively. The residual variance $\hat{\sigma}^2$ is estimated under the alternative hypothesis. The null hypothesis is rejected if the actual value of the test is larger than the critical value at the required percentile.

In the PSTR model given by Equations 3 and 5, the linearity hypothesis against a two-regime smooth transition model can be set in two different manners: $H_0 : \boldsymbol{\beta}_1 = \mathbf{0}$, or $H_0' : \gamma = 0$. Under H_0 the parameters of the transition function γ and c are not identified, whereas under H_0' the value of the location parameter c and the vector $\boldsymbol{\beta}_1$ can take any value. In this case, the identification problem is sidestepped through a first-order Taylor series expansion of the logistic distribution around $\gamma = 0$, as initially proposed by Luukkonnen, Saikkonen and Teräsvira (1988). A chi-squared test and its F version are used for the testing.

For both regime-switching specifications, if the null hypothesis of linearity is rejected in favor of a threshold (or smooth transition) model, in a second step one should test for no remaining nonlinearity. In other words one should test the null hypothesis of a two-regime model (the number of transition functions L is equal to 1) against the alternative of a model with three regimes ($L = 2$). The testing procedure should be applied until the null hypothesis is not rejected for the first time.

3.4 Transition variable selection

The selection of the transition variable is of crucial importance in our regime-switching modeling since it should exhibit variations which reflect the business cycles. We use as an appropriate indicator of risk related to business cycles the spread between 3-month and overnight interbank rates and take a lagged variable by one month to remain in a predictive regression setting. For the euro area countries the spread is identical since it is computed as the difference between the 3-month euribor and the eonia. A common transition variable for this group of countries should be suitable given that they are strongly interconnected through trade, financial system and unique monetary policy. A witness of the tight nexus among the euro area countries is the recent sovereign debt crisis which hit Greece at its inception and widely spread out among other member countries.

The empirical literature (e.g. Kuttner 2001) suggests that short-term rates respond more strongly to monetary policy actions than long-term rates. Moreover, tightening conditions in the interbank lending market and market liquidity constraints should apply pressure in favor of an increasing spread. Finally, this spread should also reflect increasing risk in the banking system and increasing risk aversion. The graphical display (not presented here) shows an effective surge of this spread from the onset of the financial crisis by July-August 2007. During calm periods this variable has been close to zero and has even become negative.

4 Data

The data set involves 20 developed countries[9] and covers the period from January 1999 to August 2011. The monthly frequency of the data is constrained by the availability of some macroeconomic variables. Indeed, measures such as inflation or investor sentiment are available monthly, whereas the output growth rate is published only quarterly. However, following Bollerslev, Marrone, Xu and Zhou (2012) the use of monthly data should not be too restrictive since they document that higher frequency data provide only limited additional predictive power.

We construct annual returns from Datastream Financials Index (DFI) in local currency available in Datastream. The DFI is a large index that involves mainly banks and insurance companies, and appropriately represents the financial markets of the countries considered in this study.[10] To compute the DFI return we consider the last price for each month and compute its percentage variation with respect to the last value of the same month during the previous year.

Similarly, for the other variables related with the DFI such as the dividend yield or the market capitalization the last value of each month is reported. The realized volatility is measured by the standard deviation computed from the daily data of the DFI annual return within a month. To control for a different number of firms within the index of each country we divide the DFI market capitalization by the constituent number of firms. Following the line of Amihud and Mendelson (1986) and Gibson and Mougeot (2004) we define liquidity as the number of shares traded monthly standardized by the number of index constituent shares to account for size and changes in the composition of the index. An alternative measure is the ratio of the monthly volume in *value* over the index market capitalization to adjust for its size. These variables measure liquidity (rather than illiquidity) and accordingly they should negatively influence future stock returns.

[9]Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States. The World Bank Group classifies Greece and Portugal as emerging countries.

[10]To assess its adequacy, we compared the DFI annual returns to the Dow Jones Financials Index (DJFI) annual returns. The within country correlations between the two series span from 75.55% to 99.93% with an overall value of 97.80%. The graphical display shows that these two series almost overlap. Nevertheless, we could not use the Dow Jones Financials Index because variables related to this index, such as dividend yield, market capitalization and trading volume are not available.

The inflation for Australia and New Zealand, and the realized real GDP growth for all countries are available solely in a quarterly frequency. In order to have a monthly frequency we report the same value three times within a quarter. To have a variable at a monthly frequency we alternatively employ the average real GDP growth forecasts with a 12-month horizon from Consensus Economics. A description of the variables used in this study is given in Table I in the Appendix.

We proxy investor sentiment by a Consumer Confidence Indicator (CCI) stemming from different data sources. In order for these indices to be comparable from a scale viewpoint, we subtract from each series the individual sample mean and divide the result by the individual standard deviation. To perform some robustness checks we use an alternative proxy for investor sentiment based on an Economic Sentiment Indicator (ESI).[11] For comparability reasons we apply the same transformation as for the CCI.

We follow the approach of Lemmon and Portniaguina (2006), Baker and Wurgler (2006, 2007) and Baker, Wurgler and Yuan (2012) and retrieve from the Consumer Confidence Indicator (CCI) the component related to economic fundamentals. To this aim we regress the CCI on the 1-month lag of real GDP growth (seasonally adjusted), consumer price inflation, unemployment rate and the change in the 3-month interbank rate.[12] The residuals from this model are assumed to reflect investor optimism or pessimism about the market dissociated to economic conditions. Given the stressful economic conditions since the inception of the global financial crisis, we consider that there has been a regime change in the consumer confidence indicator which should be appropriately modeled by a regime-switching approach. As for the predictability regression of financial market returns, we employ as transition variable the 1-month lag of the spread between 3-month and overnight interbank rates. The estimation results are displayed in Table III in the Appendix.[13]

Table 1 displays summary statistics for the dependent and the explanatory variables. In order to put in evidence the impact of the global financial downturn the data are split in two subsamples: from January 1999 to August 2007 and from September 2007 to August 2011. Table 2 shows a more detailed picture of financial markets' performance for each of the countries included in the data set. The standard deviation has shoot up from the outset of the financial crisis, with the exception of Germany, Greece and New Zealand. On the other hand, for the same period the average returns are largely negative for all the countries bar Sweden. The period previous to the financial and economic slowdown

[11] For the majority of the countries we have recourse to the Economic Sentiment Indicator (ESI) from the European Commission, a composite index of five sectoral business tendency indicators. This broad index includes the Consumer Confidence Indicator. For Switzerland we employ the KOF Economic Barometer which forecasts how the Swiss economy will perform in the next quarter or in the next two quarters. For the remaining countries (Australia, Canada, Japan, Ireland, New Zealand, Norway and U.S.) we employ a Composite Leading Indicator which is a six to nine months forward-looking measure of economic activity.

[12] Within a panel framework, Baker, Wurgler and Yuan (2012) orthogonalize each investor sentiment component by a similar set of macroeconomic variables. More precisely they use (i) consumption growth, (ii) industrial production growth, (iii) inflation, (iv) employment growth, (v) short-term rate and (vi) term premium.

[13] To compare the estimation results we fit to the data, both the PSTR and the PTR specifications. The estimated coefficients are quite similar through both specifications. For this reason, and in order to obtain estimation results for the predictive model of stock returns that are comparable through the smooth and the threshold regression specifications, we use only the residuals stemming from the PSTR on CCI as a proxy for investor sentiment. For robustness checks we use the corresponding residuals from the ESI.

exhibits positive and large average returns. Before proceeding to the estimation, we test the stationarity of the explanatory and the dependent variables having course to five panel unit root tests (augmented with one lag of the dependent variable). The results are shown in Table II in the Appendix. Overall, the tests strongly reject the null hypothesis of a unit root. The term spread and the average market capitalization per firm appear to be stationary when two lags and four lags are included, respectively. As regards the 3-month interbank rate, it should theoretically be stationary within a stable economic environment indicating for instance the ability of central banks to stabilize inflation. Nevertheless, to avoid any non-stationarity issue we consider the first difference of this variable which is found to be stationary.

5 Empirical evidence

5.1 Predictability of financial market returns

Figure 1 displays the annual returns of Datastream Financials Index (DFI). One can note that DFI returns have become negative and downward-sloping since September 2007. For most of the countries the series reached unprecedented low levels at the market bottom in February 2009 (from −75.3% for Belgium to −31.1% for New Zeland). Subsequently, financial market returns generally feature an upward spike but end up being quite low or negative by the end of the period under study. For the euro area countries, these negative returns should be related to the sovereign debt crisis. Additionally, financial markets experienced a severe drawdown (from −63.8% for Germany to −17.9% for Australia) consecutive to the dot-com burst that occurred over the period 2000-2003. Overall, stock returns seem to follow the business cycles, and as such they should contain a predictable component from variables closely related to these macroeconomic variations.

A necessary step preceding the specification of regime-switching models is testing the null hypothesis that a linear model correctly fits the data against a two-regime model. We perform two tests (Wald test and F-test) for the PSTR specification and a bootstrap-based test for the PTR model. The testing results are shown in Table 3, Panel B. The null hypothesis is rejected for the two specifications at any significance level. A further step is to test the null hypothesis of a two-regime model against a three-regime model. A two-regime model seems to accurately suit the data since this hypothesis cannot be rejected at 5% significance level for the PSTR and at any significance level for the PTR. We interpret these two regimes as the normal (low values of the logistic distribution) and the crisis (high values of the logistic distribution) regimes.

Figure 2 presents the logistic distribution, over time and for each country, evaluated at the transition variable and at the estimated values of γ and c. It points out that the financial markets' performance switched to the crisis regime at the outset of the subprime crisis in July-August 2007. Exception make Canada, Japan and Norway for which the impact of the financial downturn appears around October 2008 and lasts solely a few months. After two spikes in the crisis regime by the onset of the subprime crisis, the U.S. stock market's performance jumps from the normal to a long-lasting crisis regime from September 2008, following Lehman Brothers' bankruptcy. Subsequent to a short period of resurgence, the euro area financial markets seem to be absorbed by a crisis state by September 2010 which should reflect the European sovereign debt issue. Although of a different nature, the dot-com crash has played an important role in shaping financial markets' expected returns. Bar Japan and Norway, all the countries have experienced a crisis regime during this period which started by the end of 1999 with a varying duration.

The estimation results for the linear, PSTR and PTR specifications are shown in Table 3, Panel A.[14] Generally, both nonlinear models suggest very close values for the estimated parameters and the same direction for the marginal effect - whether it is significantly increasing or decreasing in the switch from one regime to the other. We also indicate whether the difference of impact between regimes is significant. Note that the impact of most of the variables is not constant over time, endorsing the choice of a nonlinear model. On the other hand, the estimation results from the linear model yield marginal effects from the predictors which are, in most cases, roughly an average of the coefficients across regimes.

