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ABOUT THE PROJECT

This publication emerges from a project called Essays in Financial Governance: Promoting Cooperation in Financial Regulation and Policies. The project is supported by a 2011-2012 CIGI Collaborative Research Award held by Martin T. Bohl, Badye Essid, Arne Christian Klein, Pierre L. Siklos and Patrick Stephan. In this project, researchers investigate empirically policy makers' reactions to an unfolding financial crisis and the negative externalities that emerge in the form of poorly functioning financial markets. At the macro level, the project investigates whether the bond and equity markets in the throes of a financial crisis can be linked to overall economic performance. Ultimately, the aim is to propose policy responses leading to improved financial governance.

ACRONYMS

ADF	augmented Dickey-Fuller
AR	autoregressive
BFGS	Broyden-Fletcher-Goldfarb-Shanno
CAPM	capital asset pricing model
EM	expectation maximization
ETF	exchange trade fund
GARCH	generalized autoregressive conditional heteroskedasticity
GED	generalized error distribution
MSADF	Markov switching ADF
MSGARCH	Markov switching GARCH
OLS	ordinary least square
VIX	volatility index

EXECUTIVE SUMMARY

Existing models of market herding suffer from several drawbacks. Measures that assume herd behaviour is constant over time or independent of the economy are not only economically unreasonable, but describe the data poorly. First, if returns are stationary, then a two-regime model is required to describe the data. Second, existing models of time-varying herding cannot be estimated from daily or weekly data, and are unable to accommodate factors that explain changes in this behaviour. To overcome these deficiencies, this paper proposes a Markov switching herding model. By means of time-varying transition probabilities, the model is able to link variations in herding behaviour to proxies for sentiment or the macroeconomic environment. The evidence for the US stock market reveals that during periods of high volatility, investors disproportionately rely on fundamentals rather than on market consensus.

INTRODUCTION

Herding behaviour has been the subject of considerable interest over the years. The issue of whether investors imitate each other when making investment decisions has been extensively investigated. The extent to which investors discriminate between stocks should be reflected in how returns deviate from overall market performance. If investors follow the market, then dispersion in returns should disappear entirely. It is widely observed, however, that following the market may be conditional on, for example, whether the overall market is rising or falling. More importantly, one would expect market sentiment and macroeconomic and financial conditions to have a significant influence on the extent to which investors follow the market.

Existing strategies to empirically investigate herding behaviour suffer from several deficiencies, including the inability to recognize that herding can change over time as market conditions change. For example, some herding measures are assumed to be constant. This is not only economically unreasonable, but such a view implies a mis-specification. For example, this paper shows that a unit root in the time series for dispersion can be rejected in favour of an alternative, wherein there are two regimes with stationary returns, namely, one when market volatility is high and another when volatility is low. Moreover, existing models of herding behaviour cannot be estimated from daily or weekly data, or are incapable of accommodating factors that determine investors' propensity to display herd-like behaviour.

This paper makes a start towards overcoming these drawbacks by proposing a Markov switching model of the model proposed by Chang, Cheng and Khorana (2000), and applying this model to data from the US stock market. Reliance on a Markov switching model is supported by the finding that two distinct states exist; they are found to be closely related to observed market phases that alternate between high- and low-volatility market conditions. The aftermath of the dot.com bubble represents a highly volatile regime, as does the period of the 2008–2010 financial crisis.

Time-varying transition probabilities as derived by Diebold, Lee and Weinbach (1994) enable us to consider economic and financial variables that drive changes in herding behavior over time. In particular, proxies for market sentiment were applied, such as implied volatility and trading volume, as well as term structure variables, which the literature considers to be closely linked to macroeconomic fundamentals. In addition, non-normal distributions and generalized autoregressive conditional heteroskedasticity (GARCH) effects were controlled for.

The remainder of the paper is organized as follows: in the next section, the literature on herding is reviewed; the classical approaches to measure herd formation are discussed in the third section; in the fourth section, the Markov switching models of herd behaviour are outlined and the two-regime augmented Dickey-Fuller (ADF) test is briefly sketched out; the fifth section discusses the empirical results; and the paper ends with a brief conclusion.

LITERATURE SURVEY

The literature, in general, defines intentional herding as a situation where investors imitate each other's buy and sell decisions, even though this kind of trading strategy might be at odds with their own information and beliefs. By contrast, spurious herding refers to a "clustering" of investment decisions due to similar underlying information sets. Herding behaviour can be either rational or irrational (Devenow and Welch 1996; Bikhchandani and Sharma 2001). Pure irrational herd behaviour is closely related to the theory of noise trading (De Long et al. 1990; De Long et al. 1991; Jeanne and Rose 2002), which assumes that a group of investors act irrationally or at least base investment decisions on some exogenous liquidity concerns combined with some limits to arbitrage. In contrast, information-based herding rests on the presumption that investors face uncertainty about the quality of the information they are able to access. Although information cascades attempt to address this kind of behaviour (Bikhchandani, Hirshleifer and Welch 1992; Welch 1992; Banerjee 1992; Avery and Zemsky 1998) are the first to propose a model that is applicable to the case of financial markets. However, even for an investor who has access to superior private information, it might be rational to ignore this information and to rely on herding, for example, in the case of portfolio managers facing incentives to stick with a benchmark (Scharfstein and Stein 1990; Froot, Scharfstein and Stein 1992; Graham 1999).

The empirical literature on herding can be subdivided into two branches. The first one deals with herding among institutional investors like fund managers. Research of this kind resorts to data on their trading behaviour. Work on this topic is mainly based upon the measure proposed by Lakonishok, Schleifer and Vishny (1992), who compare the actual share of managers' buy and sell decisions against the expected values under the assumption of independent trading.

