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Liquidity needs, private information, feedback trading: verifying motives to trade

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Abstract

We analyse investors' motives for trading on international stock markets and investigate whether evidence for these motives is robust when time-varying market volatility, changes between calm and turbulent periods, and existence of international financial spillovers are controlled for. Applying the Markov-switching GARCH specification of the standard model commonly used in the literature, we find that trades conducted due to liquidity needs or driven by private information cannot be identified unequivocally in any market, and positive feedback trading becomes predominant when return spillovers from the US market are taken into account.

Keywords: Informed trading, liquidity trading, feedback trading, return autocorrelation, trading volume, financial spillovers, contagion.

JEL classification: C32, G12, G15

1. Introduction

A series of heterogeneous agent models have been proposed to explain how price changes in financial markets are driven by arrivals of private information and by changes in liquidity needs or risk aversion of investors. Predominant motives underlying trading decisions have often been studied by analyzing the interaction between return autocorrelation and trading volume. Several authors (e.g. Campbell et al., 1993, Wang, 1994, and Llorente et al., 2001) demonstrate that following periods of intensive trading, stock returns tend to revert (continue) if the majority of trades were conducted due to liquidity needs or changes in risk aversion (due to private information). In addition, positive (negative) return autocorrelation points to the presence of negative (positive) feedback trading (e.g. Sentana and Wadhwani, 1992).

The question investigated in this paper is whether the predominant trading motives on large international stock exchanges, found using standard linear regression models, are still present after taking into account international information spillovers, time-varying return volatility, and changes between calm and turbulent regimes in these financial markets. This question is based on three presumptions. First, information from international markets is an important determinant of stock returns on local markets and may affect the observed links between consecutive returns and trading volume (see, e.g., Gagnon and Karolyi, 2006, for a review). Second, existing empirical studies on trading motives yield inconclusive results, as some authors find evidence of a lack of informativeness of trades (Campbell et al., 1993, Conrad et al., 1994, Gebka, 2005), whereas others argue in favour of transactions mainly driven by private information (Cooper, 1999, Llorente et al., 2001, Ciner and Karagozoglu, 2008, Bajo, 2010). Finally, a substantial body of research shows that investors' risk preferences, investment strategies, inclination to panic, herding behaviour, contagion effects and heterogenous interpretation of information all change during crisis periods (Shalen, 1993, Kaminsky et al., 2004, Coudert and Gex, 2008).

We anticipate that some motives for trading may change or become insignificant when time-varying return volatility or changes between calm and turbulent periods are controlled for. Additionally, financial spillovers from the US market have been shown to affect returns on other international stock exchanges (e.g. Gagnon and Karolyi, 2006, Ibrahim and Brzeszczyński, 2009, Ashgarian and Nossman, 2011), but are usually unaccounted for in the studies of feedback trading, potentially leading to biased conclusions about the nature of this phenomenon.

We test for the validity of these premises by constructing a two-regime Markov switching regression model (with one calm and one turbulent regime) where the parameters identifying the trading motives and financial spillovers are allowed to change depending on

the current state of the market. The GARCH specification in each regime is responsible for accurate modelling of residual volatility (e.g., Haas et al., 2004). Results from some recent studies confirm the soundness of our approach. For example, Baele and Ingelbrechts (2010) find regime switching effects of regional and global factors on local stock returns in international stock markets. In the study of Amira, Taamouti and Tsafack (2011) volatility of stock returns has a stronger impact on inter-market return correlation during down-turn periods than in other times.

The contributions of this paper are as follows. On theoretical grounds, we show how different motives to trade (liquidity needs, private information, feedback strategy) can be unified within one framework explaining autocorrelation of returns. On methodological grounds, we argue in favour of applying multiple regime models to identify periods of high and low volatility, as both theoretical considerations and our empirical results indicate their superiority vis-à-vis single regime counterparts. Further, our results demonstrate potential deficiencies of the empirical framework introduced by Campbell et al. (1993) to identify prevailing motives to trade. Lastly, empirical evidence reported in this paper highlights the importance of positive feedback trading and international spillovers as major determinants of stock return behaviour.

In the next section we present a simple theoretical model explaining the returns on the stock market with heterogeneous types of investors. Section 3 describes econometric methodology and model specifications used in our investigation. Section 4 contains empirical results and the final section concludes.

2. A simple theoretical model of heterogeneous investors

In this section, we present a series of extensions to the Sentana and Wadhwani (1992) model (SW for short) of feedback trading. By including liquidity and informed trading as well as financial spillovers from abroad, we show analytically how autocorrelation in stock returns depends on the existence of calm and volatile regimes, past trading volume, and events on the global market.

2.1 The Sentana and Wadhwani (1992) model of feedback trading

In the model proposed by Sentana and Wadhwani (1992) two types of traders are assumed to act on the market, i.e., fundamental traders (smart money) and non-informed traders, also called feedback traders. Fundamental traders' demand is proportional to expected excess return and inversely proportional to the risk premium:

$$Q_t = \frac{E_{t-1}(R_t) - R_t^0}{\mu(\sigma_t^2)} , \tag{1}$$

where Q_t is the fraction of shares held by fundamental traders, $E_{t-1}(R_t)$ is the return at time t expected at time $t-1$, R_t^0 is the risk-free interest rate, and $\mu(\sigma_t^2)$ denotes the risk premium, the latter being a function of volatility risk, σ_t^2. The demand of feedback traders is a function of past returns:

$$Y_t = \gamma \cdot R_{t-1} . \tag{2}$$

Y_t is the fraction of shares held by feedback traders. For $\gamma > 0$ $(\gamma < 0)$, the traders will be involved in the positive (negative) feedback trading strategy, implying buying at time t after an observed price increase (decline) at $t-1$.

