Relationships between Trading Volume, Stock Returns and Volatility: Evidence from the French Stock Market

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I. Introduction

Relationships between trading volume, returns and volatility have been widely investigated in both theoretical and empirical studies. The paper of Ying (1966) points out three interesting findings. First, low volume is often accompanied by a decrease in prices. Second, large volume is often accompanied by an increase in prices. Third, a substantial increase in volume is often accompanied by either a significant increase in prices or a substantial drop in prices. As a result, a number of studies have examined a theoretical hypothesis to explain the volume-return relation.

There are two popular competing theoretical explanations of the positive correlation between trading volume and (absolute) price change: the mixture of distributions hypothesis (MDH) developed by Clark (1973), Epps and Epps (1976) and Harris (1986) and the sequential information arrival hypothesis (SIAH) developed by Copeland (1976, 1977), Morse (1980), Jennings *et al.* (1981) and Jennings and Barry (1983). The MDH has led to the focus of important empirical studies on the contemporaneous relation between (absolute) price change and trading volume (see Karpoff, 1987, for a survey). Most of these studies have demonstrated a positive relationship between trading volume and returns. Since the 1990s, dynamic relationships have been widely empirically studied. Unidirectional and/or bidirectional causality between trading volume and returns have been supported by Gallant *et al.* (1992), Hiemstra and Jones (1994), Lee and Rui (2002) and, more recently, Chuang *et al.* (2009) and Chen (2012).

In line with Odean (1998) and Gervais and Odean (2001), a number of empirical studies have sought to explain the positive relation between trading volume and stock returns as a result of overconfidence. Statman *et al.* (2006) and Griffin *et al.* (2007) document a positive relationship between market turnover and stock market returns. These findings are consistent with the overconfidence hypothesis.

To the best of our knowledge, very few empirical studies on contemporaneous and dynamic relationships between trading volume and returns (volatility) have been conducted in the French stock market. Therefore, this paper intends to overcome this lack of empirical research. First, we investigate the contemporaneous relationship between trading volume and stock returns using a system of simultaneous equations via generalized method of moments (GMM) estimation. Second, we provide dynamic (causal) volume-return relations through bivariate vector autoregression (VAR) and Granger causality test analysis. Third, we study impulse response functions (IRF) using the Cholesky decomposition (orthogonalization of errors) to explain the impact of an exogenous shock in one endogenous variable on the other variables of the system of simultaneous equations.

Our empirical analysis is performed using a monthly value-weighted portfolio of 128 French firms covering at least 90% of the French market capitalization from April 1996 to October 2014. All econometric tests are applied on the total sample (April 1996 to October 2014), and on two sub-periods of nearly 10 years: the first from April 1996 to September 2005 and the second from October 2005 to October 2014. This data splitting is conducted first, to make our results comparable to those obtained in particular by Statman *et al.* (2006) on four sub-periods of 10 years on the US stock market and second, to use these sub-periods in robustness checks (Lo and Wang, 2000; Statman *et al.* 2006).

The main empirical results can be summarized as follows. (i) We find a positive relationship between market turnover and stock market returns for the total sample and the first sub-sample (1996-2005). These findings confirm the MDH. (ii) We document a unidirectional

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positive relation between market turnover and the lagged values of stock returns. This relation indicates that market turnover increases in months following high market returns. These results, consistent with the overconfidence hypothesis, are in accordance with some of the findings of Statman *et al.* (2006) and Griffin *et al.* (2007). (iii) We obtain a positive relation between market turnover and the current conditional market volatility (Karpoff, 1987). (iv) The Granger causality test confirms the unidirectional positive relation between market turnover and stock returns in the sense that stock returns cause market turnover, implying that returns contain significant information for predicting future volume. (v) IRF analysis confirms and gives more credibility to the reported findings.

The remainder of this paper is organized as follows. Section 2 reviews and discusses previous empirical research dealing with relations between trading volume and returns (volatility). Section 3 documents data, provides some descriptive statistics and presents preliminary results on contemporaneous volume-returns relations. Section 4 presents the dynamic relationships between market turnover, stock market returns and volatility by using VAR models, Granger causality test and IRF analysis. Section 5 concludes the paper.

II. Related literature

Previous studies have examined the relation between stock prices and trading volume among different markets. Karpoff (1987) cites reasons why the price-volume relation is important. First, this relation provides insight into the structure of financial markets. Second, the price-volume relation is useful for event studies that use a combination of stock prices and trading volume data from which to draw inferences. Third, this relation is acute to the debate over the empirical distribution of speculative prices. Karpoff (1987) makes an extensive review of theoretical and empirical research concerning the relation between stock prices and trading volume before the 1990s. The author observes that much of the previous research has considered the contemporaneous relationship. For example, Crouch (1970) investigated the relationships between absolute price change and trading volume. Tauchen and Pitts (1983) and Wood *et al.* (1985) studied the relationships between price change and trading volume.

MDH, first developed by Clark (1973), revealed a positive relation between trading volume and stock returns explained by the joint dependence of price and volume on an underlying common mixing variable, namely the rate of information flow. Basically, price changes and trading volume are driven by the same underlying variable: information flow. Ultimately, trading volume may be a proxy of this latent variable (Epps and Epps, 1976). MDH only suggests a positive contemporaneous relationship between volume and (absolute) returns (Tauchen and Pitts, 1983; Harris, 1986). Numerous empirical studies support a positive contemporaneous relation between trading volume and returns through a variety of econometric estimations (Karpoff, 1986; Gallant *et al.*, 1992). Finally, under MDH, it is impossible to test whether information on past values of returns (volume) can be used to explain current volume (returns). Lee and Rui (2002) have documented positive and significant relationships in the New York, Tokyo, and London stock markets. Chen *et al.* (2001) obtained the same results in five other stock markets: Japan, Switzerland, the Netherlands, Hong Kong and France. More recently, Chen (2012) investigates relationships between the S&P 500 price index and trading volume from 1973-2008. The results indicate that the relation between US stock returns and trading volume is positive and significant only over the period 1973-1999 and not for the entire sample period 1973-2008.

SIAH argues that the sequential arrival of information leads to a positive relation between volume and price changes (Copeland, 1976; Jennings *et al.*, 1981; Smirlock and Starks, 1985). SIAH suggests a gradual dissemination of information which involves intermediate equilibrium until the arrival of the final equilibrium; that is, new information is disseminated sequentially to traders. Thus, informed traders take positions and adjust their portfolios before those who are uninformed. Finally, all traders react to new information until a final equilibrium is reached. This successive reaction to new information strongly indicates that the lagged values of trading volume may help to predict current values of returns and volatility and vice versa. Therefore, the arrival of new information on the market results not only from price movements, but also from an increase in the trading volume. It follows that the lagged values of trading volume can provide information on current returns and the lagged values of returns may also contain information relating to the current volume. In this way, SIAH supports a bidirectional (causal) relationship between trading volume and price changes.

The dynamic (causal) correlation between price change and trading volume has been investigated since the 1990s (Gallant *et al.*, 1992; Hiemstra and Jones, 1994). The main objective of this strand of empirical papers is to investigate if trading volume causes (in the sense of Granger, 1969) stock returns and/or the opposite. Typically, VAR models and the Granger causality test are applied in studies examining this dynamic relationship. Using data from three stock markets (New York, Tokyo and London) and the methodology based on VAR developed by Sims (1972, 1980), Lee and Rui (2002) demonstrate that returns Granger-cause trading volume in the US and Japanese markets, but not in the UK market. Volume does not Granger-cause returns in any of the three studied stock markets. More recently, Mahajan and Singh (2009) examine the empirical relationship between returns, volume and volatility dynamics. They find, firstly, a significant positive relation between trading volume and return volatility and, secondly, a significant positive relationship between volatility and trading volume. In five emerging markets, Pisedtasalasai and Gunasekarage (2007) show that returns predict volumes, but volumes have little impact on predicting returns. Chuang *et al.* (2009) use quintile regressions to analyze the causal relation between stock returns and volume, and show that causal effects of volume on returns are usually heterogeneous across quintile and those of returns on volume are more stable.