A second strand of research deals with herding towards the market, which is given by investors who base their investment decisions entirely on the market consensus, thereby ignoring their own beliefs about the risk-return profile of particular stocks. Christie and Huang (1995) are the first to address this issue empirically. They test the conjecture that such a trading pattern is more likely to arise during times of market stress as evidenced by unusually high volatility. However, their evidence for the US market cannot corroborate a significant clustering of returns during strong market movements.

Unlike Christie and Huang (1995), the approach put forward in Chang, Cheng and Khorana (2000) does not neglect investors' behaviour during periods of low or average volatility. Their test specification aims to compare the actual dispersion of single stock returns around the market with the value implied by rational asset pricing. In particular, they exploit the fact that those pricing models imply a linear relationship between the absolute value of the market return and its dispersion. Their findings support an increased tendency to herd in emerging markets, but reveal only little evidence for such a behaviour in developed countries.

Tan et al. (2008) investigate herding in Chinese A and B stocks using the approach of Chang, Cheng and Khorana (2000). They find evidence for herding in both the A stocks available for domestic investors and in the B shares that are dominated by foreign investors. Analyzing the Polish stock market, Bohl, Gebka and Goodfellow (2009) highlight differences in trading patterns between individual and institutional investors. While the former engage in herding, particularly during market downturns, the latter are unlikely to be driven by herd behaviour. An application to the exchange trade market (ETF) market can be found in Gleason, Mathur and Peterson (2004). They estimate the models of Christie and Huang (1995) and of Chang, Cheng and Khorana (2000) from New York Stock Exchange intraday data and find strong evidence for adverse herding in this market. Adverse herding refers to a situation where, unlike the case of herding, investors disproportionately discriminate strongly between individual stocks.

The papers cited above deal with herd behaviour within a given market, but do not take potential international linkages in account. Chiang and Zheng (2010), however, investigate the impact of the US market on herding formation in several stock markets around the world. They provide favourable evidence that both the volatility as well as the cross-sectional dispersion of single stock returns in the United States influence herding activities in the rest of the world. In contrast, Tan et al. (2008) are unable to find interactions between the herding behaviour in the Chinese stock markets in Shanghai and Shenzhen.

Hwang and Salmon (2004) are the first to derive a measure of herding that allows for time variation in herding behaviour. Their approach is based on the assumption of time-varying monthly betas. Results for the United States and South Korea show a tendency of herding to mitigate, or even become adverse, in the run-up to and during periods of turmoil, for example, in the Asian and Russian financial crises as well as the tech bubble of the early 2000s. In order to establish a theoretical rationale for these facts, Hwang and Salmon (2009) put forward a testable model that incorporates the effect of investor sentiment. In this framework, herding occurs in a situation when investors broadly agree about the future direction of the market, whereas adverse herding is likely to arise when there is a high probability of divergences of opinion among market participants.

EXISTING HERDING MODELS

Research on herding rests on the seminal work of Christie and Huang (1995). Their approach considers the dispersion of single stock returns around the market. They propose the following measure:

$$S_t = \frac{1}{N(t)} \sum_{i=1}^{N(t)} |r_{i,t} - r_{m,t}| \,, \tag{1}$$

where $N\ (t)$ and T are the numbers of stocks available at time t and observations in the sample, $r_{i,t}$, stands for the return of stock i and rm,t for the market return in period t, respectively.[11] The market, in turn, is defined as a value-weighted average of single stock returns. Equation (1) is designed to measure the average absolute deviation of single stock returns from the market return and, thus, provides insights into the extent to which market participants discriminate between individual stocks. If all investors act alike and follow the market, S_t must be equal to 0.

To detect herding conditional on strong market movements, Christie and Huang (1995) regress S_t upon a constant and two dummy variables that control for both extreme positive as well as negative returns, measured by certain outer quantiles of the return distribution. Although very clear-cut, this approach obviously depends heavily on the definition of the thresholds for extreme returns. In addition, differing investor behaviour during times of low and average volatility is completely neglected.

The extension put forward by Chang, Cheng and Khorana (2000) aims to overcome these drawbacks. They highlight the notion that, under the assumption of rational asset pricing (i.e., capital asset pricing model [CAPM]-type pricing), equation (1), is linear and strictly monotonically increasing in the expected value of the absolute market return, $E\ (|r_{m,t}|)$. By contrast, herding behaviour is better captured by a function that is either non-linear or reaches a maximum at a certain threshold value of $E\ (|r_{m,t}|)$, declining thereafter. The following regression is designed to capture these effects:

$$S_t = \gamma + \delta\,|r_{m,t}| + \zeta r_{m,t}^2 + \epsilon_t, \tag{2}$$

where the realized market return is used to proxy their expected value. Rational asset pricing, then, implies a significantly positive δ and a ζ equal to 0. By contrast, a value of ζ that significantly differs from 0 indicates a violation of the linearity implied by rational asset pricing. Using daily returns, this means that $Var(rm,t) = E(r_{m,t}^2) - E(r_{m,t})2 \approx E(r_{m,t}^2)$ holds, so that $r_{m,t}^2$ can be regarded as the market return variance. If, during periods of high volatility, investors herd towards the market, this implies that S_t,

1 Actually, Christie and Huang (1995) use (1) only as a robustness check and base their main inference upon the cross-sectional standard deviation. The advantage of the absolute deviation (1) over the standard deviation is that the former is less sensitive to outliers.

the dispersion of returns around the market, becomes disproportionately low compared to the rational pricing model. This should show up as a negative coefficient for ζ.