The market equilibrium requires that the aggregate demand equals aggregate supply of 1, i.e., $Q_t + Y_t = 1$. After substitution of eq. (1) and (2) and rearrangement, this yields:

$$E_{t-1}(R_t) - R_t^0 = \mu(\sigma_t^2) - [\gamma \cdot \mu(\sigma_t^2)] \cdot R_{t-1} . \tag{3}$$

Autocorrelation in returns is a function of feedback trading: positive (negative) feedback trading results in negative (positive) autocorrelation as $-\gamma < 0$ $(-\gamma > 0)$. With no feedback trading present ($\gamma = 0$), the formula reduces to the CAPM equation, i.e., the expected excess return on an asset is solely a function of risk: $E_{t-1}(R_t) - R_t^0 = \mu(\sigma_t^2)$ (e.g. Merton, 1980).

2.2 Introducing liquidity- and private information-motivated trades into the SW model

Several authors have presented models where liquidity or informed trading affect asset prices and trading volume (e.g. Campbell, Grossman, and Wang, 1993, Wang, 1994,

Llorente, Saar, Michaely, and Wang, 2001). They show that in equilibrium, if liquidity trading prevails, periods with intense trading are characterized by large price movements, as the market is trying to absorb the buying/selling pressure of liquidity trades. However, on subsequent days, prices will tend to return to their fundamental values, thereby exhibiting a pattern of reversals and generating negative autocorrelation in stock returns. Should most trades be driven by private information, however, price movements induced by agents capitalizing on their information and accompanied by high trading volume will tend to continue on subsequent days, as the information becomes more widely available and generates further trades by broader masses of traders. These price continuations following high volume days will induce positive correlation in returns.

Our first extension to the SW model is to incorporate trading by liquidity- and information-motivated agents. We do not aim to construct an original theoretical model, but rather to reflect the main characteristics of the classical models of Campbell et al. (1993), Wang (1994), and Llorente et al. (2002), namely how current returns and volume predict future returns. Therefore, instead of analysing how investors with heterogeneous risk aversion, wealth, or access to private information rebalance their portfolios after information or liquidity shocks, we add a group of investors who use a simple trading rule to account for these shocks. We assume that there exists a group of investors whose demand for stocks depends on past returns and volume of trades:

$$L_t = \lambda \cdot V_{t-1} \cdot R_{t-1}, \qquad\qquad\qquad (4)$$

where L_t is the fraction of assets held by this group of investors and V_{t-1} denotes trading volume at time $t-1$. Whether trading of the group analysed here is driven primarily by liquidity motives or by private information of market participants is reflected in the sign of the parameter λ. We interpret this parameter in the following paragraphs.

Formula (4), after simple mathematical rearrangements presented below, fits well the econometric regressions explaining future returns with current volume and returns, derived by Campbell et al. (1993, Theorem 2, p.928) and Llorente et a. (2002; see equations 9 and 12, and the discussion on p. 1022). It also incorporates the arguments concerning the effects of liquidity and information driven trades on future returns.

In the model of Campbell et al. (1993) a group of investors characterized as "market makers" accommodates buying or selling pressure from "noninformational" traders. In line with this convention, we call the group of traders following the rule represented in formula (4) "market makers".

Prevalence of non-informational trading

The demand of the market makers group partially depends on liquidity-driven trading by other investor groups. Specifically, if buy orders are generated for liquidity reasons at time $t-1$, trading volume V_{t-1} is high, and prices rise, i.e., R_{t-1} is high. The buying pressure will cause a temporary increase of prices and the market maker will increase supply of assets off its inventories to meet the extra demand. In the next period, the price will tend to reverse to its fundamental value (e.g. Campbell et al., 1994, Wang, 1994, Llorente et al., 2002). The demand of the market makers will be high at t, as they will try to restore their optimal asset inventories and will be able to do so at a lower price at time t (due to price reversal). Hence, high values of $V_{t-1} \cdot R_{t-1}$ will result in market makers' high demand L at time t ($\lambda > 0$).

The opposite happens when liquidity needs dictate sales of assets at $t-1$; this will lead to high V_{t-1} and negative R_{t-1}, and the market makers will accommodate the selling pressure by buying assets. At time t, when prices start to reverse to the fundamental values, the market maker's demand will be low, as she purchased the assets at $t-1$ for a lower price and might instead want to reduce her inventories at t, selling for a higher price. Therefore, low values of $V_{t-1} \cdot R_{t-1}$, due to falling prices at $t-1$ ($R_{t-1} < 0$), will result in low demand L at time t. In sum, if liquidity trading prevails, then $\lambda > 0$.

Prevalence of informed trading

Trades can also be generated by agents acting on private information. If this type of trading prevails, the market maker will try to take advantage of it by mimicking the actions of informed investors. Hence, on a day with heavy trading (high V_{t-1}), increasing prices ($R_{t-1} > 0$) generated by higher demand from informed traders will be interpreted by the market maker as a signal of positive information, and she will increase her demand, too. At time t, information continues to reach broader groups of inventors who increase their demand and push the price level even further up, i.e., price continuation will result. However, the market maker's demand L at t will be low as she would have bought at $t-1$ for a lower price. If anything, she might want to sell for a high price at t. Hence, a high value of $V_{t-1} \cdot R_{t-1}$ will result in low demand L of the market maker in period t ($\lambda < 0$).