Investor sentiment becomes a crucial factor in predicting financial returns during the crisis regime. This predictor has a negative, but not significant impact during the normal regime and a positive and highly significant impact during the crisis regime. This finding is in line with the initial hypothesis concerning the essential role of noise traders during periods of financial and economic distress. During such periods, investors' risk aversion increases and confidence in the market declines. Also, the higher degree of information asymmetry magnifies the tendency to act in herd , leading to subsequent fire sales in the affected market not necessarily responding to fundamentals. Consequently, during business-cycle troughs, pessimistic investor sentiment would induce even lower future returns.

In the group of business-cycle indicators the impact of real GDP growth is positive and highly significant, but does not change magnitude when shifting from the normal to the crisis regime (the difference of impact is small and not significant). A potential explanation of this result could be that real output growth is a headline indicator of the economic activity and as such, the same predictive power could be attributed to this factor whatever the state of the economy. On the other hand, inflation strongly influences expected stock returns through a negative and significant premium which is increasing in absolute value during the second regime. This finding confirms the results from Pesaran and Timmermann (1995) and from many other studies that inflation is a much stronger predictor of stock returns during business-cycle downturns, probably explained by the more intense market frictions during high inflation states. The change in the short-term interbank rate exhibits (as expected) a positive and significant factor loading with a weaker effect during the crisis in both model specifications. The positive impact of the short-term interbank rate could plausibly be explained by the fact that investors require higher future

[14] To check whether the estimation results are robust we successively regressed the stock returns on the second to twelfth lags of the explanatory variables. The estimation results are strongly supportive of those presented. It is important to note that as the lag increases the negative impact of investor sentiment in the first regime becomes significant and larger in absolute terms. On the other hand, the predictive power of the realized GDP growth in the same regime decreases.

returns during periods of monetary policy tightening. Despite the substantial literature documenting that term spread explains future stock returns, we could not find evidence in this line of research among all the different specifications that we tried.

The financial variables included in our predictive regression are the realized volatility, the dividend yield, a liquidity measure and the average market value per firm, all related to the FDI index. The volatility exhibits the expected positive coefficient, but its impact is surprisingly smaller in bad times. A potential explanation could be that volatility dramatically increased (graphics not shown here) at the peak of the financial crisis and remained at very high levels for a relatively short period compared to the interest rate spread which widened already at the onset of the subprime crisis. So the coefficient in crisis times may also capture periods of low volatility. The relation between the dividend yield and future stock returns is negative and highly significant, although the nonlinear specifications do not lead to the same conclusion regarding the direction of the marginal effect; whether it is decreasing or constant. Investors do not seem to require higher expected returns in compensation to the heavier taxation on dividends. As expected, liquidity measured by the trading activity over the number of shares outstanding has a negative predictive power on financial market returns. This effect appears to be constant over time. The average market capitalization exhibits a positive factor loading with a weaker effect during the crisis in both nonlinear specifications. If we assume that our initial hypothesis that market size reflects fundamentals and profitability holds, then the coefficient has the right sign.

As indicated by the estimated value of the smoothness parameter $\hat{\gamma} = 8.415$ in the PSTR specification, the turning point between the two regimes is quite brusque.[15] This finding could be a potential explanation of the striking similarity of the estimated parameters between the PSTR and the PTR specifications. In the PSTR model the estimated location parameter equals $\hat{c} = 0.5692$ but it is not included (although the figures are very close) in the confidence interval of the same parameter in the PTR model which gives $\hat{c} = 0.4700$. Regarding the goodness of fit, the three measures that we consider, within R-squared, Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (BIC) show that the PSTR model fits the data the best and the PTR model is slightly inferior. On the other hand, the linear model performs the poorest considering these three measures. For instance, the R-squared is 51.78% for the PSTR model, 51.09% for the PTR model and 46.75% for the linear specification. This level of R-squared is considerably high for a panel framework, confirming the stock return predictability in international markets.

From the specification of the PTR model, country i is involved in a crisis (here second regime) for month t if $c > q_{i,t-1}$. Based on the estimation of the location parameter c from the PTR, we investigate the number of countries classified in a crisis regime for each month and present some summary statistics for each year in Table 4. One can note that in October 1999, November 2007, October 2008 almost all the sampled countries are absorbed in a crisis. In October 1999, Japan and Norway and in November 2007, Canada, Japan and

[15] In Figure I is shown the logistic distribution for different values of the smoothness parameter. With $\gamma = 10$ the transition is already very steep and the functions are very close as γ increases.

Norway are the only countries not found to be in a crisis. This finding is perfectly in line with the results from the PSTR discussed above and displayed in Figure 2. Furthermore, in October 2008, at the peak of the financial crisis only New Zealand sidesteps the general turmoil. Over the 20 countries considered, there are on average 14 of them to be involved in a crisis during 2008.

Table 5 displays for each explanatory variable and for each country the average of the marginal effect as well as its variation expressed by the standard deviation (see the notes under this table for the computation). One can note that the variation in the average marginal effect between countries is small implying that the predictive component of the financial stock returns is not an isolated country phenomenon. This evidence is in line with the results in Bollerslev, Marrone, Xu and Zhou (2012) who discover almost identical predictability patterns across six developed countries. The extreme values of the average effects are found in New Zealand and Norway. Finally, note that the marginal effect of investor sentiment turns out to be negative for several countries, but this result arises from the negative and non-significant impact of this variable at the first regime.

The above summary shows that financial returns contain a substantial predictable component by business-cycle indicators, financial variables and investor sentiment, as claimed by some recent studies. The business-cycle variations suggest the use of a regime-switching model that we find highly suitable in our international framework. The stock return predictability pattern exhibits very low variations across the countries.

5.2 Robustness checks

5.2.1 Alternative measures of investor sentiment, real activity and liquidity

In this section we test whether the estimation results are robust to alternative measures of investor sentiment, real growth and market liquidity.[16]

In a novel strand of empirical literature, Consumer Confidence Indicators are documented to be a highly appropriate proxy for investor sentiment. Nevertheless, being a broad approximation of investors' expectations about the evolution of financial perspectives, its adequacy should be tested. For this reason, we use as an alternative measure a survey-based Economic Sentiment Indicator (ESI) consisting of business and consumer surveys, and so it is a broader index than the CCI.[17]

The estimation results of the predictive regressions are shown in Table 6 and are outstandingly in line with our baseline specification in Table 3. For the PSTR model there is stronger evidence in favor of a two-regime specification with p-values in favor of this null hypothesis of around 12%. The impact of the ESI on future stock returns during the crisis regime confirms the previous finding: the coefficient is positive and significant. Conversely, during normal times this impact becomes now positive and significant instead of a negative and insignificant result with CCI. As above, the impact tends to increase, but the difference of the coefficients is significant only for the PTR.

[16] Given the robustness of the estimation results, we do not present the tables in which GDP growth forecasts or an alternative measure of liquidity is included, but they are available upon request.

[17] As for the CCI, the ESI is orthogonalized by a set of business-cycle variables (see Section 4 on the data construction and Table III in the Appendix.

As mentioned in the description of the data, the real output growth is available only quarterly. To check the sensitivity of the estimation results due to the report of the same value of the output growth three times within a quarter, we replace it by an average of 12-month fixed horizon forecasts provided by professionals such as banks and research institutes at a monthly frequency.[18] The results remain qualitatively the same, but the impact of this variable on returns is nearly two times stronger. The results for the other variables are almost identical with two exceptions: the negative impact of CCI in the first regime and the positive impact of the term spread in the second regime are now significant.

Finally, we assess the robustness of our liquidity measure replacing the number of transactions over the total number of shares in the index by the trading activity in value over the market capitalization. Dividing by the market capitalization controls for the size of the index. Both variables are used in the literature as proxies of market liquidity. The impact of this variable on future returns appears significantly negative and constant across regimes, which is in line with the previous finding. The other results and conclusions are unaltered including the goodness of fit, the number of regimes in the model, and the best specification (PSTR).

5.2.2 Predictability of monthly financial returns

Many empirical studies show that returns are predictable at long horizons, whereas the predicable component at short horizons is small. We explore the short-term predictability of stock returns - at the one-month horizon - in our international framework. In a snapshot, monthly returns are much less predictable and the predictive power of the variables used is generally not robust, with a few of them having a significant effect. The only predictor which keeps the same pattern across the different specifications is CPI inflation: its impact is negative and increasing in absolute terms during crisis times.

We show the estimation results of our baseline specification in Table 7, but we tried several alternatives with similar conclusions. The tests indicate the use of a two-regime model as previously, with the PSTR specification providing a better fit. The R-squared is slightly above 10% for the two-regime models and below 5% for the linear model. Increasing the lag of the predictors does not improve the results. The shape of the logistic distribution (not shown here to save space) is very close to what is displayed in Figure 2. Even if the smoothness parameter is half the value, the transition between regimes is substantially sharp.

For some variables the coefficients change sign in the two-regime specifications compared to the results for the long-term returns. For instance, the liquidity has now a positive impact while the average market value per firm has a negative impact at Regime 1. The variables having a predictive power during normal times are investor sentiment, inflation, liquidity and market capitalization. During crisis times only CPI inflation keeps the predictability. The linear model does not point out to the same set of predictors since the factors with a significant impact are CPI inflation, short-term rate, volatility (now with a

[18] Given that the economic forecasts we employ are not available for Australia and New Zealand we remove these two countries from the data to perform this robustness analysis.

negative sign), dividend yield and market capitalization (also negative sign).

This investigation thus supports the findings of many studies that the predictability component of stock returns is present in long horizons, whereas short-term returns may not be predictable by variables tracing the business cycles.

6 Conclusion

A large body of empirical literature provides evidence that stock returns contain a predictable component from business-cycle indicators, although there is very limited theoretical guidance about which variables should be used for prediction and why stock returns are predictable. One hypothesis why stock returns are predictable is market inefficiency triggered by investors' misperception of publicly available information (Pesaran and Timmermann 2000). In a new strand of literature this noise trading activity is called investor sentiment and could be at the origin of the herd behavior of investors in crisis times. Following this literature, we investigate the predictability power of investor sentiment on the financial stock returns of a large number of developed countries, jointly with a broad set of business-cycle indicators and financial variables.

As suggested by several studies (Pesaran and Timmermann 1995) and following the evidence from our data, we use panel regime-switching models with threshold (Hansen 1999) and smooth transition (González, Teräsvirta and van Dijk 2005) between regimes, with the latter specification fitting slightly better the data. We find evidence that the predictability power of most of the factors considered varies with the business cycles, with investor sentiment and inflation having a larger impact on returns during crisis times. Real output growth being a headline indicator of the economic activity, seems to have a constant impact across the different states of the economy. Other variables found to be important predictors of stock returns in our international framework are short-term rates, volatility, dividend yield, liquidity and market size, with a lower impact in crisis times.