Within the framework of the models outlined above, herding behaviour is constant over time in spite of different market phases or business cycles. Since the literature relates herding to investors' sentiment (Shiller, Fisher and Friedman 1984; Lee, Shleifer and Thaler 1991; Devenow and Welch 1996; Hwang and Salmon 2009), which by definition is time-varying, this assumption does not seem reasonable. Furthermore, it is conceivable that, due to the crisis-laden environment prevailing during the last decade, including the tech bubble, 9/11 and the most recent financial crisis, the time series of dispersion, S_t, may not be stationary in a single regime setting, but might be better characterized by a two-state model allowing for different dynamics in tranquil and volatile periods.

To account for time-varying effects, Hwang and Salmon (2004) propose the following state space model, which, while similar in spirit, does not directly make use of the dispersion measure (1). First of all, the model assumes that market betas are changing over time. Inference about herding can then be obtained from the cross-sectional standard deviation of the betas. For instance, a situation where the betas of all stocks in the market are approaching the value 1 implies that this cross-sectional standard deviation gets close to 0. In contrast, when all investors disproportionately strongly differentiate between stocks, such that the betas more strongly diverge from 1 than is implied by the CAPM equilibrium condition, referred to as adverse herding, this would result in a higher standard deviation.

To account for the foregoing considerations, Hwang and Salmon (2004), as a first step, estimate standard ordinary least square (OLS) betas on a monthly basis. In a second step, the cross-sectional standard deviation of these betas is calculated for all periods. The deviation is then modelled within a state space framework where the changes in the dispersion of the betas are governed by a latent herding variable. Assuming an autoregressive [AR](1) process describes its movements, the latter can be extracted by using the Kalman filter.

Although the above approach produces a continuously evolving herding variable, it suffers from several drawbacks. First, the model cannot be estimated from daily or weekly data, but relies on monthly beta estimates. Monthly betas, however, are strongly driven by "noise," for example during periods of substantial financial turmoil, such as in the case of the recent financial crisis. Reducing noise requires expanding the estimation period for the market betas, which in turn, reduces the number of observations for the state space model. Furthermore, if herding dynamics actually take place in the very short run, say on a daily or weekly basis, the model cannot capture the sought after phenomenon. Second, the model is unable to link changes in herding to proxies for investor sentiment or macroeconomic fundamentals. Third, assuming a 0 mean for the latent herding variable, the model, by definition, implies swings between herding and so-called adverse herding. Thus, this measure is unable to describe a market where investors are switching between herding, no herding or adverse herding forms of behaviour. In contrast, the Markov switching version of the herding measure (2) proposed in this paper aims to remedy these problems.

METHODOLOGY

MARKOV SWITCHING HERDING MEASURES

The authors' principal aim is to model time-varying herd behaviour based on daily data and, additionally, to allow variations in herding to be driven by exogenous variables. A straightforward way of introducing time-varying behaviour is to assume that it is subject to regime switches. Hence, equation (2) is modified to allow for switching between two regimes $j \in \{1, 2\}$:

$$S_t = \gamma_j + \delta_j \left| r_{m,t} \right| + \zeta_j r_{m,t}^2 + \epsilon_{j,t}, \tag{3}$$

where $\epsilon_{j,t} \sim N(0, \sigma_j^2)$ and the other variables were previously defined. It is well known that financial time series often display leptokurtosis. Therefore, the model given in equation (3) is re-estimated allowing one or even both regimes to be governed by a fat-tailed distribution. To this end, the t is relied on as well as on the generalized error distribution (GED).[2] We assume the latent state variable to be driven by a first-order Markov process, with transition probabilities, $p_{ij,t} = Pr\,(S_t = j \,|\, S_{t-1} = i)$, $i, j \in \{1, 2\}$, which can either be constant or time-varying. For the sake of inferring the regime the process is in at time t, based on all information available up to the end of the sample period, Γ_T, smoothed probabilities $p_{i,t|\mathrm{T}} = Pr(S_t = i \,|\, \Gamma_T)$ we recalculated as given in Kim (1994).

As stated previously, time-varying transition probabilities can provide insights into the factors driving changes in herding behaviour over time. This means making $p_{11,t}$ and $p_{22,t}$ dependent on a set of exogenous variables $\mathbf{X_{t-1}}$ including a constant.[3] Variables suitable in explaining the switches in investors' herding behaviour include investor sentiment and macroeconomic conditions relying on data available at the daily frequency. Implied volatility, here

2 The GED may provide further insights into the distributional properties of the dispersion of single stock returns since, unlike the t distribution, it also allows for thinner tails than in the case of the normal distribution.

3 These variables are lagged because the transition probabilities governing switches from $t-1$ to t must be determined in $t-1$.

measured using the Chicago Board Options Exchange Market Volatility Index (VIX), is used. Motivated by the branch of literature on sentiment (Jones 2002; Baker and Stein 2004; Baker and Wurgler 2006), the share turnover relative to market capitalization is also used.