As for negative private information, the opposite will occur: selling by informed investors at $t-1$ will drive the volume up and prices down ($R_{t-1} < 0$), a behaviour which will be mimicked by the market maker (i.e., low demand for the asset at *t-1*, possible short-selling). As prices at t continue to fall to adjust to the new, lower fundamental value, the market maker will be more willing to buy for a low price to restore her initial inventories as

well as to capitalize on the price difference between t and $t-1$. Hence, a low value of $V_{t-1} \cdot R_{t-1}$ (due to $R_{t-1} < 0$) will result in her high demand L at time t ($\lambda < 0$). In sum, if informed trading prevails, $\lambda < 0$.

Including L_t (eq. (4)) into the model of Sentana and Wadhwani (1992) yields $Q_t + Y_t + L_t = 1$ in the equilibrium, which leads to the formula:

$$E_{t-1}(R_t) - R_t^0 = \mu(\sigma_t^2) - [\gamma \cdot \mu(\sigma_t^2) + \lambda \cdot \mu(\sigma_t^2) \cdot V_{t-1}] \cdot R_{t-1}. \tag{5}$$

If liquidity trading prevails ($\lambda > 0$), negative return autocorrelation should be observed on days with heavy trading, $-\lambda \cdot \mu(\sigma_t^2) < 0$. Contrary, prevalence of trading based on private information ($\lambda < 0$) will induce positive autocorrelation in returns: $-\lambda \cdot \mu(\sigma_t^2) > 0$. These results correspond to the outcomes presented by Campbell et al. (1993), Wang (1994), and Llorente et al. (2001). If none of the motives, liquidity or private information, prevails on the market (or both are nonexistent), $\lambda = 0$ and the model is reduced to that of SW (1992). If no significant feedback trading exists, $\gamma = 0$ and the model is the CAPM.

2.3 Accounting for the impact of the global market in the SW model

In a globalized world, vanishing financial account controls, transaction costs, and increasing correlations of business cycles induce local investors to observe news and strategies of actors on the foreign markets. For instance, feedback traders look for signals of upcoming upward trends in prices by observing movements in not only domestic but also foreign prices. Similarly, agents acting as market makers, be it as liquidity providers or in response to informed trading, are not restricted to their domestic markets and can react to events occurring abroad, too. This is especially true since there are global commonalities in liquidity (Brockman, Chung, and Pérignon, 2009) and private information: liquidity needs experienced abroad might spill over to the domestic market and private information traded on abroad might be relevant for assets traded domestically, too.

The demand function of 'foreign trend watchers' will be $Y_t^* = \gamma^* \cdot R_{t-1}^*$ (Faff, Hilier and McKenzie, 2005) and the demand of market makers for domestic assets will be partially driven by foreign liquidity and private information, $L_t^* = \lambda^* \cdot V_{t-1}^* \cdot R_{t-1}^*$ (asterisks denote variables related to foreign markets). Putting these foreign motives into the equilibrium condition yields: $Q_t + Y_t + Y_t^* + L_t + L_t^* = 1$. After substitution, we obtain:

$$
\begin{aligned}
E_{t-1}(R_t) - R_t^0 &= \\
&= \mu(\sigma_t^2) - [\gamma \cdot \mu(\sigma_t^2) + \lambda \cdot \mu(\sigma_t^2) \cdot V_{t-1}] \cdot R_{t-1} - [\gamma^* \cdot \mu(\sigma_t^2) + \lambda^* \cdot \mu(\sigma_t^2) \cdot V_{t-1}^*] \cdot R_{t-1}^*
\end{aligned}
\tag{6}
$$

As can be seen, spillovers from a foreign market can be measured by $\gamma^* \cdot \mu(\sigma_t^2) + \lambda^* \cdot \mu(\sigma_t^2) \cdot V_{t-1}^*$. It is also possible to differentiate between spillovers due to feedback trading (measured by $\gamma^* \cdot \mu(\sigma_t^2)$) and due to liquidity/private information considerations (measured by $\lambda^* \cdot \mu(\sigma_t^2) \cdot V_{t-1}^*$).

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3. Econometric specification

We obtain an empirical version of the model (6) by assuming rational expectations:

$$R_t = c + (\alpha_1 + \alpha_2 \cdot V_{t-1})R_{t-1} + (\beta_1 + \beta_2 \cdot V_{t-1}^*)R_{t-1}^* + \varepsilon_t, \tag{7}$$

where $R_t = E_{t-1}(R_t) + \varepsilon_t$ and unexpected returns $\varepsilon_t \sim iid(0, \sigma_\varepsilon^2)$. The parameters: $c = R_t^0 + \mu(\sigma_t^2)$, $\alpha_1 = -\gamma \cdot \mu(\sigma_t^2)$, $\alpha_2 = -\lambda \cdot \mu(\sigma_t^2)$, $\beta_1 = -\gamma^* \cdot \mu(\sigma_t^2)$, $\beta_2 = -\lambda^* \cdot \mu(\sigma_t^2)$ all depend on the measure of risk, i.e., return volatility σ_t^2.

Model (7) embeds several approaches proposed in the literature. If we assume parameters c, α_1, α_2, β_1 and β_2 to be time-invariant, it reduces to the approach used in Gagnon and Karolyi (2003, 2009). If $\alpha_2 = \beta_2 = 0$, the model collapses to the one proposed in Faff et al. (2005) to analyse feedback trading and inter-market spillovers, and for $\beta_1 = \beta_2 = 0$, it mimics the approach to analyse informational motives to trade introduced by Campbell et al. (1993) and Llorente et al. (2002). Lastly, for $\alpha_2 = \beta_1 = \beta_2 = 0$, it would result in the Sentana and Wadhwani (1992) model of feedback trading.