In line with the extant empirical evidence, we find substantial predictability in long-term returns and a considerably weaker predictable component in the short run. Inflation is the only robust predictor across the yearly and monthly returns. Confirming the results of Bollerslev, Marrone, Xu and Zhou (2012), we find similar predictability patterns in the marginal effect of the predictors through the countries. In our regime-switching models the transition between regimes is driven by the spread between the 3-month and overnight interbank rates, found out to reflect variations of the business cycles, of the risk in the banking system, and of the risk aversion. To our knowledge, this study is the first to examine the impact of investor sentiment on future returns for an extended number of countries, the existing literature being mainly focused on the U.S. stock market

As a future line of research it would be interesting to investigate whether this stock return predictability could be exploitable in an international context. Indeed, several studies show that although stock returns can be predictable from behavioral and business-cycle measures, they are not necessary profitable because of high transaction costs (Pesaran and Timmermann 1994, 1995). Knowing that stock returns are predictable, does not tell investors which factors have predictive power at the different phases of the business cycles.

References

[1] Acharya, V. V., Pedersen, L. H., 2005. Asset pricing with liquidity risk. *Journal of Financial Economics* 77(2), 375-410.

[2] Acharya, V. V., Amihud, Y., Bharath, S., 2012. Liquidity Risk of Corporate Bond Returns: A Conditional Approach. *Journal of Financial Economics* 110(2), 358-386.

[3] Adrian, T., Rosenberg, J., 2008. Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk. *Journal of Finance* 63(6), 2997-3030.

[4] Amihud, Y., 1996. Unexpected Inflation and Stock Returns Revisited: Evidence from Israel. *Journal of Money, Credit and Banking* 28(1), 22-33.

[5] Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets* 5(1), 31-56.

[6] Amihud, Y., Mendelson, H., 1986. Asset Pricing and Bid-Ask Spread. *Journal of Financial Economics* 17(2), 223-249.

[7] Ang, A., Bekaert, G., 2007. Stock Return Predictability: Is it There? *Review of Financial Studies* 20(3), 651-707

[8] Assenmacher, K., Gerlach, S., 2008. Financial Structure and the Impact of Monetary Policy on Asset Prices. Swiss National Bank working paper.

[9] Bacchetta, P., van Wincoop, E., 2013. Sudden Spikes in Global Risk. *Journal of International Economics* 89(2), 511-521.

[10] Baker, M., Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance* 61(4), 1645-1680.

[11] Baker, M., Wurgler, J., 2007. Investor Sentiment in the Stock Market. *Journal of Economic Perspectives* 21(2), 129-151.

[12] Baker, M., Wurgler, J., Yuan, Y., 2012. Global, local, and contagious investor sentiment. *Journal of Financial Economics* 104(2), 272-287.

[13] Banz, R. W., 1981. The Relationship between Return and Market Value of Common Stocks. *Journal of Financial Economics* 9(1), 3-18.

[14] Barone-Adesi, G., Mancini, L., Shefrin, H., 2012. Sentiment, Asset Prices and Systemic Risk. In *Handbook on Systemic Risk* edited by J.-P. Fouque and J. Langsam. Cambridge University Press.

[15] Bekaert, G., Harvey, C. R., Lundblad, C., 2007. Liquidity and Expected Returns: Lessons from Emerging Markets. *Review of Financial Studies* 20(5), 1783-1830.

[16] Bernanke, B., Kuttner, K., 2005. What Explains the Stock Market's Reaction to Federal Reserve Policy? *Journal of Finance* 60(3), 1221-1257.

[17] Black, F., Scholes, M., 1974. The Effects of Dividend Yield and Dividend Policy on Common Stock Prices and Returns. *Journal of Financial Economics* 1(1), 1-22.

[18] Bollerslev, T., Marrone, J., Xu, L., Zhou, H., 2012. Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence. *Journal of Financial and Quantitative Analysis*, forthcoming.

[19] Bollerslev, T., Tauchen, G., Zhou, H., 2009. Expected Stock Returns and Variance Risk Premia. *Review of Financial Studies* 22(11), 4463-4492.

[20] Boyd, J. H., Levine, R., Smith, B. D., 1997. Inflation and Financial Market Performance. Federal Reserve Bank of Minneapolis.

[21] Brennan, M. J., Chordia, T., Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics* 49(3), 345-373.

[22] Brennan, M. J., Subrahmanyam, A., 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics* 41(3), 441-464.

[23] Campbell, S. D., Diebold, F. X., 2009. Stock Returns and Expected Business Conditions: Half a Century of Direct Evidence. *Journal of Business and Economic Statistics* 27(2), 266-278.

[24] Campbell, J. Y., Yogo, M., 2006. Efficient tests of stock return predictability. *Journal of Financial Economics* 81(1), 27-60.

[25] Camponovo, L., Scaillet, O., Trojani, F., 2012. Predictive Regression and Robust Hypothesis Testing: Predictability Hidden by Anomalous Observations. Working paper.

[26] Chan, K. S., 1993. Consistency and limiting distribution of the least squares estimator of a threshold autoregressive model. *The Annals of Statistics* 21(1), 520-533.

[27] Chen, N., Roll, R., Ross, S., 1986. Economic Forces and the Stock Markets. *Journal of Business* 59(3), 383-403.

[28] Chordia, T., Roll, R., Subrahmanyam, A., 2001. Market Liquidity and Trading Activity. *Journal of Finance* 56(2), 501-530.

[29] Clay, P., 1925. Forecasting Security Prices. *Journal of the American Statistical Association* 20(150), 244-249.

[30] Cochrane, J. H., 1999. New Facts in Finance. *Economic Perspectives, Federal Reserve Bank of Chicago* 23(3), 36-58.

[31] Cochrane, J. H., 2005. *Asset Pricing.* Princeton University Press.

[32] Cochrane, J. H., 2006. *Financial Markets and the Real Economy.* Ed., London: Edward Elgar.

[33] Cooper, I., Priestley, R., 2013. The World Business Cycle and Expected Returns. *Review of Finance* 17(3), 1029-1064.

[34] Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance* 53(6), 1839-1885.

[35] Davies, R. B., 1977. Hypothesis Testing When a Nuisance Parameter is Present Only Under the Alternative. *Biometrika* 64(2), 247-254.

[36] Davies, R. B., 1987. Hypothesis Testing When a Nuisance Parameter is Present Only Under the Alternative. *Biometrika* 74(1), 33-43.

[37] De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J., 1990. Noise Trader Risk and Financial Markets. Journal of Political Economy 98(4), 703-738.

[38] Erb, C., Harvey, C. B., Viskanta, T. E., 1995. Inflation and World Equity Selection. *Financial Analysts Journal* 51(6), 28-42.

[39] Estrella, A., Hardouvelis, G. A., 1991. The Term Structure as a Predictor of Real Economic Activity. *Journal of Finance* 46(2), 555-576.

[40] Fama, E. F., 1965. The Behavior of Stock Market Prices. *Journal of Business* 38(1), 34-105.

[41] Fama, E. F., 1981. Stock Returns, Real Activity, Inflation, and Money. *American Economic Review* 71(4), 545-565.

[42] Fama, E. F., 1990. Stock Returns, Expected Returns and Real Activity. *Journal of Finance* 64(4), 1089-1108.

[43] Fama, E. F., French, K. R., 1988. Dividend Yields and Expected Stock Returns. *Journal of Financial Economics* 22(1), 3-25.

[44] Fama, E. F., French, K. R., 1989. Business Conditions and Expected Returns on Stocks and Bonds. *Journal of Financial Economics* 25(1), 23-49.

[45] Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1), 3-56.

[46] Fasnacht, P., 2008. Liquidity and Asymmetric Return Correlations: The case of the UK stock market. Working paper, University of Geneva and Swiss Finance Institute.

[47] Fisher, K. L., Statman, M., 2003. Consumer Confidence and Stock Returns. *Journal of Portfolio Management* 30(1), 115-127.

[48] Franses, P. H., van Dijk, D., 2000. *Nonlinear Time Series Models in Empirical Finance*. Cambridge University Press.

[49] Fratzscher, M., 2011. Capital Flows, Push versus Pull Factors and the Global Financial Crisis. NBER working paper series.

[50] French, K. R., Schwert, G. W., Stambaugh, R. F., 1987. Expected Stock Returns and Volatility. *Journal of Financial Economics* 19(1), 3-29.

[51] Gibson, R., Mougeot, N., 2004. The pricing of systematic liquidity risk: Empirical evidence from the US stock market. *Journal of Banking and Finance* 28(1), 157-178.

[52] Gibson, R., Wang, S., 2011. Liquidity Risk, Return Predictability and Hedge Funds' Performance: An Empirical Study. *Journal of Financial and Quantitative Analysis* 48(1), 219-244.

[53] González, A., Teräsvirta, T., van Dijk, D., 2005. Panel Smooth Transition Regression Models. SSE/EFI working paper series in economics and finance, no. 604.

[54] Hansen, B. E., 1996. Inference When a Nuisance Parameter Is Not Identified Under the Null Hypothesis. *Econometrica* 64(2), 413-430.

[55] Hansen, B. E., 1999. Threshold effects in non-dynamic panels: estimation, testing and inference. *Journal of Econometrics* 93(2), 334-368.

[56] Hansen, B. E., 2000. Sample Splitting and Threshold Estimation. *Econometrica* 68(3), 575-603.

[57] Keim, D. B., Stambaugh, R. F., 1986. Predicting Returns in the Stock and Bond Markets. *Journal of Financial Economics* 17(2), 357-390.

[58] Kuttner, N. K., 2001. Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics* 47(3), 523-544.

[59] Lee, W. Y., Jiang, C. X., Indro, D. C., 2002. Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking and Finance* 26(12), 2277-2299.

[60] Lemmon, M., Portniaguina, E., 2006. Consumer Confidence and Asset Prices: Some Empirical Evidence. *Review of Financial Studies* 19(4), 1499-1529.

[61] Lettau, M., Ludvigson, S., 2001. Consumption, Aggregate Wealth and Excepted Stock Returns. *Journal of Finance* 56(3), 815-849.

[62] Li, H., Wang, J., Wu, C., He, Y., 2009. Are Liquidity and Information Risks Priced in the Treasury Bond Market? *Journal of Finance* 64(1), 467-503.

[63] Luukkonnen, R., Saikkonen, P., Teräsvira, T., 1988. Testing Linearity Against Smooth Transition Autoregressive Models. *Biometrika* 75(3), 491-499.

[64] Menzly, L., Santos, T., Veronesi, P., 2004. Understanding Predictability. *Journal of Political Economy* 112(1), 1-47.

[65] Pástor, L., Stambaugh, R. F., 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111(3), 642-685.

[66] Pesaran, M. H., Timmermann, A., 1994. Forecasting Stock Returns: An Examination of Stock Market Trading in the Presence of Transaction Costs. *Journal of Forecasting* 13(4), 335-367.

[67] Pesaran, M. H., Timmermann, A., 1995. Predictability of Stock Returns: Robustness and Economic Significance. *Journal of Finance* 50(4), 1201-1228.