Another strand of theoretical and empirical studies has been devoted to the analysis of price-volume relation through a behavioral paradigm. To explain this relationship between past returns and trading volume, Gervais and Odean (2001) develop a multiperiod model in which traders learn about their ability, which is affected by self-attribution bias. This bias refers to the tendency of individuals to attribute their success to personal aspects and impute their failures to outside influences, such as bad luck (Miller and Ross, 1975; Fischhoff, 1982; Taylor and Brown, 1988). This bias is what Langer and Roth (1975) summarize by "*Heads I win, tails it's chance*" (p.951). Gervais and Odean (2001) show that investors with self-attribution bias ultimately become too confident in their investments. Overconfidence leads investors to underestimate risk and exchange risky securities (Odean, 1998; Gervais and Odean, 2001). Investor overconfidence leads to high trading volumes in financial markets (Gervais and Odean, 2001; Ko and Huang, 2007; Grinblatt and Keloharju, 2009). Daniel *et al.* (2001) and Chuang and Lee (2006) show that investor behavior is asymmetric and depends on the market tendency. They demonstrate that investors are more aggressive during bullish periods than bearish times. Indeed, previous positive returns make investors more aggressive in subsequent periods, and this appears to be shown in high transaction levels. This implies a positive causal relation between previous returns and current trading volumes (Glaser and Weber, 2009).

Statman *et al.* (2006) use monthly data from the NYSE/AMEX market and individual securities over the period 1962-2002. Trading activity is measured by turnover as shares traded divided by outstanding shares. Using bivariate VAR and IRF to study the interaction of turnover and time-series returns, they show that market-wide turnover increases in the months following high market returns. This is consistent with the overconfidence hypothesis. Griffin *et al.* (2007) examined data from 46 developed and developing markets. They show a significant positive relationship between turnover and past returns in several markets. This relation is more statistically significant in markets with high volatility. These findings also hold when they control for volatility and differing sample periods. Brüggemann *et al.* (2014) implement an asymmetric VAR model to analyze non-linearity in the stock return-trading volume relationship using data from 16 European countries. They find that returns have an impact on trading volume, but there is no evidence for the influence of trading volume on returns. Responses of trading volume to return shocks are non-linear. Investors trade more after positive returns and less after negative ones for small and mid-capitalization stocks, supporting the overconfidence hypothesis.

As stated above, very few empirical studies on contemporaneous and dynamic relationships between trading volume and returns (volatility) have been conducted in the French stock market. Nevertheless, it is possible to mention in particular the papers of Chen *et al.* (2001) and more recently, Brüggemann *et al.* (2014) in the European context. We can highlight a set of extensions and differences between our research and these studies, mainly at the econometric methodology choice and the trading activity measurement.

Indeed, using daily data from nine national markets including the French market over the period 1973-2000, Chen *et al.* (2001) examine the return-volume relation by a simple contemporaneous relation between (absolute) returns and trading volume. Furthermore, using data for 16 European countries including France, Brüggemann *et al.* (2014) implement an asymmetric VAR model to investigate non-linearity in the relationship return-trading volume. In a different way, we investigate the contemporaneous relationship between trading volume and stock returns using a system of simultaneous equations via GMM estimation. Second, we provide dynamic (causal) volume-return relations through bivariate VAR and Granger causality test analysis. Third, we study IRF using the Cholesky decomposition to explain the impact of an exogenous shock in one endogenous variable on the other variables of the system of simultaneous equations. Despite the possibility of deploying the trading volume, Lo and wang, 2000, Griffin *et al.* 2006 and Statman *et al.* 2006, among others, argue in favor of privileging the market turnover over alternative measures. In line with this stream of previous research, we construct the market turnover and stock market returns by aggregating individual data. The analysis is performed using a monthly value-weighted portfolio of 128 French firms covering at least 90% of the French market capitalization from April 1996 to October 2014. As a consequence, this study contributes to the literature by developing and extending to the French context the previous research on the relations between turnover, stock returns and conditional volatility.

III. Data and preliminary results

III.1. DATA DESCRIPTION AND DESCRIPTIVE STATISTICS

Our empirical investigations were carried out on a sample containing 453 French firms listed on the French stock exchange. For each firm we extracted from Datastream the closing price adjusted for dividends, trading volume, outstanding shares and market capitalization on a monthly basis over the period from July 1991 to October 2014. This sample period was chosen due to the availability of data on trading volume on the French stock market (July 1991). We excluded all firms with missing data. We reduced the period from April 1996 to October 2014 in order to have 128 firms selected to cover at least 90% of the French market capitalization. Finally, we constructed endogenous and exogenous variables used in econometric specifications.

III.1.1. Endogenous variables

We measured trading activity with turnover for each firm (Lo and Wang, 2000; Statman *et al.*, 2006; and Griffin *et al.* 2007, among others). In the first step, we calculated individual turnover as follows: $T_i = \frac{V_i}{S_i}$ where V_i

is the trading volume and S_i is the outstanding share for security i. In the second step, we computed the market turnover (called *Tm*) defined as the value-weighted average of individual turnover as $Tm = \sum_i w_i T_i$ where w_i corresponds to the ratio between the market capitalization for security i and the total market capitalization.

Figure 1 plots both the market turnover and its trend series from April 1996 to October 2014 on a monthly basis. As we can see, the market turnover time series produced erratic movement. It is worth noting that macroeconomic and financial data are non-stationary. This is only the case for turnover that can be influenced by a couple of factors, such as bid-ask spreads or other microstructural problems (Griffin *et al.*, 2007). All these factors contribute to increased trading activity. In order to avoid this bias in the econometric specification, we used the Hodrick-Prescott (1997) filter (hereafter, the HP filter) to detrend the market turnover time series.[1] Finally, the difference between log turnover and trend derived from the HP filter, called *DTm*, was used in this study as a proxy for trading activity (Statman *et al.*, 2006). The series of individual stock returns expressed in percentages was computed from monthly adjusted closing prices, as follows: $R_t = \ln(P_t / P_{t-1}) \times 100$. Starting from individual stock returns, we computed the value-weighted market return (*Rm*).

III.1.2. Exogenous variables

Two measures of market volatility were used as control variables. The first one consists of the dispersion of the market return, called *Dm*, and is defined as the monthly cross-sectional standard deviation of individual returns weighted by w_i so that $Dm = \sum_i w_i \sigma_{i,t}$.

This control variable allowed taking into account the part of trading activity due to rebalancing portfolios to maintain the weight of each individual asset within the portfolio. Such moves led to an increase in trading activity. The second control variable, called *CVm*, is the monthly conditional market volatility. Following Griffin *et al.* (2007), we measured conditional volatility using an EGARCH specification for the stock market returns. The use of the EGARCH (1.1) model is appropriate for studying the relationship between trading volume and conditional volatility (Chen *et al.*, 2001; Griffin *et al.*, 2007) because this GARCH specification, first developed by Nelson (1991), successfully captures the asymmetric response in conditional variance that is the asymmetric relationship between market return and volatility.