Model (7) can be estimated for any market, with parameters α capturing return autocorelation in low and high-volume instances, and parameters β measuring the intensity of cross-border spillovers from the global market, again differentiated between those triggered by high volume (β_2) and those following periods of normal level of trading activity (β_1). In this way, we are able to investigate whether cross market linkages affect results on the postulated trading motives (e.g., Gagnon and Karolyi, 2009).

We propose to model the dependency of parameters c, α and β on volatility by estimating the equation (7) in the Markov-switching framework, which allows regression parameters to differ between low and high volatility regimes and does not impose any specific functional form on the relationship between risk and autocorrelation, unlike previous approaches (Sentana and Wadhwani, 1992).

The parameters c, α and β are allowed to change their values between two regimes, one with low (calm periods) and one with high (turbulent periods) volatility, to capture the time-varying nature of motives to trade. This is done empirically by estimating equation (7) using a Markov switching regression with GARCH (1,1) effects, using the novel approach of Hass et al., (2004). Therefore, our model becomes:

$$R_t = c_s + (\alpha_{1,s} + \alpha_{2,s} \cdot V_{t-1})R_{t-1} + (\beta_{1,s} + \beta_{2,s} \cdot V_{t-1}^*)R_{t-1}^* + \varepsilon_t, \tag{8a}$$

$$\varepsilon_t = \upsilon_t \sigma_{s,t}, \tag{8b}$$

where $\upsilon_t \sim iiN(0,1)$, $\{s_t\}$ is a Markov chain with finite state space $S = \{1, 2\}$ and a transition probability matrix:

$$P = \begin{pmatrix} p_{11} & 1-p_{11} \\ 1-p_{22} & p_{22} \end{pmatrix}. \qquad (8c)$$

The conditional residual variance in regime s follows the GARCH(1,1) equation:

$$\sigma^2_{s,t} = \omega_{0,s} + \omega_{1,s} \cdot \varepsilon^2_{t-1} + \omega_{2,s} \cdot \sigma^2_{s,t-1}. \qquad (8d)$$

Both mean and variance equations have parameters that switch their values depending on the regime of the model (approximating calm or turbulent state of the market). Thus, mean return and its variance also change in calm and turbulent regimes.

The Markov switching effect not only allows for identifying periods of increased return volatility, it also captures persistence of high and low volatility regimes – a feature observed on the markets, but is difficult to describe using other regime switching models, e.g., threshold regressions or structural change models. The regimes are typically interpreted as calm and turbulent (or even crisis) periods on financial markets. Our approach also accounts for heteroscedasticity of stock returns, as standard GARCH models do.

We compare the general model specification (8) with more restrictive specifications often used in empirical investigations, formulated by assuming:

- only one volatility regime on the stock market,
- no impact from the foreign markets,
- no GARCH effects (no conditional persistence of residual return volatility).

In our empirical investigation we show that assuming one or more of these constraints can lead to the results that are significantly different from those obtained using the most general model. We also demonstrate that the restricted versions of the model are rejected using statistical tests.

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4. Empirical results

Model (8) and its constrained versions were estimated for daily return series of stock market indices for each of the following countries: Canada, France, Germany, Italy, Japan, and the UK, for the period 23/03-1990-23/03/2010.[1] To capture the impact of international financial spillovers on trading motives, some model specifications incorporate lagged returns and trading volume from the US (the foreign market).[2] To measure the daily trading volume, we use a proxy of turnover ratio (number of stocks traded to stocks outstanding), detrended by taking logs and subtracting a one-year backward-moving average from daily data (Campbell et al., 1993, Llorente et al., 2002). All data are from Datastream.

It should be noted that, although the theoretical models describe the volume-return relationship for individual securities, their implications have also been extensively tested on portfolio data, both using the resulting empirical model similar to our equation (7) on marketwide data (i.e. index returns and volume, e.g., Campbell et al., 1993, Gagnon and Karolyi, 2003) as well as returns and volume of portfolios from a contrarian strategy (Conrad et al., 1994, Coopers, 1999, Parisi and Acevedo, 2001, Gebka, 2005, Alsubaie and Najand, 2009). Similarly, the Sentana and Wadhwani (1992) model of feedback trading has been widely tested on index rather than individual securities' returns (e.g., Koutmos 1997, Bohl and Siklos, 2008, Dean and Faff, 2008). Using the proposed empirical framework on aggregate data allows to conclude about the average, or dominant, motive for trading on a given market (if such a dominant motive is present) rather than providing insights into heterogeneous motives underlying trading in individual securities.