Proxies for macroeconomic conditions can be derived from term structure data (Estrella and Hardouvelis 1991; Estrella and Mishkin 1997; Estrella and Mishkin 1998). Litterman and Scheinkman (1988) and Knez, Litterman and Scheinkman (1994) show that the variation in money as well as capital markets can be very well described by models that contain from one to four common factors. Based on zero bond returns, principal components analysis is used to extract common factors. Only those principal components with eigenvalues greater than 1 are included in $\mathbf{X}_{t-1}$. This ensures that each factor has more explanatory power than any return series. If the coefficients are assembled in a vector θ_j, the transition probability associated with state j, $p_{jj,t}$ can be modelled as:

$$p_{jj,t} = \frac{e^{\mathbf{X}'_{t-1}\boldsymbol{\theta}_j}}{1 + e^{\mathbf{X}'_{t-1}\boldsymbol{\theta}_j}}. \tag{4}$$

Turning to the estimation procedures, the models that assume a normal distribution can be estimated using the expectation maximization (EM) algorithm (Dempster, Laird and Rubin 1977). A closed form solution for all parameters was put forward by Hamilton (1990), while the solutions for $\boldsymbol{\theta}_j$, the parameters for (4), are derived in Diebold, Lee and Weinbach (1994). The specifications using t and GED-distributed errors are also estimated using the EM algorithm. Unlike the case of the normal distribution, no analytic solutions for the regression parameters are available. Nevertheless, since the conditions for the closed-form solution for the transition probabilities, $p_{ij,t} = Pr\ (S_t = j\,|\,S_{t-1} = i)$, given in Hamilton (1990) still hold, these can be calculated as a by-product of the smoothed probabilities, $p_{i,t|T}$. Thus, obtaining estimates for the remaining regression and distributional parameters requires a whole numeric optimization in each iteration of the EM algorithm relying on the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm.

In the case of the t distribution, first (3) is estimated, assuming $\epsilon_{j,t}{\sim}t(0, \sigma_j^2, \upsilon_j)$, where υ_j is the (regime-dependent) degrees of freedom parameter governing the kurtosis. In principle, this parameter can take on any value in the region]2, ∞[. Nevertheless, it is well known that the t distribution is empirically indistinguishable from the normal one for degrees of freedom greater than 30 (Hansen 1994; Jondeau and Rockinger 2003). Thus, if for state j, the estimate for υ_j takes on a value above 30, it again fits the model, this time with one regime being governed by a t and the other one by a normal distribution. When applying the GED distribution to the errors, $\epsilon_{j,t}{\sim}GED(0, \sigma_j^2, \kappa_j)$, a one-step estimation procedure can be followed since this distribution reduces to the normal for a tail thickness parameter, κ_j, equal to 1.

To account for autocorrelation, the authors make use of the covariance matrix proposed by Newey and West (1987) where a lag length equal to 8 is set as suggested by the Newey and West (1994) criterion. Since the construction of this error matrix and the selection of the appropriate lag length rests on several assumptions that might be crucial for the results, a robustness check is conducted by performing the analysis based on different numbers of lags. Since the autocorrelations in S_t are in general found to be relatively large (Chang, Cheng and Khorana 2000), all models are re-estimated for 6, 10, 12 and 14 lags.

For some markets, studies report different herding dynamics during falling and rising markets (Chang, Cheng and Khorana 2000; Bohl, Gebka and Goodfellow 2009). In addition, evidence from fund managers' trading reveals differences in their herding behaviour between buying and selling decisions (Keim and Madhavan 1995; Grinblatt, Titman and Wermers 1995). These phenomena are also accounted for by estimating an asymmetric version of the baseline model:

$$\begin{aligned} S_t = {} & \gamma_j + \gamma_j^{asy} * I^{R_{m,t}<0} + \delta_j\,|r_{m,t}| + \delta_j^{asy} * I^{R_{m,t}<0}\,|r_{m,t}| \\ & + \zeta_j r_{m,t}^2 + \zeta_j^{asy} * I^{R_{m,t}<0} r_{m,t}^2 + \epsilon_{j,t}, \end{aligned} \tag{5}$$

where $I^{R_{m,t}<0}$ is a dummy variable that is equal to 1 if the market return is negative and equal to 0 otherwise and $\epsilon_{j,t}{\sim}N\ (0, \sigma_j^2)$.

Finally, the authors want to control for ARCH effects, volatility clustering and skewness, which are often present in financial time series. In order to do so, (3) is estimated in a Markov switching GARCH(1, 1) (MSGARCH[1, 1]) framework, thereby, modelling the GARCH component as proposed by Gray (1996b). The first lag of S_t is included, to take into account autocorrelation since the Newey and West (1987) errors cannot be used for GARCH models. To model skewness, a skewed t distribution, is applied as proposed by Fernandez and Steel (1998). The density function is given as follows:

$$f_t(\epsilon_{j,t}) = \frac{2\beta_j}{1+\beta_j^2}\left(t(0, \beta_j\epsilon_{j,t}, \upsilon_j)I^{\epsilon_{j,t}<0} + t(0, \frac{\epsilon_{j,t}}{\beta_j}, \upsilon_j)(1 - I^{\epsilon_{j,t}<0})\right), \tag{6}$$

where $I^{\epsilon_{j,t}<0}$ is an indicator function that is equal to 1 if $\epsilon_{j,t}$ is negative and equal to 0 otherwise. $\beta_j > 1$ indicates a distribution that is skewed to the right while β_j is smaller than 1 in case of a left skewed density. For $\beta_j = 1$, (6) reduces to a standard t distribution. The MSGARCH(1, 1) model is estimated using numerical optimization according to the BFGS algorithm. As the forward-looking algorithm provided in Gray (1996a) is used to calculate smoothed probabilities, $p_{i,T} = Pr\ (S_t\,|\,\Gamma_T\ )$, this approach can also be considered as a robustness check for Kim's (1994) smoother.[4]

MARKOV SWITCHING ADF TEST

Under rational asset pricing (see equation [2]) S_t should be stationary. To investigate the stationarity properties of a time series, it is common practice to rely on a unit root test such as ADF tests. Typically, these tests ignore possible regime switching effects often present in financial time series. To take these effects into account, Hall and Sola (1994) and Hall, Psadarakis and Sola (1999) propose a Markov switching ADF test. Allowing for deterministic trending and a regime-depending variance, the test equation is given as follows:

$$\Delta S_t = \varphi_j S_{t-1} + \sum_{d=0}^{D} \alpha_{d,j} t^d + \sum_{h=1}^{H} \rho_{d,j} \Delta S_{t-h} + \eta_{j,t}, \quad (7)$$

where $\eta_{j,t} \sim N(0, \pi_j^2)$. $j \in \{1, 2\}$ again denotes the state the process is in at time t, while $D = 0, 1, 2, 3$ indicates the degree of the polynomial defining the deterministic trend.