Figure 1 provides plots of log stock market returns, the conditional market volatility and the cross-sectional standard deviation from April 1996 to October 2014.

Figure 2 shows a high variability in transaction volumes with peaks on a grade scale from 1996 to 2008. It is important to note that capital markets experienced a sharp increase in transaction volume in the late 1990s to 2008. Chordia *et al.* (2011) documented this stylized fact for the US financial markets from 1993 to 2008. One of the explanatory elements is the use of high-frequency trading, which has developed in the vast majority of capital markets since the mid-2000s.

We observe from the end of 2008 a significant reduction in transaction volumes, probably due to the following three factors. The first factor is the repercussions of the financial crisis of 2008. Second, the implementation of the Markets in Financial Instruments Directive (MiFID) in November 2007 for all European Union countries has made significant changes to the

Figure 1. Plots of stock market returns and exogenous variables

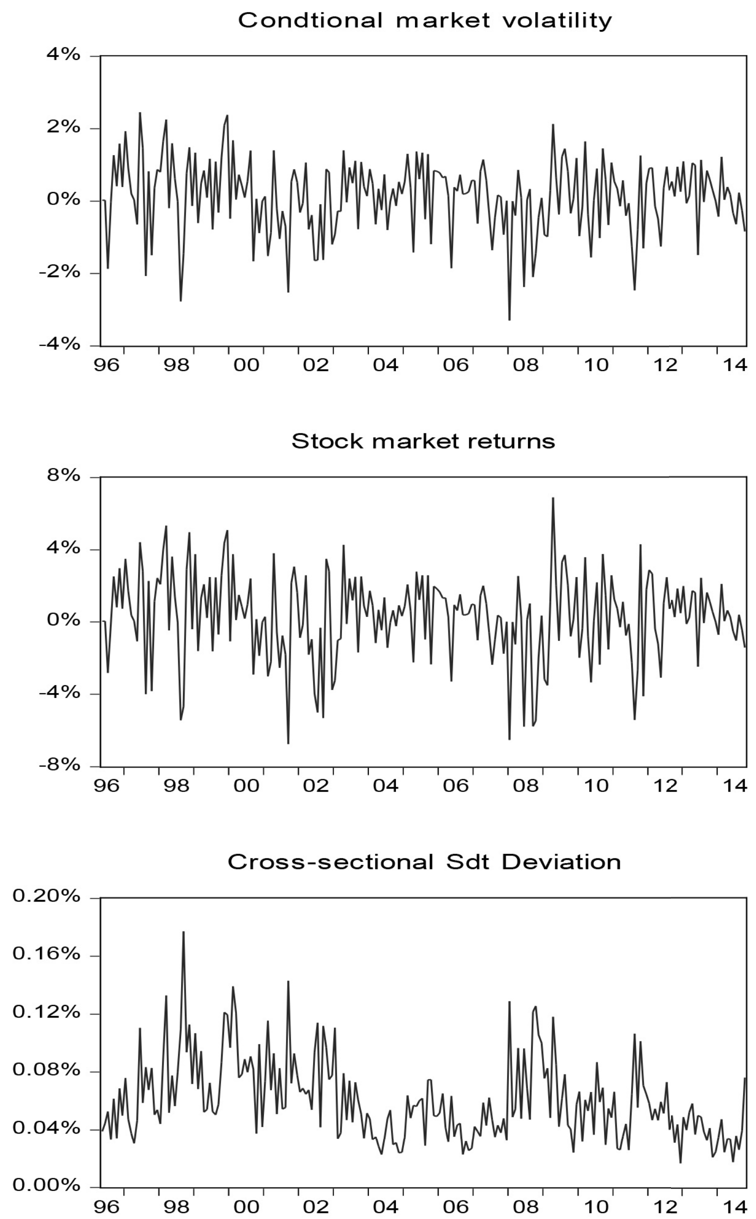
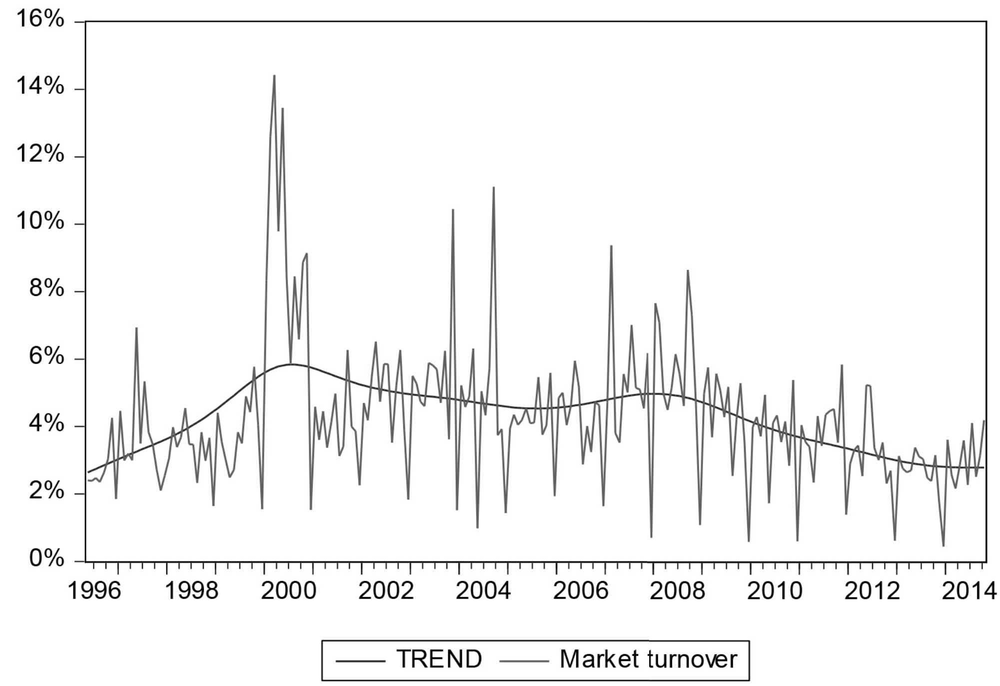


Figure 2. Market turnover with trend line on the French stock market



European securities industry, notably by creating a new competitive environment for trading systems. In particular, the MiFID has contributed to creating new trading platforms in Europe. One of the consequences of the MiFID is that trades can be executed outside a national stock exchange. The presence of multilateral trading facilities (MTFs), Chi-X, BATS and Turquoise, among other things, has reduced traded volume for traditional European stock exchanges (e.g. Euronext for French orders). Third, this decrease was reinforced by the introduction of the financial transaction tax (FTT) on the French stock market on August 1st, 2012. Indeed, France introduced a national tax (0.2% of the purchase price) on certain financial transactions, especially for trading in large-cap stocks with a market capitalization of at least €1 billion (of which there are 108 firms). Our sample contained 68 of the 108 large-cap firms that are affected by the FTT (see Appendix 1 in Colliard and Hoffmann, 2013, p. 30 for a list of stocks).

In what relates to the stability of findings, a number of previous studies choose to split the total sample into sub-periods of time. Gallant and al. (1992) use three sub-periods, Lo and Wang (2000) use 5-year periods and Statman *et al.* (2006) consider four 10-year subsamples. Following this approach, we split our total period of time into two different sub-periods of nearly 10 years: April 1996-September 2005 and October 2005-October 2014[2]. These two periods are used to apply the robustness checks of our analysis.