4.1. Evidence on predominant motives to trade

The relevant estimation results of model (8) and its restricted versions are presented in Table 1. The first three columns with numbers contain parameter estimates of regressions without financial spillovers from abroad ($\beta_1 = \beta_2 = 0$), while the latter five columns contain estimates from the regressions accounting for spillovers from the US (as in model (8)). For each country eight model specifications are considered. First, the regressions are estimated using ordinary least squares and assuming no GARCH effects. These models are denoted as SRR (single-regime regressions). The statistical significance of parameters is assessed using standard t-statistics, but the tests employing a block-bootstrap method provide very similar

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[1] The stock indices are total market indices calculated by Datastream except for Canadian S&P/TSX Composite Index and German DAX 30 index. Series for some countries are marginally shorter due to unavailability of data.
[2] Spillovers from the US market are lagged by one period to account for the fact that the US market closes after the European and Asian markets (e.g., Dungey and Martin 2007; Gagnon and Karolyi 2009). In our empirical results, even this "lagged" information from the US market (possibly not reflecting all possible news from the market, but surely adding more information to the empirical market model) still allows us to negate the conjecture from some earlier studies that negative feedback traders and non-informational trades dominate stock markets.

results and the statistics adjusted with a Newey-West method are marginally less significant. Second, the GARCH effects are incorporated to regressions in order to account for changing volatility of returns on stock markets (SRR-GARCH). Third, the parameters of the models are presented in the two regimes of the Markov switching regressions which capture changing motives to trade in calm and turbulent periods. Both regime-switching models assuming time-invariant volatility (MSR) and those with GARCH effects (MSR-GARCH) are considered. Lastly, all models are estimated with and without international spillovers.

Introducing GARCH(1,1) effects into our Markov switching models usually reduces persistence of at least one regime, i.e., one of the parameters p_{11} or p_{22} is significantly smaller than 1 (similar to the empirical results in Haas et al., 2004). Therefore, in the empirical investigation we restrict conditional variance in one of the regimes by setting $\omega_{2,s} = 0$ or $\omega_{1,s} = \omega_{2,s} = 0$ to ensure that both regimes are persistent (p_{11} or p_{22} are greater than 0.95), hence the model captures calm and turbulent states with a long duration rather than possible outliers in one of the states. The significance of parameters in the latter three specifications is measured using robust t-statistics.

The classical SRR models with no international spillovers included point to the presence of positive return autocorrelation ($\alpha_1 > 0$) following days with average levels of trading activity in four out of seven countries. This result could indicate the predominant presence of negative feedback traders on these markets (Sentana and Wadhwani, 1992) but could also be driven by non-synchronous trading (Lo and MacKinlay, 1990), time-varying expected returns (Conrad and Kaul, 1988) or transaction costs (Mech, 1993). The negative values of parameter α_2 for all countries (significant in five markets) suggest that the majority of trades on high-volume days have been conducted due to non-informational motives, resulting in price reversals.

When more precise models are employed to control for changing volatility and states of the market (i.e., SRR-GARCH, MSR, and MSR-GARCH), the significant positive autocorrelation of returns remains in Canada, France and Japan. However, the non-informational motives to trade dominate only in Germany and France. Negative values of the parameter α_2 remain in all specifications (not in all regimes), but they are rarely statistically significant.

The inclusion of lagged returns and volume from the US market into the four model specifications also drastically affects the interpretation of motives to trade, as discussed below. In addition, for nearly all markets, models and regimes the parameter β_1 is significantly larger than zero, showing a strong positive impact of US returns on international

stock returns. According to Faff et al. (2005), this result can also be interpreted as evidence of prevalence of negative feedback trading on foreign news.

One important effect of this US impact is the switch of the 'domestic' autocorrelation parameter α_1 from the positive value observed in SRR specifications to the significantly negative value in all specifications in five out of six markets. This result could suggest that the presence of negative feedback traders on these stock exchanges indicated by purely domestic models was spurious and due to model misspecification; when a correct model with international spillovers is applied, results point to the prevalence of positive feedback trading. Interestingly, the exceptional market is Japan, the only market with robust impact of both US variables on local stock returns.

The second effect of using models accounting for international spillovers is a much weaker evidence of non-informational motives to trade. When single-regime regressions estimated with OLS method are considered, the negative values of the parameter α_2 are present in five cases, but they are statistically significant only in three cases. The results from SRR-GARCH, MSR and MSR-GARCH specifications are less likely to show dominance of non-informational motives as they are found to be significant in only three out of eighteen models. Hence, results from simple models seem to be inaccurate, as more general, superior model specifications report much weaker evidence of prevalence of liquidity-motivated trading. In fact, the estimates obtained do not allow to distinguish between liquidity- and information-motivated trading, as α_2 is mostly insignificant.

As for the trading based on foreign liquidity and private information, most estimates of β_2 are insignificant. This result further demonstrates that the approach employed in this paper and originated by Campbell et al. (1993) cannot distinguish between motives to trade, at least for the countries and daily returns data used here. The only exception is Japan, a country with significantly negative estimates of β_2. This result is in line with Gagnon and Karolyi (2003) and suggests that heavy trading in the US is believed by the market participants in Japan to be driven by liquidity needs, rather than to convey private information about US traded companies.

To sum up, we observe a substantial impact of the US variables on all markets investigated. Positive feedback traders dominate on four out of six markets ($\alpha_1 < 0$) and negative feedback traders do not dominate anywhere according to the most general MSR-GARCH models, while the most constrained SRR models identify negative feedback trading in four markets and no positive feedback trading. This is in line with the literature reporting the dominant role of positive feedback trading, after controlling for time-varying volatility of stock returns (e.g., Koutmos 1997, Bohl and Siklos, 2008, Dean and Faff, 2008). Similarly,

the finding of almost no evidence of prevailing informed or liquidity trading motives in MSR-GARCH models contradicts the evidence of predominant liquidity motives on some markets obtained from the single-regime regressions. Yet again, results generated using model specifications accounting for time-varying volatility, regimes and international spillovers contradict those obtained from simple models. In the next section, we demonstrate that the former provide a better data fit than the latter, therefore it is justified to say that simple models are inferior and can generate incorrect results.