Obviously, if $D = 0$, (7) this reduces to a Markov switching ADF (MSADF) test with a constant. When $D = 1$, a regime-depending linear trend is added while, in case of $D = 2$, the trend can be changing and for $D = 3$, this trend may have a turning point. H indicates the number of lags included. Due to strong autocorrelations in S_t, the maximal lag length is set at a relatively high value of 25, and then the number of lags is successively reduced until the coefficient of the last lag H is found to be statistically significant at the 10 percent level in at least one state.[5] The MSADF test is estimated using the EM algorithm.

DATA

The analysis covers the entire US stock market for the period 2001–2010. Total returns were obtained for all listed stocks and a capitalization weighted market index from the Center for Research in Security Prices at the University of Chicago. To ensure that the results are not sensitive to the selection of the sample period, the baseline model was also run for the periods 1999–2010 and 2003–2010. The second sample omits the period of the 2001 tech bubble period. The analysis is also carried out based on a sample that is free of cross-listings, listings in foreign currencies, shares from minor exchanges, ETFs and preferred stocks as well as stocks that are not marked as major securities. Data are taken from Thomson Reuters Datastream. The extent to which the results for these data differ relative to the more comprehensive sample may be informative about the contribution of classical blue chips to herding compared with more opaque, illiquid and smaller stocks. The principal components of the term structure are extracted using the Datastream Zero Curve with maturities of 0, 3, 6 and 9 months as well as 1–10, 12, 15, 20, 25 and 30 years. Aggregated trading volume and market capitalization for the United States-Datastream Market are employed, and the VIX is also obtained from Thomson Reuters Datastream.

EMPIRICAL RESULTS

First, the stationarity properties of the time series of the cross-sectional absolute deviations given in (1) are considered. To this end, the ADF and the MSADF tests described above are applied to the series of dispersion, S_t. The Dickey-Fuller test statistics are given in Table 1.

When the standard (single regime) ADF test is considered, a unit root can only be rejected by the version of the test that does not account for deterministic trending. By contrast, the two-state MSADF test rejects the null in both states and all specifications for the deterministic trend.[6] These findings corroborate the use of a time-varying herding measure, since the assumption of constant herding is not only economically unreasonable but in the present context also ignores structural shifts in the time series dynamics of S_t such as when markets move from a low- to a high-volatility state.

Table 1: Dickey-Fuller Test Statistics

	Single State	2 States
$S_t = 1$		
$D = 0$	-2.990**	-10.145***
$D = 1$	-3.051	-15.116***
$D = 2$	-3.083	-18.047***
$D = 3$	-3.790	-17.751***
$S_t = 2$		
$D = 0$		-3.559***
$D = 1$		-3.851**
$D = 2$		-3.988**
$D = 3$		-4.330**

Notes: Single State refers to a standard ADF test where 2 States stands for the two regimes version of the test outlined in the section on Markov switching herding measures. The test statistic provided is the pseudo t-statistic.***, ** and * denote statistical significance at the one percent, five percent and 10 percent level, respectively. Significance is based on asymptotic critical values obtained by Monte Carlo simulation.

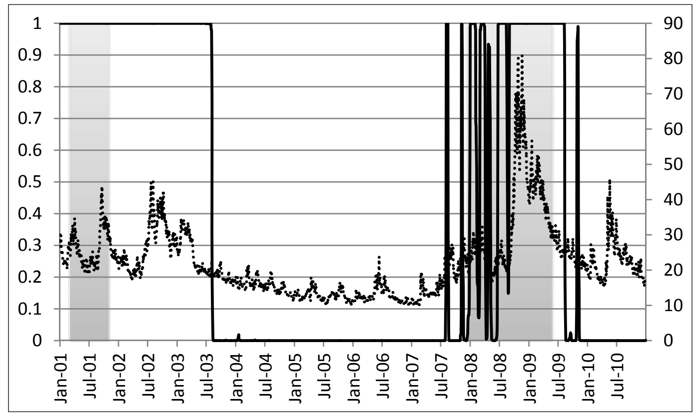
4 To control for potential overparameterization, a simple MSGARCH(1, 1) is also estimated with normally distributed errors and without lagged dependent variables.

5 As a robustness check, the procedure is also performed for a maximal lag length of 15.

6 A maximal number of lags, H, equal to 25 are used, but these results also hold for $H = 15$.

Turning to the baseline model, equation (3) with normal errors, the smoothed probabilities, $p_{i,t|T}$, which are plotted in Figure 1 (left-hand side scale), reveal two clearly distinct herding states. The smoothed probabilities are plotted against the VIX (right-hand side scale). It is immediately clear that the high volatility state typically coincides with deteriorating investors' sentiment, that is, a relatively high implied volatility. The high-volatility regime can be related to periods of large market movements and is characterized by a herding parameter, $\hat{\zeta}_1$, that is significantly positive, indicating adverse herding. Unlike the case of herding, this indicates that investors differentiate more strongly between particular stocks than implied by rational asset pricing behavior. By contrast, the second regime seems to prevail during more tranquil times. Here, $\hat{\zeta}_2$ is found to be positive, but statistically insignificant, which is in line with CAPM-type models. Parameter estimates are reported in Table 2.