III.1.3. Descriptive statistics

Table 1 gives some descriptive statistics for the total sample (222 observations) and for both sub-periods with 112 and 110 observations, respectively. Table 1 provides descriptive statistics and unit root tests on monthly market turnover (*Tm*), detrended market turnover (*DTm*) and stock market returns (*Rm*), as well as the market-wide control variables of conditional market volatility (*CVm*) and cross-sectional standard deviation of returns (*Dm*). This is very similar to Statman *et al.* (2006), who used four 120-month sub-periods (for a total sample of 40 years). Focusing on market turnover, it appears that the mean settled at 3.943% for the second sub-period against 4.628% for the first sub-period, with respective maximums of 9.37% and 14.43%. This result clearly indicates that transaction volume dramatically decreased during the second sub-period. This is probably explained as a consequence of the financial crisis and by the introduction of the FTT in August 2012 to the French stock market. This result is in line with that of Colliard and Hoffman (2013) who fined that trading volume has decreased by about 30% for all French market segments since 2012. This trend is also confirmed by a European Commission report (2014).[3] According to this report, the introduction of the FTT provoked a decline of around 10% in trading volume.

Table 1. Descriptive statistics and Unit root tests

Panel A : Descriptive statistics					
	Tm	**DTm**	**Rm**	**CVm**	**Dm**
Total sample April 1996 – October 2014					
Mean	4.293	0.000	0.286	1.286	6.061
Maximum	14.43	86.90	6.901	2.451	17.72
Minimum	4.459	– 42.68	– 6.751	– 3.298	1.693
Std. Dev.	20.77	18.11	2.352	0.995	2.778
First sub-period April 1996 – September 2005					
Mean	4.628	0.008	0.456	2,071	6.815
Maximum	14.43	86.63	5.340	2.452	17.70
Minimum	9.785	– 42.22	– 6.751	– 2.772	2.253
Std. Dev.	23.91	21.481	2.459	1.050	2.933
Second sub-period October 2005 – October 2014					
Mean	3.943	– 0.062	0.1333	0.574	5.311
Maximum	9.375	45.53	6.901	2.126	12.88
Minimum	4.459	– 42.68	– 6.522	– 3.298	1.693
Std. Dev.	1.624	13.85	2.236	0.934	2.399
Panel B : Unit root tests					
ADF	– 1.95	– 11.81	– 13.37	– 13.63	– 5.32
PP	– 1.23	– 12.23	– 13.46	– 13.74	– 10.71

Tm is the market turnover defined as the value-weighted individual securities (128 firms), DTm is the detrended log turnover derived from the Hodrick-Prescott (1997) filter, Rm is the stock market returns, CVm is the conditional market volatility corresponding to the residuals of an EGARCH (1.1) model and Dm is the monthly cross-sectional deviation of returns. Panel A gives some useful descriptive statistics on both the full-sample period and the two sub-periods of time. Unit root tests are examined in panel B where ADF, PP are respectively Augmented Dickey-Fuller and Phillips-Perron test statistics. In each test, the null hypothesis is that the series has a unit root. Critical values for ADF and PP tests are -3.46 (1%), -2.87 (5%) and -2.57 (10%).

Concerning our control variables, the mean of *Dm* is about 6% for the total sample, and 6.8% for the first sub-period. This result is in line with those obtained by Campbell *et al.* (2001) and Statman *et al.* (2006) on the US stock market. We observe this same trend in conditional market volatility (CVm). In addition, the results are comparable to those obtained by Griffin *et al.* (2007), who also used the EGARCH specification (1.1) to measure this exogenous variable in a VAR model. Before applying this model to our database, we adopted augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to ensure that every variable is stationary. Panel B gives two unit root statistics for the tests of stationarity for all variables used in this study. We found that the ADF and PP tests reject the null hypothesis of a unit root at the 1% level for both endogenous and exogenous variable series. Therefore, these results allow the following statistical analysis.

III.2. CONTEMPORANEOUS RELATIONSHIPS BETWEEN TRADING VOLUME AND RETURNS

The contemporaneous relation between trading volume and returns has been widely studied (see previous section) through a number of econometric methodologies (Karpoff, 1987). More recently, numerous empirical studies have investigated contemporaneous relations by estimating a system of simultaneous equations within which trading volume and returns are treated as endogenous variables (Lee and Rui, 2002; Floros and Vougas, 2007). In line with these empirical studies, we investigated the volume-returns relation using a GMM estimator. The GMM was developed by Hansen (1982) and can produce estimators using only few assumptions. For instance, this method does not require any distribution of data. Moreover, GMM estimators have two important statistical properties. First, they avoid simultaneity bias. Second, they provide heteroscedasticity-consistent estimators. Nevertheless, the advantages of GMM over ordinary least squares (OLS) estimators are evident if and only if heteroskedasticity is present. Thus, a test for the presence of heteroskedasticity is required. We run the Breusch-Pagan-Godfrey (BPG) standard tests for the total sample and for each investigated sub-period. The BPG test is a Lagrange multiplier test of the null hypothesis of no heteroskedasticity (homoskedasticity) against heteroskedasticity of the form $\sigma_t^2 = \sigma^2 h\left(z_t'\alpha\right)$ where z_t is a vector containing regressors from the OLS regression. BPG is performed by completing an auxiliary regression of squared residuals from each original equation of the system. Table 2 Panel B gives a Koenker statistic distributed as a chi-square. All the coefficients indicate a rejection of the null at 5% level. According to these results, the use of GMM estimators appears relevant to investigate the relationships between stock market returns and market turnover.

In order to avoid simultaneity bias, we defined a list of instrumental variables that are correlated with our endogenous variables (trading volumes and returns) but not with the residuals in either of the equations in the above system. Following Ciner (2002) and Lee and Rui (2002), among others, we used the lagged values of trading volume and stock returns as instruments. Hence, the contemporaneous relationships between trading volume and stock returns can be tests using the following simultaneous equations system (Lee and Rui, 2002):

$$\begin{aligned} Rm_t &= \alpha_0 + \alpha_1 DTm_t + \alpha_2 DTm_{t-1} + \alpha_3 Rm_{t-1} + \varepsilon_t \\ DTm_t &= \beta_0 + \beta_1 Rm_t + \beta_2 DTm_{t-1} + \beta_3 DTm_{t-2} + \eta_t \end{aligned} \quad (1)$$

Where Rm_t and DTm_t are both the dependent variables and the explanatory variables, and Rm_{t-1}, DTm_{t-1}, DTm_{t-2}, the lagged values of stock returns and detrended turnover included in the system. The same lag values are used in the instruments list.

Table 2 Panel A reports the GMM tests of the contemporaneous relationships between detrended market turnover and stock market returns, respectively, for the total sample period and the first and second sub-periods of time. At first, we observed rather contrasting results depending on the period of time. For the first sub-period (1996-2005), the α_1 and β_1 coefficients were statistically significant at the 5% level, which indicates a bidirectional relationship between turnover and returns. Whereas, only β_1 appeared to be significant for the total sample.