4.2. Relative performance of empirical models applied

We aim to demonstrate that the notably different results between the unrestricted models and those assuming strong restrictions on parameters are due to the fact that the latter are a poor description of returns on the six (plus the US) stock markets in comparison to the unrestricted MSR-GARCH models.

Our testing strategy is to start with the most restrictive specifications and verify more general specifications if needed (i.e., specific to general). First, we note that GARCH effects are statistically significant in each specification of the single-regime regression (cf. the first row of Table 2). This suggests that the OLS estimation technique may provide not only inefficient but also biased parameter estimates even when the single-regime specifications are correct (Hamilton, 2010).

Second, we look at the estimated single-regime specifications of the model, controlling for the GARCH effects in residuals (SRR-GARCH). Using the moving window technique, we estimate the parameters and find that their values change significantly in different periods (cf. Figure 1). This is especially important for the parameters α_1 and α_2 as it affects economic interpretation of predominating trading strategies and motives to trade. We find parameters of most models to vary significantly over time in the investigated time interval, as demonstrated in Figure 1. The changing parameter values may suggest that the parameters depend on some external factors, e.g., market volatility as in the models (6) and (8).

Moreover, we test the stability of the parameters and the linear specification of each model using the Chow test and the RESET test, respectively. Both tests reject the linear specification with stable parameter values for the overwhelming majority of cases (cf. the second and third row of Table 2). These results suggest that a nonlinear specification such as MS may better explain stock returns on the analyzed markets.

The two-regime specification describing the calm and turbulent regimes on the stock markets seems reasonable and several studies have already found the Markov switching models successful in explaining changes in asset prices (e.g. Hamilton, 2008 and citations

therein). Nevertheless, it is difficult to formally test the presence of two regimes in the Markov switching framework against the null hypothesis of a single regime due to some parameters being unidentified under the null hypothesis. The typically applied likelihood ratio (LR), F or Lagrange multiplier tests do not have their standard distributions and simulation techniques need to be used to derive approximated critical values.

We employ the modified LR test of Hansen (1992), where the null hypothesis assumes the linear single-regime regression, while the alternative hypothesis allows one regression parameter and the residual variance to change values depending on the regimes of calm and turbulence. As our interest is in the changes of dominant trading motives, we select the parameter α_2 in the regression to change between regimes. Hansen (1992) argues that the test statistic may in theory be rather conservative, i.e., it may reject the false null hypothesis too rarely. However, in our case all tests reject the null hypothesis at any standard levels of significance (cf. the fourth row of Table 2)[3].

Having empirically established that the Markov-switching regressions are a better approximation of the stock market behaviour than the linear specification, we can test if the regression parameters responsible for international spillovers are significant and change between regimes. The null hypothesis states that $\beta_1 = \beta_2 = 0$ in each regime of the model (8). The typical likelihood ratio (LR) statistic has an asymptotic standard χ^2 distribution in this case. As presented in the fifth row of Table 2, there is strong evidence of the US market affecting returns on all local markets.

Additionally, we verify the presence of GARCH effects in the residuals of Markov-switching regressions by using the LR statistic (cf. the sixth row of Table 2). Controlling for time-varying volatility on financial markets also improves the fit of models to the data significantly. Thus, employing both the LR tests we find that the best models are the MSR-GARCH specifications controlling for the impact of foreign markets on stock returns in the local markets.

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[3] We use the GAUSS program written by Bruce Hansen to compute these test statistics.

5. Conclusions

In this paper we find that financial spillovers from the US market and changes between calm and turbulent regimes have a significant impact on the analysis of the presence of feedback trading, liquidity and informed trading on the developed international stock markets. Statistical tests confirm the preference for Markov-switching models with GARCH effects over single-regime regressions. Controlling for time varying volatility and international spillovers not only improves the fit of estimated models, but also changes the economic interpretation of prevailing motives of trading.

Employing the recently developed techniques to estimate the Markov-switching regressions with GARCH effects, we find evidence of positive feedback trading driven by past home-market information on large international stock markets. Positive return spillovers from the US market are another finding robust to model changes. However, the results from the most comprehensive, best-fitting model specifications show that the approach to determination of trading motives widely employed in the literature fails to produce unambiguous outcomes. Specifically, accounting for spillovers, changing volatility and market regimes weakens the evidence of prevalence of the non-informational motive for trading on international stock exchanges.

These findings suggest that future analyses of the empirical relationship between return and volume in different financial markets should incorporate the impact of news and investor strategies on local and foreign markets, as well as the current (calm or turbulent) state of financial markets. Possible reasons for differences in predominating trading strategies between international stock markets could be the frequency of volatile shocks and the strength of financial links with the global markets. These reasons clearly need further empirical investigation.

5

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Figure 1: Moving window estimates of parameter α_2 from the SRR-GARCH models with international spillovers.