Figure 1: Smoothed Probabilities and Implied Volatility



Notes: VIX (dotted line) and smoothed probabilities calculated as proposed by Kim (1994). The smoothed probabilities are plotted on the left-hand side axis while the right-hand side displays the VIX. The shaded areas represent NBER recession dates.

Table 2: Estimation Results for Four Herding Models

	OLS		Markov_norm		Markov_t_norm		Markov_GED	
	Coeff.	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
$S_t = 1$								
$\hat{\gamma}_1$	0.017***	(0.000)	0.025***	(0.000)	0.024***	(0.000)	0.023***	(0.000)
$\hat{\delta}_1$	0.549***	(0.043)	0.356***	(0.042)	0.375***	(0.015)	0.378***	(0.014)
$\hat{\zeta}_1$	0.622	(0.746)	1.676**	(0.735)	1.494***	(0.205)	1.510***	(0.197)
$\hat{\sigma}_1^2$	4.064 10^{-5}		3.536 10^{-5}		3.548 10^{-5}***	(0.000)	3.347 10^{-5}***	(0.000)
$\hat{\upsilon}_1/\hat{\kappa}_1$					4.750***	(0.972)	1.615***	(0.107)
$\hat{p}_{11}$			0.991		0.991		0.991	
$S_t = 2$								
$\hat{\gamma}_2$			0.015***	(0.000)	0.015***	(0.000)	0.015***	(0.000)
$\hat{\delta}_2$			0.253***	(0.021)	0.253***	(0.012)	0.247***	(0.014)
$\hat{\zeta}_2$			0.873	(0.769)	0.987**	(0.440)	1.051**	(0.453)
$\hat{\sigma}_2^2$			4.042 10^{-6}		3.884 10^{-6}	(0.038)	3.869 10^{-6}	(0.000)
$\hat{\upsilon}_2/\hat{\kappa}_2$							0.842***	(0.090)
$\hat{p}_{22}$			0.995		0.994		0.993	

Notes: Autocorrelation and heteroskedasticity consistent standard errors as proposed by Newey and West (1987) are provided in brackets. OLS refers to the basic ordinary least squares estimates while Markov norm, Markov t norm and Markov GED stand for the Markov switching models with normal, t-/normal and generalized error distribution, respectively. ***, **, and * denote statistical significance at the one percent, five percent and 10 percent level, respectively.

The high-volatility state initially prevails from the beginning of our sample in 2001, that is the bursting of the tech bubble, the time around 9/11 as well as the start of wars in Afghanistan and Iraq. Shortly thereafter, in mid-August 2003, a switch into the calmer regime takes place. This switch coincides with a strong US economy. The second regime then ends in mid-2007 when, around August 6, a switch into the high volatility state takes place, a couple of days before central banks around the world started to intervene in order to stabilize the money market at the onset of the financial crisis. Subsequently, the process switches several times between both regimes, consistent with uncertainty about the existence of a grave crisis prevailing among market participants during this period. Again, we also see this reflected in the behaviour of the VIX. On September 2, 2008, a switch into the high-volatility state is indicated, a couple of days before Lehman Brothers released news about severe losses for the first time. In mid-August 2009, the process then moves back into the calmer regime and remains there until the end of the sample at the end of 2010.[7]

Applying the procedures described in the section "Markov Switching Herding Measures" to allow for fat-tailed distributions produces virtually unchanged inferences about regimes, the smoothed probabilities and very similar parameter estimates compared to the assumption of normality. The only substantial difference found is that $\hat{\zeta}_j$ is significantly different from zero in both states. Thus, adverse herding is significantly stronger during volatile periods, but remains significant in more tranquil market phases. The estimates for the model allowing for both t and normally distributed regimes indicate that, during the high volatility state, the errors follow a t distribution while they are well characterized by a normal distribution during calm periods.[8] Taken together, these findings highlight that in the first state the dispersion of returns around the market and, thus, investor sentiment, is not only relatively volatile but also subject to large shocks.

The results for the asymmetric specification given in equation (5) suggest that herding in US stocks does not differ as much between market upturns and downswings since the t values for $\hat{\zeta}_j^{asy}$ are far from being statistically significant. This is shown in Table 3. By contrast, the use of the MSGARCH model is corroborated by the data since strong volatility clustering and ARCH effects are found. In addition, the values of $\hat{\upsilon}_j$ and $\hat{\beta}_j$ are found to be significantly different from the values implied by a normal distribution. The smoothed probabilities for the MSGARCH(1, 1) specification with skewed t distribution, given in Figure 2, are even more clear-cut than those for the above models with constant variances. Again, we find adverse herding to be much stronger when the high volatility state prevails.[9]

This paper now turns to the approach with time-varying transition probabilities, $p_{jj,t}$, which are made conditional on the VIX, the relative turnover and the principal components of the yield curve. The latter is extracted from the sample of US zero rates. In what follows, only the first two components are of interest for the model since they are associated with eigenvalues greater than zero. Further interpretations, of course, depend on the loadings of these components.[10] They were found to be perfectly in line with the patterns known in the literature as shift and twist (Litterman and Scheinkman 1988; Knez, Litterman and Scheinkman 1994). This means that the first component has very evenly distributed loadings and stands for a shift in the overall interest rate level. By contrast, the second one is characterized by loadings, which monotonically decrease with a change in the slope of the term structure, in particular a rise in short-term interest rates, which is not accompanied by a proportional rise in long-term rates or vice versa. So, starting from a normal yield curve, a rise in this factor comes along with a flattening of the term structure.