Table 2. Contemporaneous relationships between turnover and returns

	Total sample April 1996 – October 2014		First sub-period April 1996 – September 2005		Second sub-period October 2005 – October 2014	
Panel A: GMM Tests						
GMM tests of contemporaneous relationships between detrended market turnover (DTm) and Stock market returns (Rm) are carried out based on the following system: $Rm_t = \alpha_0 + \alpha_1 DTm_t + \alpha_2 DTm_{t-1} + \alpha_3 Rm_{t-1} + \varepsilon_t$; $DTm_t = \beta_0 + \beta_1 Rm_t + \beta_2 DTm_{t-1} + \beta_3 DTm_{t-2} + \eta_t$						
	Coefficient	**t-stat p-value**	**Coefficient**	**t-stat p-value**	**Coefficient**	**t-stat p-value**
α_0	0.072	0.459 (0.647)	0.474	2.008 (0.046)**	0.072	0.459 (0.647)
α_1	0.054	1.174 (0.242)	0.413	2.205 (0.028)**	– 0.054	– 1.174 (0.242)
α_2	0.002	0.234 (0.816)	– 0.212	– 1.754 (0.081)*	– 0.082	– 1.282 (0.222)
α_3	0.127	1.963 (0.050)**	– 0.251	– 4.020 (0.000)***	0.127	1.962 (0.050)**
β_0	0.281	0.372 (0.710)	– 0.592	– 2.255 (0.026)**	0.281	0.372 (0.714)
β_1	0.435	2.013 (0.048)**	0.495	2.002 (0.048)**	– 0.253	1.208 (0.228)
β_2	– 0.107	– 1.794 (0.074)*	0.238	2.043 (0.042)**	– 0.172	– 1.794 (0.074)*
β_3	– 0.139	– 2.201 (0.0282)**	0.232	4.387 (0.000)***	– 0.219	– 2.209 (0.028)**
Panel B: Breusch-Pagan-Godfrey tests of heteroskedasticity						
Relationship between stock market return and market turnover						
	Obs*R-squared	Prob Chi²	Obs*R-squared	Prob Chi²	Obs*R-squared	Prob Chi²
	7.2498	0.0634*	3.7141	0.2940	6.3837	0.0944*
Relationship between market turnover and stock market return						
	6.1941	0.1025	1.9127	0.5907	1.4835	0.6861

*, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively. BPG test the null hypothesis of no heteroskedasticity, H_0 against heteroskedasticity H_1. Obs*R-squared is the Koenker statistics distributed as a Chi² with 3 degrees of freedom. The critical value for Chi² at 5% level is 7.815. Then, we reject the null hypothesis of no heteroskedasticity caused by endogeneous variables.

This result confirms the overconfidence hypothesis. When prices increase, investors are immediately more confident. This makes them more aggressive, which leads to a higher trading volume in the same month. Conversely, investors trade less after negative returns. For the second sub-period (2005-2014), there were no statistical relations between turnover and returns. Evidence on the contemporaneous relation between trading volume and returns appears relatively coherent with that of previous studies (Lee and Rui, 2002).

In the rest of the paper, we investigate the dynamic (causal) relation between trading volume and stock returns using the statistical properties of bivariate VAR.

IV. Dynamic relationship

The VAR model assumes that each endogenous variable depends on both its past values and the past values of all the other exogenous variables in the system of equations. It is used as a consistent econometric model to investigate dynamic (causal) relations between market turnover, stock market returns and volatility. The general form of the VAR model can be expressed as follows:

$$Y_t=\alpha+\sum_{p=1}^{P} A_p Y_{t-p}+\sum_{q=1}^{Q} B_q X_{t-q}+e_t \qquad (2)$$

Where Y_t is an $n \times 1$ vector of endogenous variables at time t, X_t is an $n \times 1$ vector of the exogenous variables (control variables) at time t, and e_t is a vector of serially uncorrelated errors. A_p and B_q represent the regression coefficients, estimating the time-series relationship between endogenous and exogenous variables, respectively, where P and Q are the number of lags. Relative to our database, we can rewrite equation (2) with two endogenous variables (Rm and DTm) and two exogenous variables (Dm and CVm), used as control variables:

$$\begin{bmatrix} DTm_t \\ Rm_t \end{bmatrix} = \begin{bmatrix} \alpha_{DTm} \\ \alpha_{Rm} \end{bmatrix} + \sum_{p=1}^{P} A_p \begin{bmatrix} DTm_{t-p} \\ Rm_{t-p} \end{bmatrix} + \sum_{q=1}^{Q} B_q \begin{bmatrix} Dm_{t-q} \\ CVm_{t-q} \end{bmatrix} + \begin{bmatrix} e_{DTm,t} \\ e_{Rm,t} \end{bmatrix} \qquad (3)$$

This econometric specification builds on the notion that the current value of an endogenous variable is partly explained by past values of this variable. Thus, it is possible to explain two relations. The first one establishes the relation between current detrended market turnover and the past values of stock market returns, and the second demonstrates the relation between current stock market returns and the past values of detrended market turnover. Our methodology required two control variables: the cross-sectional standard deviation of market returns (Dm) and conditional market volatility (CVm) filtered by an EGARCH (1.1) model. The introduction of these two exogenous variables in the VAR model is required to control for volatility effects in the dynamic relation between trading volume and stock return.

The lag length for the VAR model was determined using model selection criteria. The general approach is to run VAR models with a determined number of lags for both endogenous and exogenous variables and choose the values of the lag which minimize the value of some model section criteria.

IV.1. BIVARIATE VAR MODEL

Table 3 provides the results of the bivariate VAR models for the detrended log market turnover (DTm) and stock market returns (Rm) for the total sample and the two sub-periods in panel A and the results for the control variables plus a constant in panel B. For each coefficient, we report the t-stats in brackets with the significance level. For each model the length of the lag structure of the endogenous variables is determined using a couple of tests that are based on a number of information criteria. We used four criteria for information: the final prediction error (FPE), the Akaike information criterion (AIC), the Schwarz information criterion (SIC) and the Hannan-Quinn information criterion (HQIC). In order to obtain the lag order selection we run, as a first step, the VAR with a maximum lag and, second, we tested the obtained VAR system with the four criteria listed above. The results of the lag order selection criteria appeared somewhat different depending on the chosen test. These different results probably come from the main characteristics of each information criterion (Lütkepohl, 1991 for more details). For each VAR model we performed a lag exclusion Wald test to avoid misspecification. Panel C of Table 3 provides the Wald statistics, associated p-values and a joint test. All these tests clearly indicate an optimal structure of three lags for the total sample and the first sub-period and just one lag for the second sub-period. The model selection criterion leads to one lag for the control variables (Dm and CVm) for both sub-periods but not for the entire period of time. We only tested for the stability of each bivariate VAR model using the inverse roots of the characteristic AR polynomial (Lütkepohl, 1991). All roots had a modulus of less than 1 and lie inside the unit circle. These tests indicate that each VAR satisfies the stability condition.

The first key empirical finding consists of a positive and highly significant relation between market turnover and lagged stock market returns (third lag), especially for the total sample and the first sub-period and at the first lag for the second sub-period. This finding implies that past returns explain a part of the trading activity. In other words, lagged stock market returns could have predictive power for current market turnover. These results agree with some empirical studies that used a similar methodology in a number of markets (Lee and Rui, 2002; Statman *et al.* 2006 and Griffin *et al.* 2007, to name a few). This shows that market turnover increases in the months following high market returns, which is consistent with the overconfidence hypothesis.