[68] Pesaran, M. H., Timmermann, A., 2000. A Recursive Modelling Approach to Predicting UK Stock Returns. *The Economic Journal* 110(460), 159-191.

[69] Qiu, L., Welch, I., 2006. Investor Sentiment Measures. NBER working paper no 10794.

[70] Rangvid, J., 2006. Output and expected returns. *Journal of Financial Economics* 81(3), 595-624.

[71] Rosa, C., 2011. Words that shake traders. The stock market's reaction to central bank communication in real time. *Journal of Empirical Finance* 18(5), 915-934.

[72] Shefrin, H., 2008. *A Behavioral Approach to Asset Pricing*. Elsevier.

[73] van Dijk, D., Teräsvirta, T., Franses, P. H., 2002. Smooth Transition Autoregressive Models - a Survey of Recent Developments. *Econometric Reviews* 21(1), 1-47.

Table 1: Summary statistics of the dependent and the explanatory variables from Jan. 1999 to Aug. 2011

	Jan. 1999 - Aug. 2007					Sep. 2007 - Aug. 2011				
	Obs.	Mean	Std.	Min	Max	Obs.	Mean	Std.	Min	Max
<u>DEPENDENT VARIABLE</u>										
DFI annual return (%)	2,080	10.054	25.233	-63.839	268.126	960	-10.492	32.894	-75.302	169.226
DFI monthly return	2080	0.703	5.522	-27.564	31.083	960	-1.424	8.977	-38.935	32.188
<u>EXPLANATORY VARIABLES</u>										
Investor sentiment (CCI)	2,040	0.0244	0.669	-2.163	2.3903	960	-0.0518	0.788	-2.663	2.221
Investor sentiment (ESI)	2,040	-0.0256	0.633	-2.544	2.138	960	0.0544	0.806	-2.681	2.924
Real GDP growth rate (SADJ, %)	700	2.651	1.555	-1.869	6.564	320	0.220	3.165	-9.905	7.625
Real GDP forecasts (%)	1,872	2.319	0.865	-1.211	4.619	864	0.962	1.659	-4.675	3.95
CPI inflation (%)	2,080	1.977	1.138	-1.834	6.078	960	2.054	1.568	-2.524	5.912
3-month interbank rate	2,080	3.443	1.639	0.046	8.65	960	2.443	2.036	-0.24	9.45
Term spread (%)	2,080	1.058	0.940	-2.711	3.957	960	1.527	2.129	-2.721	15.097
Volatility (%)	2,080	3.345	2.507	0.459	40.108	960	4.544	3.988	0.538	39.439
Dividend yield (%)	2,080	3.205	2.242	0.52	24.65	960	4.137	2.812	0	22.68
Liquidity (VO/NOSH)	2,080	0.0830	0.0586	0.0016	0.5641	960	0.1034	0.0955	0.00113	0.975
Liquidity (VA/MV)	2,080	0.0599	0.0368	0.0010	0.3414	960	0.0882	0.0692	0.000807	0.5647
Market capitalization (MV)	2,080	308,338.9	576,986.1	86.826	3,701,226	960	311,385.4	496,664.6	1,966.039	3,381,000
Number of firms	2,080	41.384	48.844	3	234	960	51.180	60.182	4	251
<u>TRANSITION VARIABLE</u>										
Spread: 3-month-overnight interb.	2,080	-0.00562	0.469	-2.849	2.96	960	0.453	0.374	-0.567	2.806

Data sources: Datastream, KOF, Bank of Denmark.

Notes: The data set contains a panel of 20 developed countries (see Table 2) for the period from January 1999 to August 2011. In order to put in evidence the impact of the recent global financial crisis the data set is split in two subsamples, the threshold between the two being the outset of the downturn, August 2007. The financial variables are observed at the end of the month.

The market size is expressed in millions of U.S. dollars. The real GDP growth, seasonally adjusted (SADJ), is available only quarterly, whereas the monthly forecasts of this variable are not available for Australia and New Zealand. The investor sentiment is obtained from the residuals of a model explaining Consumer Confidence Indicator (CCI) or Economic Sentiment Indicator (ESI) as a function of a set of macroeconomic variables (see Table III in the Appendix). The monthly volatility of financial returns is computed from daily observations of the annual return within a month. The liquidity measures defined as the ratios of the turnover by volume on the total number of shares in the index (VO/NOSH) and the turnover by value on the market size (VA/MV) are multiplied by 1000. The trading volume in value and in number of shares is the monthly sum of the daily observations. The term spread is the difference between the 10-year and the 1-year benchmark government bond yields. See also Table I in the Appendix for a description of the variables.

Table 2: Summary statistics for the annual return of Datastream Financials Index from Jan. 1999 to Aug. 2011

	Overall sample					Jan. 1999 - Aug. 2007					Sep. 2007 - Aug. 2011				
	Obs.	Mean	Std.	Min	Max	Obs.	Mean	Std.	Min	Max	Obs.	Mean	Std.	Min	Max
Australia	152	4.818	18.551	-47.016	52.855	104	10.261	10.388	-17.879	27.640	48	-6.975	25.720	-47.016	52.855
Austria	152	11.046	31.016	-70.108	107.265	104	18.016	19.009	-25.810	52.163	48	-4.056	44.253	-70.108	107.265
Belgium	152	-1.140	29.721	-75.302	67.563	104	6.646	22.747	-42.524	52.931	48	-18.009	35.766	-75.302	67.563
Canada	152	8.206	19.305	-44.373	65.552	104	12.265	15.240	-19.379	52.785	48	-0.588	23.967	-44.373	65.552
Denmark	152	10.595	32.100	-66.211	94.084	104	19.092	24.610	-23.837	91.591	48	-7.816	38.434	-66.211	94.084
Finland	152	8.561	26.340	-46.695	78.304	104	11.400	24.693	-38.440	61.935	48	2.411	28.920	-46.695	78.304
France	152	5.324	26.978	-58.581	71.355	104	12.758	20.943	-35.765	57.575	48	-10.783	31.461	-58.581	71.355
Germany	152	0.374	28.261	-63.839	65.021	104	4.778	28.491	-63.839	65.021	48	-9.166	25.519	-52.921	45.943
Greece	152	5.261	57.247	-72.427	268.126	104	22.062	58.975	-50.814	268.126	48	-31.143	30.478	-72.427	37.197
Italy	152	-1.475	25.023	-61.143	43.224	104	6.746	21.177	-35.953	38.681	48	-19.286	23.567	-61.143	43.224
Japan	152	-1.796	32.891	-50.916	109.413	104	7.934	34.130	-36.512	109.413	48	-22.879	16.107	-50.916	9.975
Netherlands	152	-0.800	28.543	-72.446	74.958	104	4.192	21.862	-52.738	39.869	48	-11.617	37.356	-72.446	74.958
New Zealand	152	0.690	15.180	-31.080	32.726	104	6.188	13.604	-23.698	32.726	48	-11.220	11.089	-31.080	9.590
Norway	152	12.987	36.862	-70.856	169.2	104	14.117	22.220	-41.396	73.858	48	10.537	57.223	-70.856	169.22
Portugal	152	-3.640	27.541	-67.817	56.476	104	6.516	21.224	-35.739	56.476	48	-25.647	26.962	-67.817	32.343
Spain	152	2.244	24.087	-55.702	61.630	104	8.917	19.268	-33.379	46.452	48	-12.214	27.171	-55.702	61.630
Sweden	152	7.945	28.456	-51.412	85.785	104	11.191	24.898	-35.999	53.160	48	0.911	34.194	-51.412	85.785
Switzerland	152	-0.020	26.490	-54.031	61.517	104	6.127	24.445	-47.078	61.517	48	-13.338	26.082	-54.031	55.660
United Kingdom	152	0.419	21.720	-60.044	68.244	104	4.904	14.816	-34.248	33.174	48	-9.300	29.892	-60.044	68.244
United States	152	1.718	22.054	-63.831	76.632	104	6.972	12.836	-21.011	43.397	48	-9.665	31.752	-63.831	76.632

Data source: Datastream.

Notes: In this table are presented summary statistics by country for the annual rate of return of Datastream Financial Index. The data set contains a panel of 20 developed countries for the period starting from January 1999 to August 2011. In order to put in evidence the impact of the recent global financial crisis, the data set is split in two subsamples, the threshold between the two being the outset of the downturn, August 2007. The summary statistics for the overall sample are also displayed.

Table 3: Linear, PSTR and PTR models for the predictability of financial returns

PANEL A	Linear model	PSTR			PTR		
		Regime 1	Regime 2	Difference	Regime 1	Regime 2	Difference
	$\boldsymbol{\beta}$	$\boldsymbol{\beta}_0$	$\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1$	$\boldsymbol{\beta}_1$	$\boldsymbol{\lambda}_1$	$\boldsymbol{\lambda}_2$	$\boldsymbol{\lambda}_2 - \boldsymbol{\lambda}_1$
Investor sentiment (CCI)	1.481	-0.9997	6.2804***	7.2802***	-0.7419	4.6956***	5.4375***
	(1.04)	(-1.5646)	(4.8064)	(4.5732)	(-1.2146)	(5.1066)	(4.9257)
Real GDP growth	3.197***	2.5189***	2.3982***	-0.1207	2.5794***	2.6473***	0.0679
	(10.29)	(10.0659)	(7.2974)	(-0.2616)	(10.8887)	(11.2508)	(0.2134)
CPI inflation	-5.730***	-4.2041***	-6.4725***	-2.2684**	-4.3068***	-6.2755***	-1.9687***
	(-4.91)	(-9.1731)	(-9.5629)	(-2.5598)	(-9.8755)	(-12.8151)	(-3.1968)
FDIFF.3-month interbank	9.925***	20.9724***	4.8736*	-16.0988***	19.1215***	7.3617***	-11.7598***
	(4.13)	(7.6433)	(1.8215)	(-3.8609)	(7.1930)	(3.3010)	(-3.4032)
Term spread	0.118	-0.4694	0.4709	0.9403	-0.4846	0.4737	0.9583*
	(0.19)	(-1.2764)	(0.8033)	(1.2784)	(-1.4067)	(1.0392)	(1.7981)
Volatility	2.885***	3.2876***	1.6674***	-1.6202***	3.1514***	1.9420***	-1.2094**
	(19.16)	(15.5437)	(3.5153)	(-2.8408)	(16.4724)	(3.9966)	(-2.3269)
Dividend yield	-2.817***	-2.5725***	-1.6507***	0.9218**	-2.4597***	-2.4733***	-0.0136
	(-3.53)	(-10.3338)	(-5.3129)	(2.2898)	(-10.2384)	(-8.6718)	(-0.0413)
Liquidity (VO/NOSH)	-59.70***	-45.7656***	-27.4577***	18.3079*	-45.8926***	-40.1247***	5.7679
	(-3.85)	(-5.3987)	(-3.6915)	(1.6474)	(-5.7745)	(-5.6424)	(0.6101)
Ln(Market value/Firms)	16.35***	16.3347***	13.8048***	-2.5298***	16.1013***	15.1103***	-0.9910***
	(5.53)	(15.0292)	(12.1065)	(-5.7594)	(14.7945)	(13.7529)	(-2.9111)
γ			8.4150 [5.8215, 12.5128]				
c			0.5692 [0.5045, 0.6377]			0.4700 [0.4591, 0.4894]	
Observations	2,980		2,980			2,980	
Number of id	20		20			20	
R-squared	0.4675		0.5178			0.5109	
AIC	6.0692		5.9675			5.9944	
BIC	6.0873		6.0073			6.0326	