Canada

France

Germany

Italy

Japan

UK
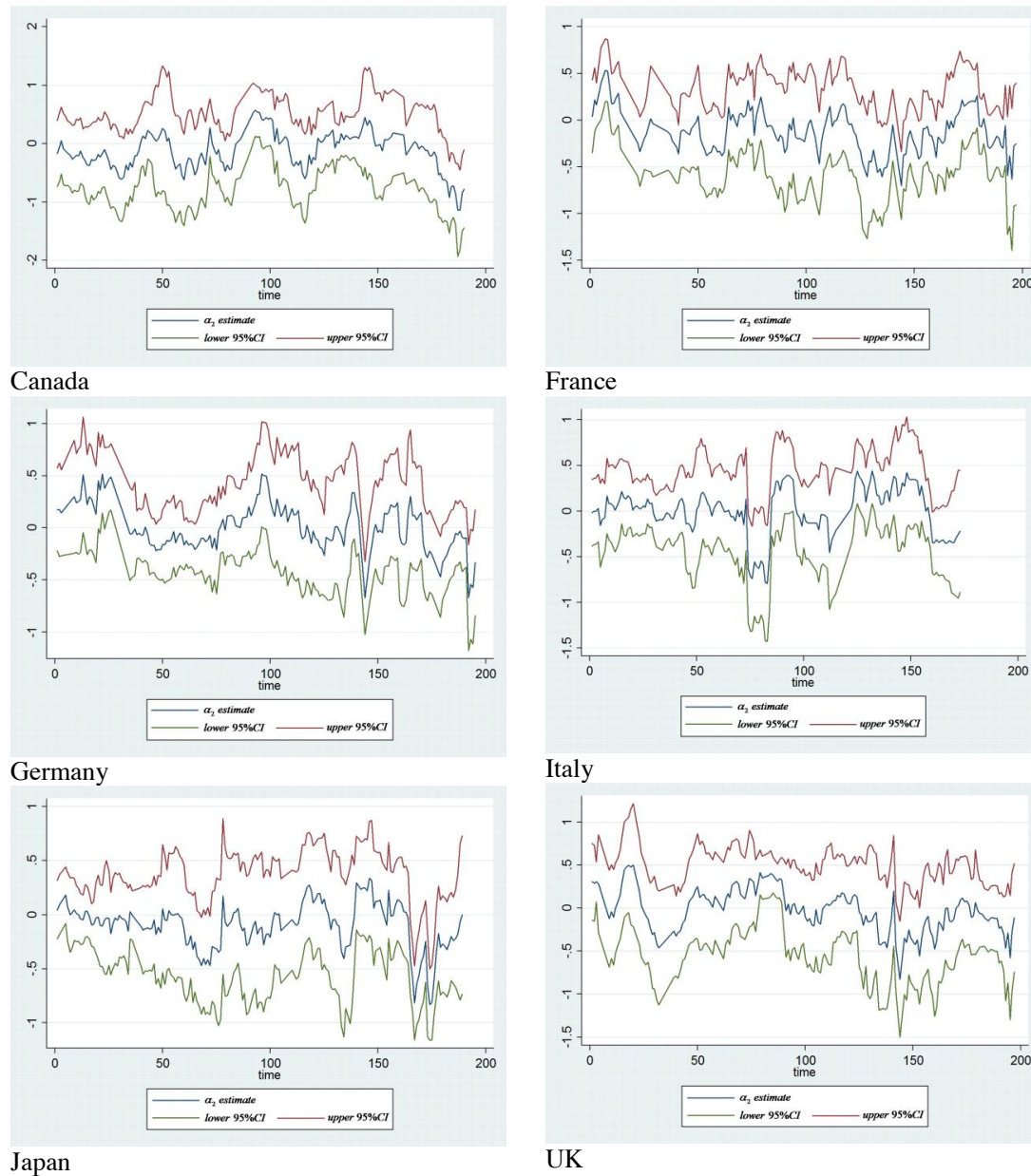
Note: Estimates of parameter α_2 were obtained from single regime GARCH models with international spillovers. Window size: one year (252 trading days), step size: one month (21 working days).

Table 1: Regression parameter estimates of the models with and without financial spillovers from the US market

			Model without financial spillovers			Model with financial spillovers from the US market				
			α_0	α_1	α_2	α_0	α_1	α_2	β_1	β_2
Canada	SRR		0.0250	0.0472**	-0.1838***	0.0237	-0.0736***	-0.1233**	0.1541***	-0.0953*
	SRR-GARCH		0.0556***	0.1057***	-0.1017*	0.0006***	0.0434*	-0.0910*	0.0752***	0.0288
	MSR	regime 1	0.0782***	0.0985***	-0.0516	0.0770***	0.0023	-0.0150	0.1172***	0.0622
		regime 2	-0.1768***	0.0041	-0.1669	-0.1851***	-0.1529**	-0.0833	0.2032***	-0.1505
	MSR-GARCH	regime 1	0.1102***	0.1571**	-0.1087	0.1100***	0.0920	-0.0550	0.0290	0.1940
		regime 2	-0.0105	0.0699***	-0.0911	-0.0240	-0.0330	-0.0680	0.1300***	-0.0380
France	SRR		0.0197	0.0463***	-0.1727***	0.0159	-0.1658***	-0.0901*	0.4007***	0.0687
	SRR-GARCH		0.0634***	0.0397**	-0.1418**	0.0005***	-0.1189***	-0.0750	0.3605***	0.0766
	MSR	regime 1	0.0664***	0.0444**	-0.0756	0.0640***	-0.0701***	0.0083	0.3297***	-0.0706
		regime 2	-0.1386**	0.0479	-0.2318**	-0.1318**	-0.2457***	-0.0872	0.4623***	0.0653
	MSR-GARCH	regime 1	0.1289***	-0.0077	-0.3122***	0.0870***	-0.1200***	-0.2110*	0.3460***	0.2300
		regime 2	0.0299	0.0462**	-0.1234*	0.0290	-0.1200***	-0.0510	0.3650***	0.0390
Germany	SRR		0.0123	0.0178	-0.1713***	0.0048	-0.1298***	-0.1359***	0.3357***	-0.0884
	SRR-GARCH		0.0512***	0.0118	-0.0844*	0.0004**	-0.1358***	-0.0412	0.4016***	-0.0923
	MSR	regime 1	0.0690***	0.0065	-0.0017	0.0496***	-0.1222***	0.0478	0.3767***	-0.1275*
		regime 2	-0.1414**	0.0155	-0.2004***	-0.1422*	-0.1362***	-0.1666***	0.3030***	-0.0472
	MSR-GARCH	regime 1	0.1285***	-0.0080	0.0487	0.1020**	-0.1680	-0.0820	0.4960***	0.0340
		regime 2	-0.0268	0.0107	-0.1261*	-0.0180	-0.1150***	-0.0480	0.3320***	-0.0830
Italy	SRR		0.0111	0.0316*	-0.0966**	0.0049	-0.1234***	-0.0219	0.2978***	0.2040***
	SRR-GARCH		0.0547***	0.0093	-0.0246	0.0005***	-0.0947***	-0.0011	0.2411***	0.1078
	MSR	regime 1	0.0518***	0.0185	0.0576	0.0431***	-0.0653***	0.0631	0.2022***	-0.0506
		regime 2	-0.0574	0.0371	-0.1346*	-0.0519	-0.1543***	-0.0209	0.3552***	0.2050*
	MSR-GARCH	regime 1	0.1325**	-0.1024	-0.0964	0.1260***	-0.1800***	-0.0990	0.1930***	0.0810
		regime 2	0.0008	0.0244	-0.0307	-0.0140	-0.0910***	-0.0020	0.2620***	0.0970