The second finding clearly indicates that lagged detrended turnover does not explain the current stock

Table 3. VAR estimation

	Total sample April 1996 – October 2014		First sub-period April 1996 – September 2005		Second sub-period October 2005 – October 2014	
	DTm_t	Rm_t	DTm_t	Rm_t	DTm_t	Rm_t
Panel A: Endogenous Variables						
Rm_{t-1}	0.264 (0.525)	0.021 (1.319)	– 2.891 (– 0.851)	0.014 (0.148)	4.879 (2.111)**	0.159 (1.678)*
Rm_{t-2}	0.668 (1.335)	– 0.027 (– 1.703)*	0.231 (0.304)	– 0.019 (– 0.925)	–	–
Rm_{t-3}	1.365 (2.717)***	– 0.007 (– 0.466)	2.603 (3.431)***	– 0.022 (– 1.037)	–	–
DTm_{t-1}	0.173 (2.595)***	0.000 (0.239)	0.245 (2.590)***	0.002 (0.911)	– 0.126 (– 1.291)	– 0.001 (– 0.222)
DTm_{t-2}	0.146 (2.176)**	– 0.002 (– 0.951)	0.264 (2.753)***	– 0.004 (– 1.512)	–	–
DTm_{t-3}	0.061 (0.916)	0.000 (– 0.449)	– 0.047 (– 0.479)	– 0.001 (– 0.306)	–	–
Panel B: Exogenous Variables						
Dm_t	1.245 (2.955)***	– 0.448 (– 0.339)	1.393 (2.000)**	– 3.281 (– 1.680)*	1.247 (2.238)**	1.736 (2.068)**
Dm_{t-1}	–	–	– 0.547 (– 0.777)	4.222 (2.139)**	0.005 (0.017)	– 2.867 (– 2.529)**
CVm_t	2.680 (2.265)**	2.316 (6.275)***	0.372 (0.206)	2.315 (5.733)***	2.389 (4.1)***	2.346 (4.320)***
CVm_{t-1}	–	–	0.733 (0.916)	– 0.011 (– 0.049)	– 1.284 (– 2.30)**	– 0.337 (– 1.471)
Constant	– 0.786 (– 2.72)***	0.014 (0.161)	– 0.715 (– 1.267)	– 0.087 (– 0.551)	– 0.629 (– 1.761)*	0.061 (0.415)
Panel C: Lag exclusion tests						
Lag 1	6.746 [0.034]	2.741 [0.118]	7.731 [0.021]	0.839 [0.658]	6.288 [0.023]	2.888 [0.077]
Lag 2	5.736 [0.056]	3.375 [0.185]	7.661 [0.021]	3.122 [0.209]		
Lag 3	7.667 [0.022]	1.367 [0.232]	12.069 [0.002]	1.157 [0.162]		
Joint	7.955 [0.032]		13.08 [0.011]		9.496 [0.039]	

This table reports coefficients and t-stats between parentheses. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively. Endogenous variables are DTm (detrended market turnover) and Rm (stock market returns). Exogenous variables are CVm (conditional market volatility) and Dm (monthly cross-sectional standard deviation of returns). In panel C, we computed, for each period of time, the lag exclusion tests (we use until 8 lags for these tests). The χ^2 Wald statistic is computed to test the joint significance of all endogenous variables reported in each equation of the VAR model. *Indicates statistical significance of a Chi-squared test statistics for lag exclusion. Numbers between brackets are associated p-values.

market returns because these relations exhibit insignificant coefficients. This suggests that seeking to improve the predictability of stock market returns is not a simple matter of publishing additional information about trading volume, since the informative content of trading volume in terms of forecasting returns is low. These results are in accordance with those of Lee and Rui (2002), Pisedtasalasai and Gunasekarage (2007), Chuang *et al.* (2009) and Brüggemann *et al.* (2014), and directly comparable to those obtained by Chen *et al.* (2001) on the French stock market.

The third empirical finding concerns the presence of the market turnover autocorrelation. Indeed, our results show highly significant relations between current market turnover and its lagged coefficients (0.173 and 0.245, respectively, for the total sample and the first sub-period, with significance at the 1% level). The magnitude of the coefficients generally decline on the second and higher lags in the VAR. This result is consistent with numerous empirical studies (Statman *et al.*, 2006).

The fourth finding concerns the informational role of the stock market dispersion and the conditional market volatility we used as exogenous variables in the VAR. We found significant positive relations between the detrended market turnover and the contemporaneous dispersion (*Dm*) for each period of time with rather large estimated coefficients (1.245 to 1.393 depending on the sub-period). These results are in accordance with those of Statman *et al.* (2006). Current conditional market volatility exhibits a statistically significant positive correlation with the detrended market turnover, especially for the second sub-period, and a positive correlation with stock market returns for both periods of time. These results confirm those obtained by most empirical studies that deal with the contemporaneous relationship between transaction volume and volatility (Karpoff, 1987; Gallant *et al.*, 1992). We ran alternative specifications of the bivariate VAR model without, respectively, one or both of the exogenous variables (*CVm* and *Dm*) for each period of time. Whatever the model considered, our results concerning the relationship between market turnover and market returns remained unchanged.[4]

IV.2. CAUSAL RELATIONSHIPS BETWEEN TURNOVER AND RETURNS

The causal relationship between market turnover, stock market returns and market volatility can be appreciated by the causality structure among the variables (Lee and Rui, 2002). One way to address this is to follow Granger (1969). Causality in the Granger sense involves (Chi-square) tests of whether lagged information on detrended turnover market Y provides any statistically significant information about stock market returns X in the presence of lagged X. If not, then "Y does not Granger-cause X". There are several ways to implement a test of Granger causality. In this study, we followed the bivariate VAR approach:

$$\begin{aligned} X_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{i=1}^{q} \beta_i Y_{t-i} + \varepsilon_t \\ Y_t &= \gamma_0 + \sum_{i=1}^{p} \gamma_i X_{t-i} + \sum_{i=1}^{q} \delta_i Y_{t-i} + \eta_t \end{aligned} \tag{4}$$

Suppose that X_t and Y_t are, respectively, the detrended market turnover and the stock market returns. "Returns" cause, in the Granger sense, "turnover" if the β_i coefficients are statistically significant. This means that the past values of returns, in addition to the past values of turnover, explain future values of turnover. Parameters α_i and δ_i represent the effect of lagged turnover on the current turnover and the effect of lagged returns on the current returns, respectively. It is interesting to note that if all β_i and γ_i coefficients are statistically different from 0, then bidirectional causality exists between returns and volumes (feedback relation).

Table 4 documents Granger causality tests based on bivariate VAR, respectively, for the total sample period and for the two sub-periods. Our first key result concludes that turnover does not Granger-cause stock market returns for all periods of time. One can conclude that turnover does not add predictive power to forecasting returns. In other words, it implies that there is no scope for improving the predictability of returns by considering information flow in the form of trading volume. In contrast, stock returns Granger-cause turnover for each period of time. Returns contain significant information for predicting future volume. This result shows a statistically significant tendency for market-wide turnover to increase in the months following high market returns, which is consistent with the overconfidence hypothesis. Statman *et al.* (2006) found this positive relationship for many months even after controlling for turnover trend and contemporaneous volume-volatility relationships. This positive relation between past returns and current trading volume can be explained by the self-attribution bias, which increases the degree of overconfidence. Investors subject to self-attribution bias attribute positive market returns to personal aspects. They are more confident of their investment and more aggressive after positive market returns that lead to high trading volumes (Gervais and Odean, 2001). This result confirms those obtained by most empirical studies (Ko and Huang, 2007; Grinblatt and Keloharju, 2009; Brüggemann *et al.*, 2014).

Moreover, this finding is consistent with Clark's (1973) MDH, which predicts no causal relation between trading volume and stock returns. Numerous empirical studies also confirm this result (Gallant *et al.* 1992 and Hiemstra and Jones, 1994 in the US stock market and Lee and Rui, 2002 for the Japanese and UK stock markets). More recently, Chen (2012) has provided results in accordance with some previous studies but only in the first sub-period from 1973 to 1999. Chen (2012) indicates that Granger causality tests and linear models are more sensitive to the sample period chosen. This result contradicts the SIAHs of Copeland (1976) and Jennings *et al.* (1981), which argue, first, that the information content of trading volume serves as a predictor of future returns and, second, that there exists a bidirectional (causal) relationship between volume and return.