PANEL B	Testing the null hypothesis of linearity, and subsequently the null hypothesis of a two-regime specification		
	LM test	F test	$F_{1(PTR)}$ test
$H_0: L = 0$ vs $H_1: L = 1$	161.075 (0.000)	18.736 (0.000)	269.958 (0.000)
$H_0: L = 1$ vs $H_1: L = 2$	16.413 (0.059)	1.805 (0.062)	81.121 (1.000)

Notes. PANEL A. The estimated models are the following. Linear model: $r_{i,t} = \mu_i + \boldsymbol{\beta}'\boldsymbol{x}_{i,t-1} + \varepsilon_{i,t}$, PSTR: $r_{i,t} = \mu_i + \boldsymbol{\beta}_0'\boldsymbol{x}_{i,t-1} + \boldsymbol{\beta}_1'\boldsymbol{x}_{i,t-1}G(q_{i,t-1}, \gamma, c) + \varepsilon_{i,t}$, PTR: $r_{i,t} = \mu_i + \boldsymbol{\lambda}_1'\boldsymbol{x}_{i,t}\mathbb{1}_{(q_{i,t-1}<c)} + \boldsymbol{\lambda}_2'\boldsymbol{x}_{i,t}\mathbb{1}_{(q_{i,t-1}\geq c)} + \varepsilon_{i,t}$.
The dependent variable is the annual return of Datastream Financials Index and the transition variable ($q_{i,t-1}$) is spread between 3-month and overnight interbank rates. "FDIFF.3-month interbank" stands for the first difference of the 3-month interbank rate. In parentheses are reported robust t-statistics and ***, ** and * denote significance at 0.01, 0.05 and 0.1 levels.
We obtain 95% confidence intervals for γ and c in the PSTR specification through a parametric bootstrap procedure by resamping in the time dimension with 1000 iterations. For the threshold parameter c in the PTR model, Hansen (1999) derives a non-standard likelihood ratio test and obtains the confidence interval from a no-rejection region. The confidence level is 95%.

PANEL B. We report the values of the test statistics testing the null hypothesis of linearity ($L = 0$) against a two-regime PSTR (PTR) model ($L = 1$) with L the number of transition functions. If the linearity hypothesis is rejected, one should test the null hypothesis of no remaining nonlinearity ($H_0 : L = 1$) against the alternative of three regimes ($L = 2$). For the PSTR specification we compute two tests. The LM-type test is given by $LM = TN\frac{RSS_0 - RSS_1}{RSS_0}$ and follows a χ^2_K ($K = 9$). The F-test statistic is given by $F = \frac{(RSS_0 - RSS_1)/K}{RSS_1/(NT-N-(L+1)K)}$ and follows $(F_{K,TN-N-(L+1)K})$. RSS_0 and RSS_1 represent respectively the residual sum of squares of the linear panel model with fixed effects and the residual sum of squares of a first-order Taylor series approximation of a two-regime PSTR model when we are testing for linearity. When we test for no remaining nonlinearity RSS_0 and RSS_1 are the residual sum of squares for the PSTR and the auxiliary regression of a first-order expansion of a three-regime PSTR model. For the computation of the F_1 statistic for the PTR, obtained by a bootstrap procedure to overcome the nuisance parameter issue (see Hansen 1999). The p-values are reported in parentheses.

Table 4: Number of countries in the crisis regime based on the PTR model

Transition variable:		3-month-overnight interbank spread			
Year	Obs	Mean	Std. Dev.	Min	Max
1999	11	2.8	5.18	0	[a]18
2000	12	1.9	1.31	0	5
2001	12	0.17	0.39	0	1
2002	12	0.58	0.79	0	2
2003	12	0.083	0.29	0	1
2004	12	0.83	0.72	0	2
2005	12	0.5	0.52	0	1
2006	12	0.33	0.65	0	2
2007	12	5.25	7.03	0	[b]17
2008	12	14	5.82	2	[c]19
2009	12	8.75	6.08	1	[d]15
2010	12	4.1	4.83	1	13
2011	8	6	5.15	0	12

Notes. In this table we present summary statistics concerning the number of countries in the crisis regime for each month within a year, basing our analysis on the PTR estimation results. We take the estimated location parameter from the PTR specification in Table 3 and compare it with the value of the transition variable for each month and for each country. If $\hat{c} > q_{i,t-1}$, than for month t, country i is classified as being in a crisis regime.

"Obs" stands for the number of months within a year for which we have the data, "Mean" is the average number of countries for each month within a year estimated to be involved in a crisis. "Std. Dev", "Min", "Max" are respectively the standard deviation, the minimum and maximum number of countries to undergo a downturn within a month.

[a]October 1999, [b]November 2007, [c]October 2008, [d]January, February 2009.

Table 5: Average marginal effect through time for the PSTR estimation results

	Sentiment		GDP growth		Inflation		Interbank 3M		Term spread		Volatility		Dividend yield		Liquidity		Ln(MV/Firms)	
	$\bar{e}_1$	σ_1	$\bar{e}_2$	σ_2	$\bar{e}_3$	σ_3	$\bar{e}_4$	σ_4	$\bar{e}_5$	σ_5	$\bar{e}_6$	σ_6	$\bar{e}_7$	σ_7	$\bar{e}_8$	σ_8	$\bar{e}_9$	σ_9
Euro Area	0.267	(2.306)	2.441	(0.082)	-4.637	(0.817)	18.608	(4.751)	-0.238	(0.235)	3.033	(0.411)	-2.363	(0.268)	-43.102	(4.334)	15.703	(0.705)
Australia	-0.035	(1.495)	2.452	(0.053)	-4.530	(0.529)	19.229	(3.079)	-0.269	(0.153)	3.087	(0.266)	-2.398	(0.174)	-43.669	(2.808)	15.795	(0.457)
Canada	-0.495	(1.097)	2.468	(0.039)	-4.367	(0.389)	20.178	(2.260)	-0.316	(0.112)	3.169	(0.196)	-2.452	(0.127)	-44.535	(2.062)	15.936	(0.335)
Denmark	1.029	(2.586)	2.414	(0.092)	-4.906	(0.916)	17.039	(5.328)	-0.160	(0.264)	2.897	(0.461)	-2.275	(0.300)	-41.672	(4.860)	15.471	(0.790)
Japan	-0.523	(0.980)	2.469	(0.035)	-4.357	(0.347)	20.236	(2.019)	-0.318	(0.100)	3.174	(0.175)	-2.455	(0.114)	-44.588	(1.842)	15.945	(0.299)
New Zealand	1.280	(2.520)	2.405	(0.089)	-4.995	(0.892)	16.521	(5.190)	-0.134	(0.257)	2.852	(0.449)	-2.245	(0.293)	-41.199	(4.734)	15.394	(0.770)
Norway	-1.021	(1.108)	2.487	(0.039)	-4.180	(0.392)	21.262	(2.282)	-0.369	(0.113)	3.262	(0.197)	-2.513	(0.129)	-45.523	(2.082)	16.097	(0.338)
Sweden	-0.171	(1.370)	2.457	(0.049)	-4.481	(0.485)	19.511	(2.823)	-0.283	(0.140)	3.111	(0.244)	-2.414	(0.159)	-43.926	(2.575)	15.837	(0.419)
Switzerland	-0.207	(1.772)	2.458	(0.063)	-4.469	(0.628)	19.585	(3.651)	-0.286	(0.181)	3.117	(0.316)	-2.418	(0.206)	-43.993	(3.330)	15.848	(0.541)
United Kingdom	0.560	(2.586)	2.431	(0.092)	-4.740	(0.916)	18.005	(5.327)	-0.208	(0.264)	2.981	(0.461)	-2.329	(0.300)	-42.553	(4.859)	15.614	(0.790)
United States	0.220	(2.305)	2.443	(0.082)	-4.620	(0.816)	18.706	(4.748)	-0.243	(0.235)	3.041	(0.411)	-2.369	(0.268)	-43.192	(4.331)	15.718	(0.704)

Notes. In this table are presented the average marginal effects through time ($\bar{e}_i^{(j)}$) as well as the corresponding standard deviation ($\sigma_i^{(j)}$ in parentheses) for each explanatory variable and for each country. The average marginal effects are computed by the following formula: $\bar{e}_i^{(j)} = \frac{1}{T-1}\sum_{t=2}^{T}[\beta_{0,j} + \beta_{1,j} G(q_{i,t-1};\gamma,c)]$ and the standard deviation by the square root of $\sigma_i^{2(j)} = \sum_{t=2}^{T}\left(e_{i,t}^{(j)} - \bar{e}_i^{(j)}\right)^2$ with $e_{i,t}^{(j)}$ given in Equation 6 for $i = 1,\ldots,11$ (country index) and $j = 1,\ldots,9$ (variable index). For the euro area countries the average marginal impact is identical because of the common transition variable given by the spread between the 3-month euribor and the eonia.
"GDP Growth" stands for the real GDP growth, "MV/Firms" is the ratio of market capitalization of the number of firms composing the index, "Interbank 3M" stands for the change in 3-month interbank rate.