7 Robustness checks using the sample periods 1999–2010 and 2003–2010 broadly confirm the findings. The 12-year period actually reveals that already in 1999 and 2000, the process is in the high volatility state. This supports the interpretation of the first regime as being closely related to periods of strong market movements rather than only strong downward movements or crises periods. Moreover, the results using different lag lengths in calculating the Newey and West (1987) covariance matrix broadly confirm the results.

8 The use of the GED reveals that the calm period regime displays tails being even thinner than those of a normal distribution. Filtered and smoothed probabilities for the non-normal models are available upon request.

9 The smoothed probabilities for the MSGARCH(1, 1) with normal errors closely resemble those for the homoskedastic models and are available upon request, as are the parameter estimates for both MSGARCH models and the asymmetric specification. The results for the sample that is adjusted for minor stocks, ETFs, etc. are similar in spirit. The main difference is that the coefficients ζ_j are larger in absolute values. This suggests that adverse herding is stronger in the stocks of large and transparent firms.

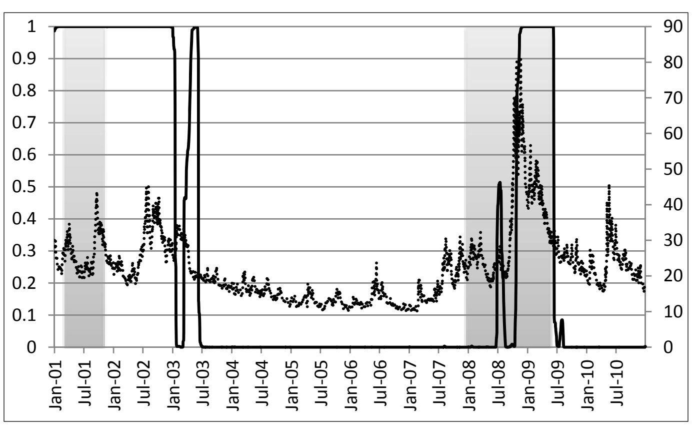
10 The components are linear combinations of the underlying zero bond rates and the respective parameters are referred to as loadings. There are always as many components as there are different zero rates.

Table 3: Estimation Results for the Asymmetric Herding Model

	Markov_norm_asy	
	Coeff.	Std. Error
$S_t = 1$		
$\hat{\gamma}_1$	0.024***	(0.001)
$\hat{\gamma}_1^{asy}$	$8.643\ 10^{-4}$	$(5.953\ 10^{-4})$
$\hat{\delta}_1$	0.454***	(0.056)
$\hat{\delta}_1^{asy}$	-0.176***	(0.060)
$\hat{\zeta}_1$	1.248	(0.918)
$\hat{\zeta}_1^{asy}$	0.553	(0.798)
$\hat{\sigma}_1^2$	$3.411\ 10^{-5}$	
$\hat{p}_{11}$	0.991	
$S_t = 2$		
$\hat{\gamma}_2$	0.015***	$(1.626\ 10^{-4})$
$\hat{\gamma}_2^{asy}$	$3.523\ 10^{-4}$**	$(1.750\ 10^{-4})$
$\hat{\delta}_2$	0.275***	(0.023)
$\hat{\delta}_2^{asy}$	-0.057*	(0.034)
$\hat{\zeta}_2$	1.316*	(0.772)
$\hat{\zeta}_2^{asy}$	-0.308	(1.175)
$\hat{\sigma}_2^2$	$3.991\ 10^{-6}$	
$\hat{p}_{22}$	0.995	

Notes: Autocorrelation and heteroskedasticity consistent standard errors as proposed by Newey and West (1987) are provided in brackets. Markov_t_norm_asy refers to the Markov switching models with normally distributed errors given in equation (5). ***, **, and * denote statistical significance at the one percent, five percent and 10 percent level, respectively.

Figure 2: Smoothed Probabilities for the Model MSGARCH(1, 1) with Skewed *t* Distribution and Implied Volatility



Notes: VIX (dotted line) and smoothed probabilities calculated as proposed by Gray (1996a). The smoothed probabilities are plotted on the left-hand side axis while the right-hand side displays the VIX. The shaded areas represent NBER recession dates.

Table 4: Parameters of the Time-varying Transition Probabilities

	$S_t = 1$	$S_t = 2$
Constant	-0.003	10.414
*PC*1	-1.651	-0.384
*PC*2	-2.603	0.361
VIX	0.225	-0.179
TURN	-124.680	-176.966

Notes: PC1 and PC2 refer to the first and second principle component of the yield curve while VIX and TURN stand for the Chicago Board Options Exchange Market Volatility Index and the relative volume measure defined by turnover in US$ divided by market capitalization times 1000.

This paper now turns to the approach with time-varying transition probabilities, $p_{jj,t}$, which are made conditional on the VIX, the relative turnover and the principal components of the yield curve. The latter is extracted from the sample of US zero rates. In what follows, only the first two components are of interest for the model since they are associated with eigenvalues greater than zero. Further interpretations, of course, depend on the loadings of these components.[11] They were found to be perfectly in line with the patterns known in the literature as shift and twist (Litterman and Scheinkman 1988; Knez, Litterman and Scheinkman 1994). This means that the first component has very evenly distributed loadings and stands for a shift in the overall interest rate level. By contrast, the second one is characterized by loadings, which monotonically decrease with a change in the slope of the term structure, in particular, a rise in short-term interest rates, which is not accompanied by a proportional rise in long-term rates or vice versa. So, starting from a normal yield curve, a rise in this factor comes along with a flattening of the term structure.