Our second key result indicates that there is a causal relation between conditional volatility and turnover in the sense that *CVm* Granger-causes *DTm*. In other words, conditional volatility contains information for predicting trading volume. In contrast, turnover does not Granger-cause volatility. Thus, there exists no feedback relation between these two variables. This result contrasts with the feedback relation obtained by Lee and Rui (2002) and contradicts the MDH, according to which trading volume can be used as a proxy for the stochastic mixing variable in the conditional volatility process (Clark, 1973).

IV.3. IMPULSE RESPONSE FUNCTIONS

According to the seminal works of Sims (1972, 1980), IRF simulate the effects of a shock in one variable on the conditional forecast of other system variables. More precisely, IRF plots the effects of a standard deviation shock in one variable on current and future values of endogenous variables through the dynamic structure of our bivariate VAR. Therefore, the starting point is to run an unrestricted VAR following equation (3). In our case, changes in $e_{DTm,t}$ will immediately change the current

Table 4. Granger causality tests

Null hypothesis	X Granger-causes Y	F-statistic p-value in brackets
Panel A : Granger causality tests between turnover and returns		
Total sample period (3 Lag)		
$H_0 : \gamma_i = 0$	$DTm \rightarrow Rm$	1.145 (0.334)
$H_0 : \beta_i = 0$	$Rm \rightarrow DTm$	4.301 (0.007)****
Sub-period 1 (3 Lag)		
$H_0 : \gamma_i = 0$	$DTm \rightarrow Rm$	3.015 (0.389)
$H_0 : \beta_i = 0$	$Rm \rightarrow DTm$	13.63 (0.003)***
Sub-period 2 (1 Lag)		
$H_0 : \gamma_i = 0$	$DTm \rightarrow Rm$	0.050 (0.824)
$H_0 : \beta_i = 0$	$Rm \rightarrow DTm$	4.459 (0.035)**
Panel B : Granger causality tests between turnover and conditional volatility		
Total sample period (3 Lag)		
$H_0 : \gamma_i = 0$	$DTm \rightarrow CVm$	2.431 (0.297)
$H_0 : \beta_i = 0$	$CVm \rightarrow DTm$	1.527 (0.466)
Sub-period 1 (3 Lag)		
$H_0 : \gamma_i = 0$	$DTm \rightarrow CVm$	1.117 (0.346)
$H_0 : \beta_i = 0$	$CVm \rightarrow DTm$	5.073 (0.003)***
Sub-period 2 (1 Lag)		
$H_0 : \gamma_i = 0$	$DTm \rightarrow CVm$	0.852 (0.632)
$H_0 : \beta_i = 0$	$CVm \rightarrow DTm$	3.862 (0.004)***

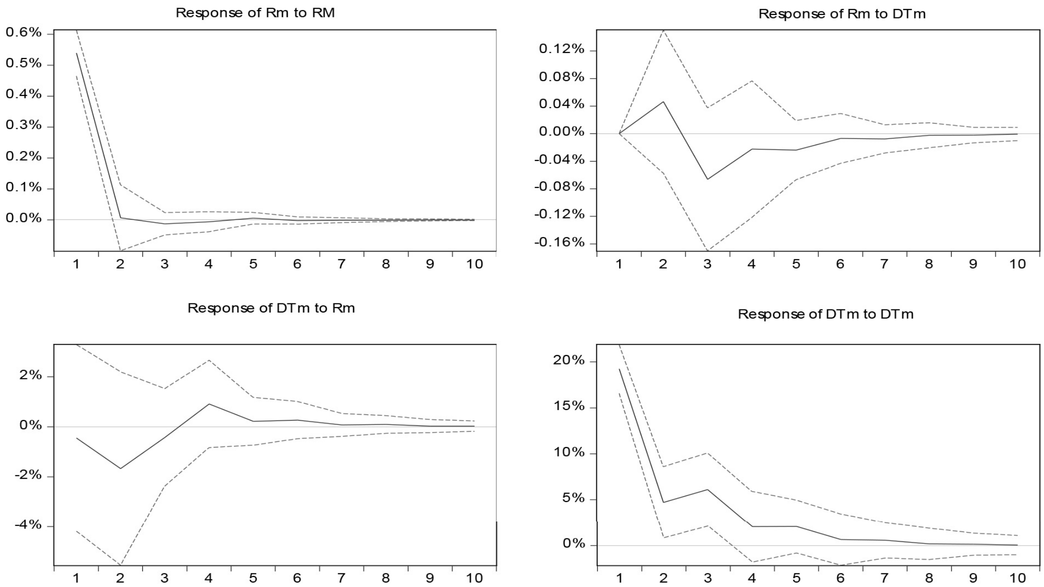
This table reports coefficients and F-stats and associated p-values between parentheses. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively. Endogenous variables are DTm (detrended market turnover) and Rm (stock market returns). Exogenous variables are CVm (conditional market volatility). "X Granger-causes Y" is denoted $X \rightarrow Y$. For example if the F-test does not reject the null hypothesis $H_0 : \beta_i = 0$ for 3 Lag for the total sample period, then Rm does not cause DTm.

value of DTm_t and also change future values of DTm and Rm because endogenous variables appear in both equations through A_p. However, the main problem of using unrestricted VAR to perform IRF is the possibility of having correlated residuals. Indeed, if residuals are correlated, then they have a common component which cannot be associated with a specific endogenous variable. In line with Sims (1980), Statman *et al.* (2006) specify that it is possible to avoid this problem by using the Cholesky decomposition so that the variance-covariance matrix of residuals could be diagonal[5]. Another important feature to better perform the IRF is the causal ordering in the VAR. It is well known that residuals from VAR are generally correlated. Using the Cholesky decomposition is equivalent to assuming recursive causal ordering from the top to the bottom variables. Finally, changing the variable order can significantly affect the results of IRF, especially for a high-dimensional VAR model (Lütkepohl, 1993). In our case, this change is very narrow because we have only two endogenous variables in the VAR. Figure 3, Panels A and B display IRF graphs using the bivariate VAR estimation for two different sample periods. For each range, we have four graphs. The first two graphs indicate the response of the stock market return (Rm) to a standard deviation shock in Rm and DTm with 5% and 95% confidence intervals, respectively. The two last graphs plot the response of the detrended market turnover (DTm) to a standard deviation shock in Rm and DTm, respectively. The log transformations of the stock market return and the detrended market turnover make it possible to have a vertical axis expressed in percentage.