Table 6: ROBUSTNESS CHECK 1: linear, PSTR and PTR estimation results for DFI returns with an investor sentiment measure based on ESI

PANEL A	Linear model	PSTR			PTR		
		Regime 1	Regime 2	Difference	Regime 1	Regime 2	Difference
	$\boldsymbol{\beta}$	$\boldsymbol{\beta}_0$	$\boldsymbol{\beta}_0+\boldsymbol{\beta}_1$	$\boldsymbol{\beta}_1$	$\boldsymbol{\lambda}_1$	$\boldsymbol{\lambda}_2$	$\boldsymbol{\lambda}_1-\boldsymbol{\lambda}_0$
Investor sentiment (ESI)	3.353*	1.9266***	3.3567**	1.4301	1.9640***	4.7798***	2.8158***
	(1.84)	(2.9118)	(2.0099)	(0.7374)	(3.1812)	(4.1099)	(2.1728)
Real GDP growth	3.231***	2.5677***	2.4318***	-0.1359	2.6262***	2.6882***	0.0620
	(9.76)	(10.3631)	(7.0895)	(-0.2883)	(11.0831)	(11.5799)	(0.1964)
CPI inflation	-5.797***	-4.2339***	-6.5019***	-2.2680**	-4.2899***	-6.5291***	-2.2392***
	(-4.92)	(-9.2597)	(-9.2833)	(-2.5039)	(-9.8123)	(-13.2749)	(-3.6332)
FDIFF.3-month interbank	9.138***	19.9922***	5.5252*	-14.4669***	18.4024***	7.9107***	-10.4916***
	(3.99)	(7.4360)	(1.9273)	(-3.3921)	(6.9894)	(3.4224)	(-3.0018)
Term spread	0.0338	-0.5622	0.8331	1.3953*	-0.5596	0.6868	1.2464**
	(0.05)	(-1.5161)	(1.5048)	(1.9560)	(-1.6033)	(1.5740)	(2.3949)
Volatility	2.889***	3.2543***	1.6995***	-1.5548***	3.1306***	1.9905***	-1.1401**
	(18.19)	(15.5929)	(3.6450)	(-2.7737)	(16.3988)	(4.2768)	(-2.2791)
Dividend yield	-2.682***	-2.4045***	-1.6966***	0.7080*	-2.2915***	-2.4190***	-0.1275
	(-3.22)	(-9.6835)	(-5.1983)	(1.7086)	(-9.5305)	(-8.5042)	(-0.3871)
Liquidity (VO/NOSH)	-64.79***	-48.4507***	-37.1236***	11.3272	-48.7994***	-50.0760***	-1.2766
	(-4.48)	(-5.7440)	(-4.1844)	(0.9348)	(-6.1122)	(-6.3723)	(-0.1290)
Ln(Market value/No.firms)	15.91***	15.5061***	13.0792***	-2.4270***	15.2491***	14.4148***	-0.8343**
	(5.62)	(14.4612)	(11.6013)	(-5.4932)	(14.2635)	(13.3241)	(-2.5108)
γ			8.6232 [5.8630, 13.0015]				
c			0.5773 [0.5097, 0.6476]			0.4700 [0.4591, 0.4894]	
Observations	2,980		2,980			2,980	
Number of id	20		20			20	
R-squared	0.4724		0.5182			0.5123	
AIC	6.0599		5.9666			5.9915	
BIC	6.0780		6.0065			6.0298	

PANEL B	Testing the null hypothesis of linearity, and subsequently the null hypothesis of a two-regime specification		
	LM test	F test	$F_{1(PTR)}$ test
$H_0: L=0$ vs $H_1: L=1$	162.750 (0.000)	18.942 (0.000)	259.538 (0.000)
$H_0: L=1$ vs $H_1: L=2$	14.100 (0.119)	1.549 (0.125)	67.6803 (1.000)

Notes. We replace the investor sentiment based on a Consumer Confidence Indicator (CCI) by a proxy based on an Economic Sentiment Indicator (ESI). The transition variable is the spread between 3-month and overnight interbank rates. See also the notes under Table 3.

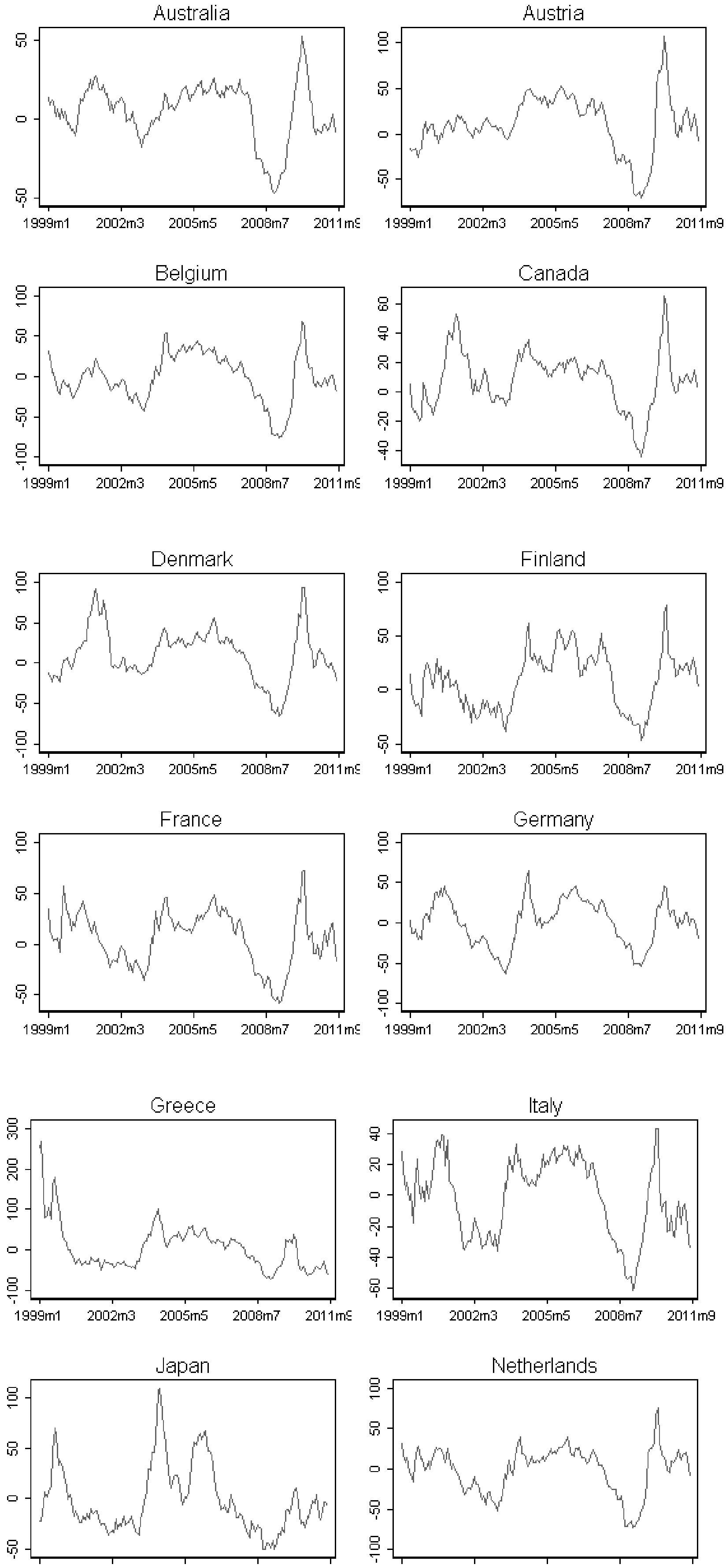
Table 7: ROBUSTNESS CHECK 2: Linear, PSTR and PTR models for the predictability of *monthly* financial returns

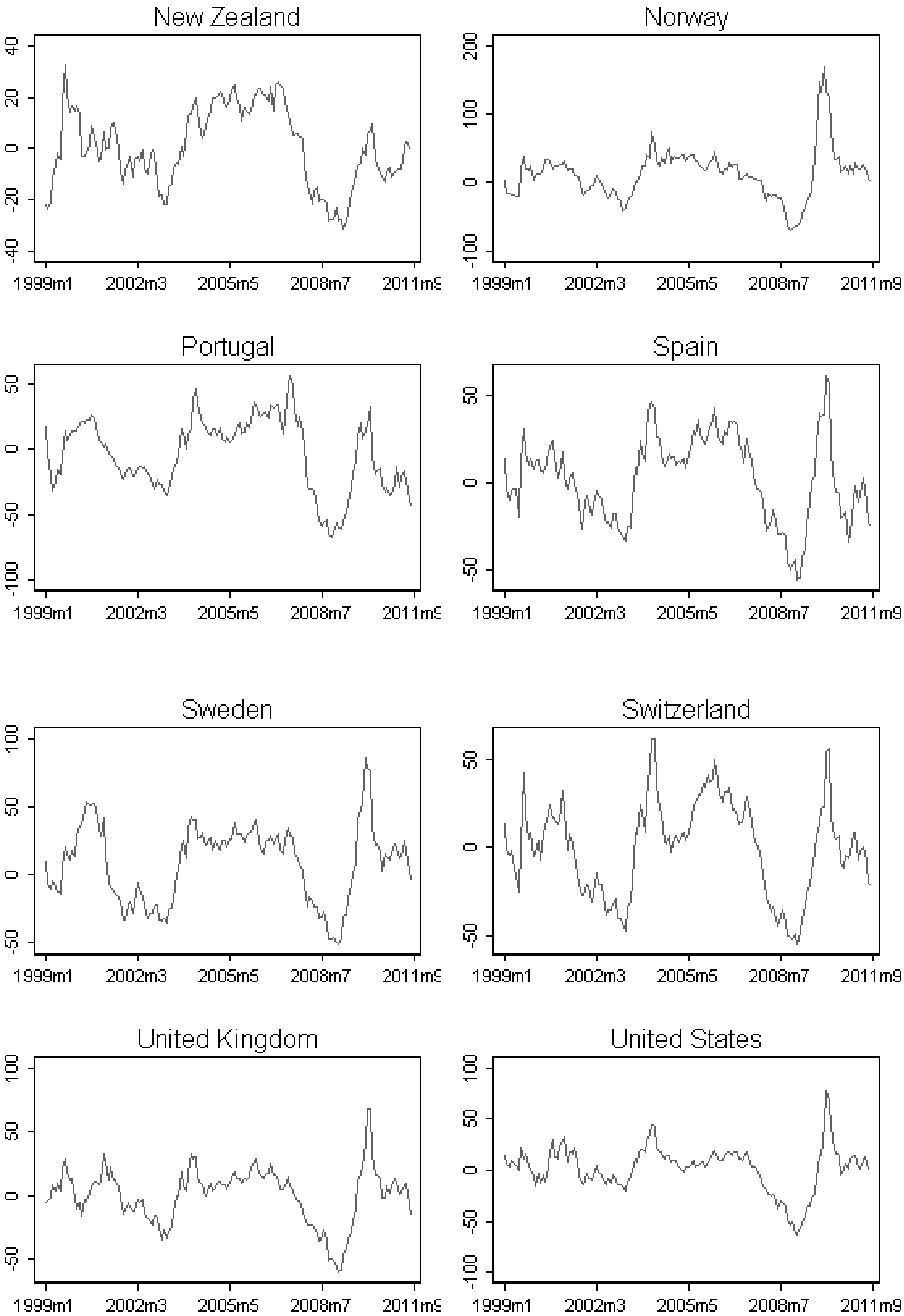
PANEL A	Linear model	PSTR			PTR		
		Regime 1	Regime 2	Difference	Regime 1	Regime 2	Difference
	$\boldsymbol{\beta}$	$\boldsymbol{\beta}_0$	$\boldsymbol{\beta}_0 + \boldsymbol{\beta}_1$	$\boldsymbol{\beta}_1$	$\boldsymbol{\lambda}_1$	$\boldsymbol{\lambda}_2$	$\boldsymbol{\lambda}_2 - \boldsymbol{\lambda}_1$
Investor sentiment (CCI)	-0.0404	-0.6003***	1.3134	1.9137	-0.5082***	0.6523	1.1606
	(-0.19)	(-2.9132)	(1.0203)	(1.3755)	(-2.8811)	(0.7643)	(1.3335)
Real GDP growth	0.101	0.0538	-0.3917	-0.4455	0.0163	-0.1056	-0.1219
	(1.03)	(0.5352)	(-1.0184)	(-1.0142)	(0.2043)	(-0.4754)	(-0.5219)
CPI inflation	-1.266***	-0.2962*	-5.2002***	-4.9040***	-0.7080***	-3.2868***	-2.5787***
	(-7.65)	(-1.8298)	(-7.3542)	(-6.2915)	(-4.9063)	(-7.2175)	(-5.4420)
FDIFF.3-month interbank	1.675***	2.4634***	3.9488*	1.4854	1.1231	3.5139**	2.3907
	(3.23)	(2.8306)	(1.8691)	(0.5998)	(1.3267)	(2.0921)	(1.2742)
Term spread	0.281	0.1976	0.5542	0.3566	0.1542	0.4342	0.2800
	(1.30)	(1.4624)	(0.7788)	(0.4795)	(1.3101)	(1.0741)	(0.6814)
Volatility	-0.0777**	-0.0149	-0.3286	-0.3138	-0.0411	-0.3674*	-0.3263
	(-2.37)	(-0.3243)	(-1.0692)	(-0.9618)	(-0.9963)	(-1.8014)	(-1.5710)
Dividend yield	-0.148**	0.0067	0.0154	0.0087	0.0181	-0.2594	-0.2775
	(-2.26)	(0.0707)	(0.0474)	(0.0243)	(0.2115)	(-1.1792)	(-1.2144)
Liquidity (VO/NOSH)	-2.028	7.6748***	-10.0063	-17.6811**	4.8629*	-5.8415	-10.7043
	(-0.79)	(2.7623)	(-1.2775)	(-2.0158)	(1.9162)	(-0.9085)	(-1.5973)
Ln(Market value/Firms)	-1.217**	-1.2759***	-0.3908	0.8851**	-1.1599***	-0.4757	0.6842***
	(-2.68)	(-3.5070)	(-0.7898)	(2.4764)	(-3.2286)	(-1.1388)	(2.9240)
γ			4.8251 [2.8486, 7.4781]				
c			0.8187 [0.7115, 0.9935]			0.6900 [0.5433, 0.7161]	
Observations	2,980		2,980			2,980	
Number of id	20		20			20	
R-squared	0.0486		0.1147			0.1011	
AIC	3.814		3.754			3.7640	
BIC	3.833		3.794			3.8022	