Note: The symbols ***, **, and * denote that corresponding parameters are statistically significantly different from zero at the 0.01, 0.05, and 0.10 levels of significance, respectively.

Table 1 continued

		Model without financial spillovers			Model with financial spillovers from the US market				
		α_0	α_1	α_2	α_0	α_1	α_2	β_1	β_2
Japan	SRR	-0.0036	0.0505***	-0.0511	-0.0177	-0.0167	-0.0052	0.4792***	-0.1577***
	SRR-GARCH	0.0255	0.0751***	-0.0261	0.0001	0.0260	0.0002	0.4337***	-0.1291*
	MSR regime 1	0.0249	0.0795***	0.0277	0.0173	0.0588***	0.0418	0.3589***	-0.1864***
	MSR regime 2	-0.0733	0.0354	-0.0722	-0.0821*	-0.0607*	0.0110	0.5581***	-0.2151**
	MSR-GARCH regime 1	0.0549	0.0584	0.0236	0.0140	0.0290	0.0300	0.3730***	-0.0660
	MSR-GARCH regime 2	-0.0347	0.0792***	-0.0505	-0.0130	0.0240	-0.0140	0.4550***	-0.1700*
UK	SRR	0.0193	-0.0003	-0.0630	0.0157	-0.2217***	0.0458	0.3510***	0.1698***
	SRR-GARCH	0.0464***	0.0195	-0.0032	0.0004***	-0.1394***	0.0712	0.3058***	0.0734
	MSR regime 1	0.0550***	0.0661***	-0.1276*	0.0444***	-0.0702***	-0.0614	0.2818***	0.0236
	MSR regime 2	-0.0705	-0.0286	-0.0401	-0.0635	-0.3051***	0.1152	0.4046***	0.1685
	MSR-GARCH regime 1	0.0784***	0.0426	-0.2388	0.0590***	-0.0640	-0.1600	0.2600***	0.0350
	MSR-GARCH regime 2	0.0097	0.0078	0.0459	0.0100	-0.1780***	0.1250	0.3350***	0.0720
USA	SRR	0.0263	-0.0145	-0.1243**					
	SRR-GARCH	0.0546***	0.0211	-0.0622					
	MSR regime 1	0.0787***	0.0320*	0.0954					
	MSR regime 2	-0.0841*	-0.0374	-0.1272					
	MSR-GARCH regime 1	0.0782***	0.0337	0.1034					
	MSR-GARCH regime 2	0.0091	0.0006	-0.1101					

Table 2: Test statistics used to verify model specifications

Test	Canada	France	Germany	Italy	Japan	UK	USA
1. Engle and Ng (1993) test of the null hypothesis: "no ARCH effects in single-regime linear regressions"	108.81***	49.98***	43.64***	44.48***	70.77***	34.67***	53.75***
2. Chow test of the null hypothesis: "all parameters are constant in the sample"	9.84***	2.16*	0.86	0.98	4.43***	5.73***	215.25***
3. RESET test of the null hypothesis: "linear specification of the model is correct"	1.71	13.72***	21.85***	10.93***	2.80*	17.78***	8.34***
4. Hansen (1992) test of the null hypothesis: "no Markov-switching effects present in the model"	27.62***	20.52***	20.33***	23.91***	15.52***	25.79***	30.84***
5.LR test of: "no significant impact of the US market in the MSRGARCH models"	32.08***	403.74***	351.41***	192.43***	618.88***	449.31***	N/A
6. LR test of: "no GARCH effects in the Markov-switching regressions"	347.51***	223.09***	374.10***	262.14***	167.57***	348.84***	452.90***

Note: The symbols ***, **, and * denote that the null hypothesis is rejected at the 0.01, 0.05, and 0.10 levels of significance, respectively. For each stock market the test of Hansen (1992) verifies the null hypothesis that the residual variance and the parameter α_2 do not depend on the Markov-switching regime changes. There are two (adequate) exceptions due to estimation problems. Namely the tests for the German and Italian markets, where the null hypothesis assumes that the residual variance and the parameter α_0 do not depend on the Markov-switching regime changes.