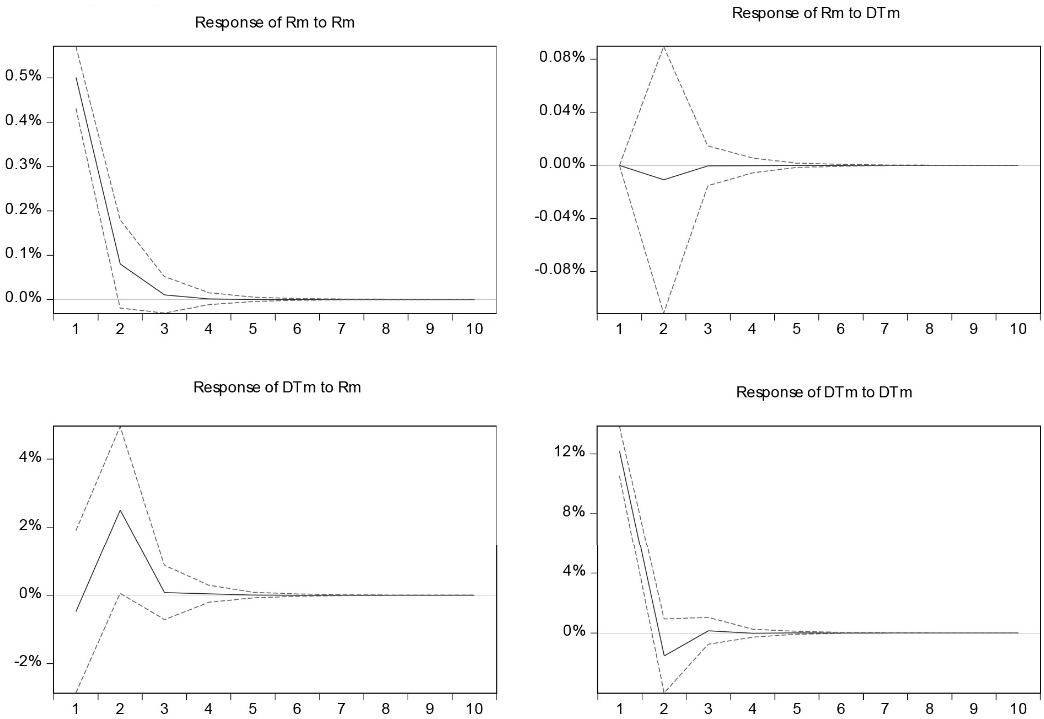
Figure 3 contains, for each sub-period (Panels A and B), the four possible IRF graphs using the bivariate VAR estimation shown in Table 2. The main findings can be presented as follows. First, IRF indicate that a standard deviation shock at market turnover results in nearly 5% increase of market turnover in the next period for the first sample. This result confirms the serial dependence of market turnover in that the positive impact of a market turnover shock persists for about six months. Second, a response of market turnover to stock market returns

Figure 3. Impulse response functions

Panel A: The solid line denotes the IRF and the dotted lines denote the 5% and 95% confidence intervals. IRF trace the effects of a shock in one endogenous variable (Rm or DTm) on the other variables (DTM or Rm) of bivariate VAR. We use the Cholesky decomposition to ensure the diagonalization of the covariance matrix of residuals. Sample range goes from April 1996 to September 2005.



Panel B: Sample range October 2005 - October 2014.



produces a decrease of about 2% of turnover for the two last periods, and an increase of almost 1% for the third and fourth periods for the first sample. We interpret this finding as evidence that stock market returns affect investor confidence and, as a result, trading activity. Third, a response of current stock returns to market turnover indicates that a standard deviation shock to market turnover has a negligible impact on future returns. Thus, turnover is not able to predict future stock returns. This result is consistent with the efficient market hypothesis, according to which trading volume cannot help forecasting stock returns. On the whole, our IRF results present qualitatively similar results to those obtained by Statman *et al.* (2006), especially for the first sub-sample. Indeed, these IRF results confirm our initial findings. Thus, returns can enhance the predictability of market turnover but turnover cannot improve the forecasting of stock returns.

V. Conclusion

Relationships between trading volume, returns and volatility have been intensively studied in numerous theoretical and empirical studies. However, to the best of our knowledge, very few studies have investigated the French stock market over a long period of time (1996-2014). Therefore, this study aimed at overcoming this lack of empirical research. We followed the Statman *et al.* (2006) methodology to aggregate monthly individual trading volumes and stock returns in order to construct market turnover and value-weighted portfolios used as a proxy for the French stock market from April 1996 to October 2014.

A battery of econometric tests was used to investigate (i) the contemporaneous relationship between trading volume and stock returns (conditional volatility) using a system of simultaneous equations via a GMM estimation, and (ii) the dynamic (causal) volume-returns relations through bivariate vector autoregression (VAR) with Granger causality test and impulse response functions (IRF) analysis.

With regards to contemporaneous relations, we obtained different results depending on the investigated period of time. We found a significant bidirectional correlation between turnover and stock returns for the first sub-period (1996-2005).This result confirms both the MDH and the overconfidence hypothesis.

Further, we investigated the dynamic (causal) link between market turnover and stock market returns by using the statistical properties of bivariate VAR. The empirical analysis revealed a positive and significant relation between market turnover and stock market returns (conditional volatility) but a statistically insignificant link between stock returns and market turnover. This finding implies that lagged stock returns have a predictive power for current market turnover, whereas lagged market turnover does not explain current stock returns (unidirectional correlation). These results confirm those of Lee and Rui (2002), Pisedtasalasai and Gunasekarage (2007), Chuang *et al.* (2009) and, more recently, Brüggemann *et al.* (2014). Results obtained by the Granger causality tests and IRF confirmed that market turnover is not able to predict future stock returns. These results are in line with numerous empirical findings using comparable econometrics methodologies (Gallant *et al.*, 1992; Hiemstra and Jones, 1994; Lee and Rui, 2001 and Chen, 2012). The reported evidence is consistent with the overconfidence hypothesis. In other words, prior successful trading experience is likely to lead to overconfidence among investors. Thus, in accordance with Daniel *et al.* (1998) and Gervais and Odean (2001), among others, the positive relation between past returns and current trading volume can be explained by behavioural biases, in particular the self-attribution bias. ■

1 There is no consensus about the methodology used in previous empirical research to handle the non-stationarity of transaction volume. Chen (2012) uses the log of trading volume for first differences, whereas other authors employ detrended methods (Griffin *et al.*, 2007). In this study, we follow the Statman *et al.* (2006) strategy to detrend the market turnover time series by using the Hodrick and Prescott (1997) filter.

2 Another possible strategy to split the total sample is to use a structural break analysis on stock market returns and turnover, respectively. Chow tests (and CUSUM square test) indicate the existence of multiple breaks into these two endogenous variables. At this point, it is important to consider not only separate time-series but also the dynamic between stock returns and trading volume. By using the Quandt-Andrews breakpoint test, it is possible to examine whether the parameters of our model are stable across different periods of time. Several models have been tested. Some of these models reveal the existence of at most two change-points. The first is detected in December 2000 and the second in March 2006. Thus, we consider a combination of alternative sub-periods and run our bivariate VAR with these different samples. In particular, we test the following sub-periods: April 1996 to March 2006, April 2006 to October 2014 and December 2000 to October 2014. For some of these sub-intervals, the magnitude of certain endogenous or exogenous coefficients may change in the VAR. However the direction of the relation does not change. Regardless of the investigated period of time, lagged stock returns have a predictive power for the current trading volume (stock returns Granger cause turnover) but not vice versa, which is consistent with our main findings. The estimations of these alternative bivariate VAR are available upon request.

3 For more details on the implementation of the FTT, the reader may refer to a recent report of the European Commission entitled: “Did the new French tax on financial transactions influence trading volume, price levels and/or volatility in the taxed market segment? A trend analysis” This document is downloadable at the following address: http://ec.europa.eu/taxation_customs/resources/documents/taxation/other_taxes/financial_sector/effect_french_ftt.pdf.

4 The estimations of these alternative specifications are available upon request.

5 To go further, we perform a structural VAR model. Following Blanchard and Quah (1989), we apply long run restrictions in order to obtain restrictions on the long-run properties of the impulse responses. Unreported structural IRF analysis gives similar results to those reported using the Cholesky decomposition. These results are available upon request.

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