PANEL B	Testing the null hypothesis of linearity, and subsequently the null hypothesis of a two-regime specification		
	LM test	F test	$F_{1(PTR)}$ test
$H_0 : L = 0$ vs $H_1 : L = 1$	130.676 (0.000)	15.038 (0.000)	178.659 (0.000)
$H_0 : L = 1$ vs $H_1 : L = 2$	13.897 (0.126)	1.527 (0.132)	48.218 (1.000)

Notes. In this table we present the estimation results for the *monthly* financial returns and for the linear model, for the PSTR and for the PTR. For more information on the content of the table refer also to the notes under Table 3.

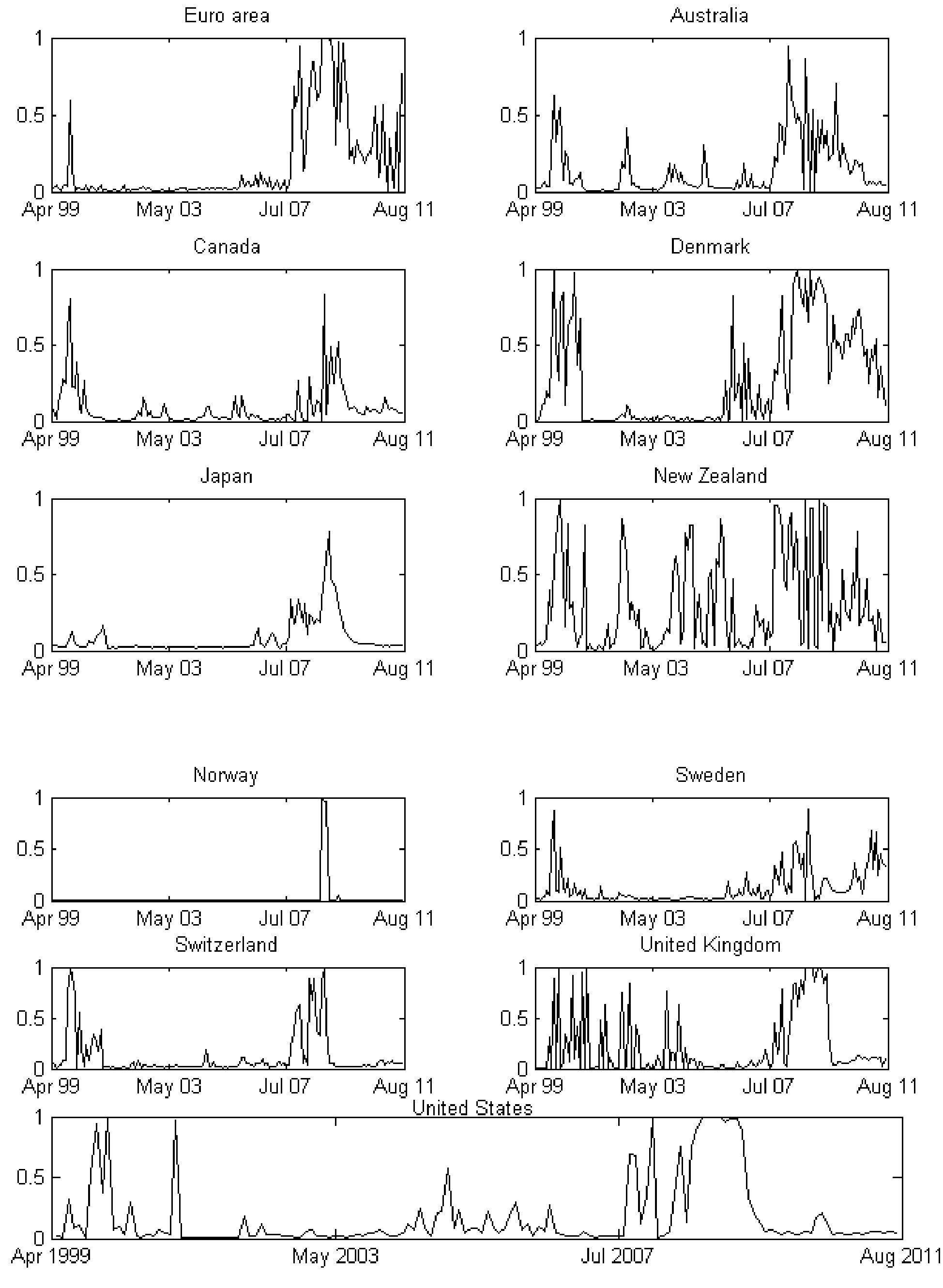
Figure 1: Annual financial returns





Notes: The annual return of Datastream Financials Index is computed as the year on year percentage change.

Figure 2: Estimated transition function for each country



Notes: The transition variable is the first lag of the spread between 3-month and overnight interbank rates. The logistic distribution is given by the following formula: $G(q_{i,t-1}; \hat{\gamma}, \hat{c}) = \left(1 + e^{\hat{\gamma}(q_{i,t-1} - \hat{c})}\right)^{-1}$ where $\hat{\gamma}$ and $\hat{c}$ correspond to the estimated values exhibited in Table 3, Panel A. For the euro area countries the transition variable is identical and is given by the difference between the 3-month euribor and the eonia.

Appendix

Table I: Variable description

Variable	Description
DEPENDENT VARIABLE	
DFI return	Annual and monthly return of the Datastream Financial Index.
EXPLANATORY VARIABLES	
1. Investor sentiment proxies	
Investor sentiment (CCI)	We proxy investor sentiment by a Consumer Confidence Indicator (CCI) stemming from different data sources.
Investor sentiment (ESI)	Economic Sentiment Indicator as an alternative proxy for investor sentiment.
2. Economic variables	
Real GDP growth	The frequency is quarterly. To obtain a monthly series we repeat the same value three times within a quarter.
Real GDP growth forecasts	Real output growth average forecasts from professionals such as research institutes and banks in monthly frequency.
CPI inflation	Percentage change of the Consumer Price Index.
FDIFF. 3-month interbank rate	3-month interbank rate taken in first difference to obtain stationary series.
Term spread	Spread between 10-year and 1-year government bond yields.
3. Financial variables	
Volatility	Annual realized volatility of the Datastream Financial Index.
Dividend yield	Dividend yield of the Datasteam Financial Index.
Liquidity (VA/MV)	Ratio of the DFI monthly volume in value over the index market capitalization.
Liquidity (VO/NOSH)	Number of shares traded monthly standardized by the number of index constituent shares to account for size.
Ln(Market value/Firms)	Natural logarithm of the market value of the country-specific financial index over the number of firms included in this index.

Note: All the variables are in monthly frequency, except the real GDP growth which is reported only quarterly.

Table II: Stationarity tests, January 1999 to August 2011

Variable	Pesaran $\bar{t}-$statistic		Fisher D-Fuller		Fisher P-Perron		LLC $t-$statistic		IPS $\bar{t}-$statistic	
<u>DEPENDENT VARIABLE</u>										
DFI annual return	-3.409	(0.000)***	124.582	(0.000)***	93.607	(0.000)***	-15.271	(0.000)***	-3.406	(0.000)***
DFI monthly return	-6.190	(0.000)***	1055.616	(0.000)***	1581.241	(0.000)***	-41.582	(0.000)***	-9.300	(0.000)***
<u>EXPLANATORY VARIABLES</u>										
Investor sentiment (CCI)	-3.005	(0.000)***	152.434	(0.000)***	220.321	(0.000)***	-12.231	(0.000)***	-2.985	(0.000)***
Investor sentiment (ESI)	-3.141	(0.000)***	144.163	(0.000)***	212.814	(0.000)***	-12.223	(0.000)***	-2.958	(0.000)***
Real GDP growth rate (SADJ)	-2.600	(0.000)***	159.296	(0.000)***	64.610	(0.008)***	-11.454	(0.000)***	-2.669	(0.000)***
Real GDP forecasts	-1.898	(0.306)	77.263	(0.000)***	23.706	(0.943)	-6.987	(0.5419)	-1.844	(0.062)*
CPI inflation	-2.603	(0.000)***	114.528	(0.000)***	87.897	(0.000)***	-10.837	(0.015)**	-2.584	(0.000)***
3-month interbank rate	-1.303	(0.992)	26.694	(0.947)	12.467	(1.000)	-6.883	(0.903)	-1.758	(0.119)
FDIFF.3-month interbank rate	-6.131	(0.000)***	588.276	(0.000)***	942.426	(0.000)***	-36.357	(0.000)***	-8.597	(0.000)***
Term spread (2 lags)	-2.220	(0.016)**	69.003	(0.003)***	221.826	(0.000)***	-8.085	(0.724)	-2.425	(0.000)***
Volatility	-5.858	(0.000)***	455.443	(0.000)***	840.464	(0.000)***	-25.915	(0.000)***	-5.973	(0.000)***
Dividend yield	-2.406	(0.001)***	87.426	(0.000)***	70.700	(0.002)***	-10.262	(0.001)***	-2.556	(0.000)***
Liquidity (VA/MV)	-4.308	(0.000)***	299.828	(0.000)***	531.270	(0.000)***	-15.415	(0.000)***	-3.988	(0.000)***
Liquidity (VO/NOSH)	-4.190	(0.000)***	326.455	(0.000)***	521.287	(0.000)***	-16.713	(0.000)***	-4.155	(0.000)***
Ln(Market size/No. firms)(4 lags)	-1.904	(0.285)	41.934	(0.387)	21.942	(0.991)	-9.355	(0.041)**	-2.357	(0.000)***
<u>TRANSITION VARIABLE</u>										
Spread: 3-month-overnight interb.	-5.537	(0.000)***	214.292	(0.000)***	468.291	(0.000)***	-19.912	(0.000)***	-5.702	(0.000)***

Data sources: Datastream, KOF, Bank of Denmark.

Notes: In this table are presented the results of five panel unit root tests (with 1 lag): the Pesaran test, the Fisher tests (augmented Dickey-Fuller and Phillips-Perron), the Levin, Lin and Chu (LLC) test, the Im, Pesaran and Shin (IPS) test. ***, **, * denote significance at 0.01, 0.05, 0.1 level, respectively and p-values are in parentheses. The tests assume under the null hypothesis that all the series composing the panel are non-stationary. The LLC test assumes that each individual unit in the panel shares the same AR(1) coefficient. Consequently, under the alternative hypothesis all cross-sections are stationary with the same parameter. In the other tests, not all individual series need to be stationary under the alternative hypothesis. For the realized real output growth the tests are performed from the quarterly data. The forecasts of the real output growth are not available for Australia and New Zealand. “FDIFF” is a prefix for the variables taken in first difference.

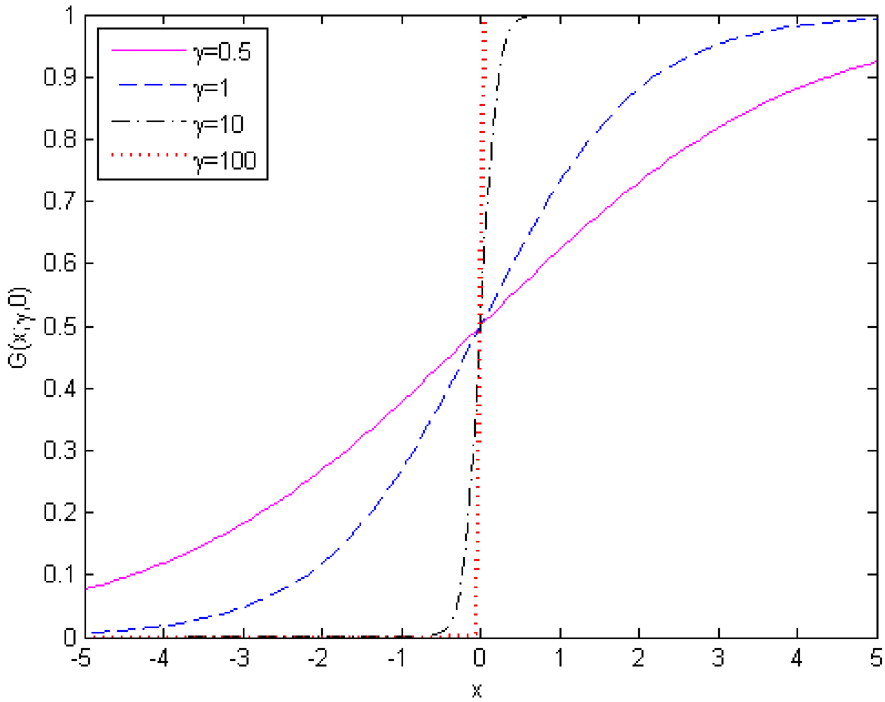
Table III: Auxiliary regression for CCI and ESI: PSTR and PTR specifications

PANEL A	Consumer Confidence Indicator (CCI)				Economic Sentiment Indicator (ESI)			
	PSTR		PTR		PSTR		PTR	
	Regime 1 $\boldsymbol{\delta}_0$	Regime 2 $\boldsymbol{\delta}_0 + \boldsymbol{\delta}_1$	Regime 1 $\boldsymbol{\theta}_1$	Regime 2 $\boldsymbol{\theta}_2$	Regime 1 $\boldsymbol{\delta}_0$	Regime 2 $\boldsymbol{\delta}_0 + \boldsymbol{\delta}_1$	Regime 1 $\boldsymbol{\theta}_1$	Regime 2 $\boldsymbol{\theta}_2$
GDP growth	0.2083***	0.2484***	0.2329***	0.2438***	0.2283***	0.2631***	0.2255***	0.2805***
	(17.8516)	(12.8823)	(22.4332)	(24.8802)	(25.2575)	(9.3477)	(25.8313)	(17.2974)
CPI inflation	-0.0588***	-0.5032***	-0.0614***	-0.3275***	-0.1050***	-0.2694***	-0.1115***	-0.2015***
	(-3.1319)	(-15.5346)	(-3.6317)	(-17.6589)	(-6.2024)	(-5.8473)	(-6.5713)	(-7.8033)
Unemployment rate	-0.1165***	-0.0708***	-0.1195***	-0.0687***	-0.0318***	-0.1024***	-0.0376***	-0.0635***
	(-10.4885)	(-4.5655)	(-10.9055)	(-6.5245)	(-3.6890)	(-4.1316)	(-4.3065)	(-4.6373)
FDIFF 3-month interbank	0.8413***	0.6474***	0.7239***	0.7813***	1.1485***	0.4239***	1.0312***	0.8161***
	(7.4191)	(4.4668)	(6.7332)	(7.3930)	(12.0737)	(2.6318)	(11.0786)	(6.5404)
Smoothness parameter γ	4.3262 [2.7073, 6.9308]				6.0292 [1.9089, 13.2933]			
Location parameter c	0.5440 [0.4222, 0.6715]		0.2276 [0.2136,0.2660]		0.8844 [0.7492, 1.7098]		0.6050 [0.3878, 0.6299]	
Observations	3,000		3,000		3,000		3,000	
Number of id	20		20		20		20	
R-squared	0.4928		0.4886		0.5179		0.5143	
AIC	-0.6812		-0.6674		-0.7274		-0.7142	
BIC	-0.6613		-0.6493		-0.7075		-0.6962	

PANEL B	Testing the null hypothesis of linearity, and subsequently the null hypothesis of a two-regime specification					
	Consumer Confidence Indicator			Economic Sentiment Indicator		
	LM test	F test	$F_{1(PTR)}$ test	LM test	F test	$F_{1(PTR)}$ test
$H_0 : L = 0$ vs $H_1 : L = 1$	126.407 (0.000)	32.728 (0.000)	203.650 (0.000)	58.110 (0.000)	14.696 (0.000)	80.5497 (0.000)
$H_0 : L = 1$ vs $H_1 : L = 2$	10.779 (0.029)	2.676 (0.030)	64.214 (1.000)	28.631 (0.000)	7.150 (0.000)	62.191 (1.000)

Notes. In this table are displayed the estimation results (Panel A) of the PSTR and PTR models for Consumer Confidence Indicator (CCI) and Economic Sentiment Indicator (ESI) as a function of 1-month lags of real GDP growth (RGDP), CPI inflation (INFL), unemployment rate (URATE), first difference of 3-month interbank interest rate (D.IRATE). The transition variable is the 1-month lag of the spread between the 3-month and overnight interbank rates. We follow Lemmon and Portniaguina (2006) and Baker and Wurgler (2006, 2007) and consider the residuals from these estimations ($\hat{\upsilon}_{i,t}$, $\hat{\vartheta}_{i,t}$ below) as an investor sentiment unrelated to economic fundamentals. In parentheses are presented t-statistics with standard errors corrected for heteroskedasticity. ***, ** and * denote statistical significance at 0.01, 0.05 and 0.1 level, respectively.
The PSTR model can be written as: $I_{i,t} = \mu_i + \left[\delta_{0,1} RGDP_{i,t-1} + \delta_{0,2} INFL_{i,t-1} + \delta_{0,3} URATE_{i,t-1} + \delta_{0,4} D.IRATE_{i,t-1}\right] + \left[\delta_{1,1} RGDP_{i,t-1} + \delta_{1,2} INFL_{i,t-1} + \delta_{1,3} URATE_{i,t-1} + \delta_{1,4} D.IRATE_{i,t-1}\right] G(q_{i,t-1}, \gamma, c) + \upsilon_{i,t}$. $I_{i,t}$ stands for the level of either CCI, or ESI.
The PTR model is written as: $I_{i,t} = \mu_i + \left[\theta_{1,1} RGDP_{i,t-1} + \theta_{1,2} INFL_{i,t-1} + \theta_{1,3} URATE_{i,t-1} + \theta_{1,4} D.IRATE_{i,t-1}\right] \mathbb{1}_{(q_{i,t-1} \leq c)} + \left[\theta_{2,1} RGDP_{i,t-1} + \theta_{2,2} INFL_{i,t-1} + \theta_{2,3} URATE_{i,t-1} + \theta_{2,4} D.IRATE_{i,t-1}\right] \mathbb{1}_{(q_{i,t-1} > c)} + \vartheta_{i,t}$.
In Panel B are displayed some tests for the null hypothesis of linearity ($L = 0$) against the null hypothesis of a two-regime model ($L = 1$), with L the number of transition functions in the PSTR and the number of location parameters in the PTR. Subsequently, the null hypothesis of two regimes ($L = 1$) is tested against the alternative of a three-regime model ($L = 2$). For the PSTR we perform two tests, LM (Wald test, χ^2 distribution), F (F-distribution), and for PTR we perform the $F_{1(PTR)}$ test whose value is obtained by a bootstrapping procedure (see Hansen 1999). The p-values are reported in parentheses.

Figure I: Logistic distribution with different values of γ



Notes: In this figure is displayed the logistic distribution with different values of the smoothness parameter γ. The distribution is given by the following formula: $G(x;\gamma,c) = \left(1 + e^{\gamma(x-c)}\right)^{-1}$ with the location parameter c set equal to 0.