Using the principal components and the other two covariates for (4), the logit specification for $p_{jj,t}$, the estimates for the parameters in (3) and the variances are found to be very close to those for the model with constant probabilities and a normal distribution. For this reason, Table 4 only reports $\hat{\boldsymbol{\theta}}_j$, the parameters estimates for (4), the specification governing the transition probabilities.[12] Those parameters estimates, which differ with respect to the signs between the states, are of particular interest since a change in a given exogenous variable always increases the probability for one regime while decreasing the one for the other regime, irrespective of the level of the covariates (see specification [4]). Put differently, high values of such a variable could be linked to one state while

11 The components are linear combinations of the underlying zero bond rates and the respective parameters are referred to as loadings. There are always as many components as there are different zero rates.

12 It must be borne in mind that there are no standard errors for the parameters of the transition probabilities within the EM framework.

below-average values would always be consistent with the other regime, independent of the behaviour of other exogenous variables. While the parameters for the first principal component representing the level as well as the turnover measure have a negative sign for both states, this is not the case for the second component and the VIX. The interpretation of the latter is straightforward, namely that state 1 is associated with a positive coefficient. Hence, an increase in the implied volatility makes it more likely to switch into or remain in regime 1 while the reverse holds for regime 2.

More interestingly, the coefficient for the second principal component, which stands for a flattening of the term structure, is negative for the first state and positive for the second one. At first glance, this is counterintuitive since a flat (or even inverse) term structure is, in general, associated with a contracting economy. This should presage a switch into the high volatility. However, when the model is re-estimated employing two quarter lagged principal components, the sign turns negative for both states and, in particular, more negative for the second, the tranquil state.

CONCLUSIONS

This paper models the time-varying herd behaviour reflected in movements in stock market returns. The authors argue that extant empirical treatments of herding behaviour suffer from several drawbacks. Models that assume constant herding dynamics are economically implausible since the literature links herding to investor sentiment, which by definition, is time varying. Unit root tests corroborate this view since one is only able to reject the unit root null unambiguously when the process is allowed to switch between two distinct regimes. Moreover, existing models of time-varying herding require data at monthly or lower sampling frequencies and, thus, cannot be used to generate evidence about investors' short-term behaviour.

The procedure proposed by Christie and Huang (1995) and Chang, Cheng and Khorana (2000) is relied on to examine investors' herd behaviour. However, their approach is adapted by fitting a Markov switching model to allow for different dynamics between high and low volatility regimes. In addition, the time-varying transition probabilities proposed by Diebold, Lee and Weinbach (1994) are used to reveal factors explaining changes in herd behaviour over time, driven by proxies for macroeconomic conditions and investor sentiment.

The authors' models are estimated for US stock market data, thereby controlling for non-normalities, autocorrelation and GARCH effects. The findings suggest that during times of high volatility in the market, investors discriminate more strongly between single stocks than during tranquil times and more strongly than implied by rational asset pricing models.

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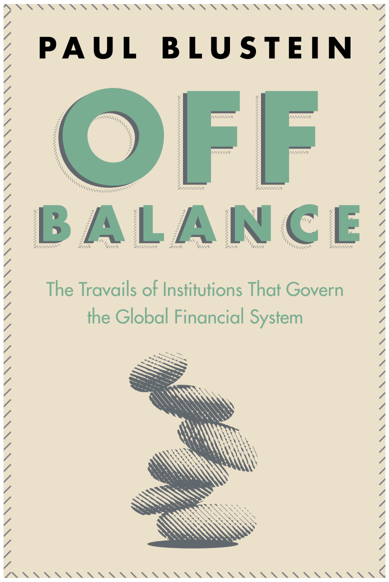

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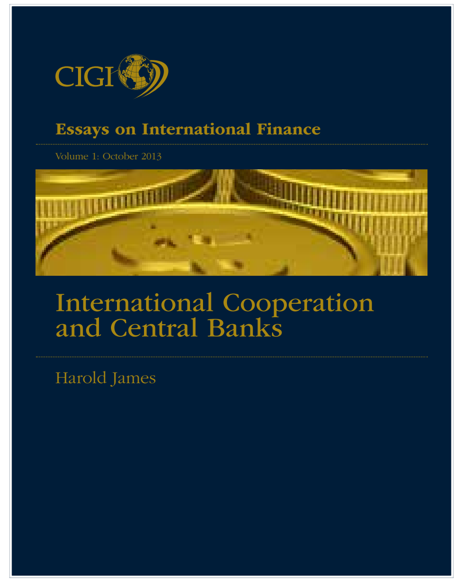

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Short-selling Bans and Institutional Investors' Herding Behaviour: Evidence from the Global Financial Crisis

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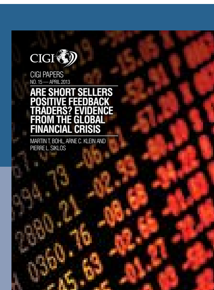
Martin T. Bohl, Arne C. Klein and Pierre L. Siklos

During the recent global financial crisis, regulatory authorities in a number of countries imposed short-sale constraints aimed at preventing excessive stock market declines. This paper focusses, in particular, on short-sale constraints' effect on institutional investors' trading behaviour and the possibility of generating herding behaviour. The authors conclude that the empirical evidence shows that short-selling restrictions exhibit either no influence on herding formation or induce adverse herding.

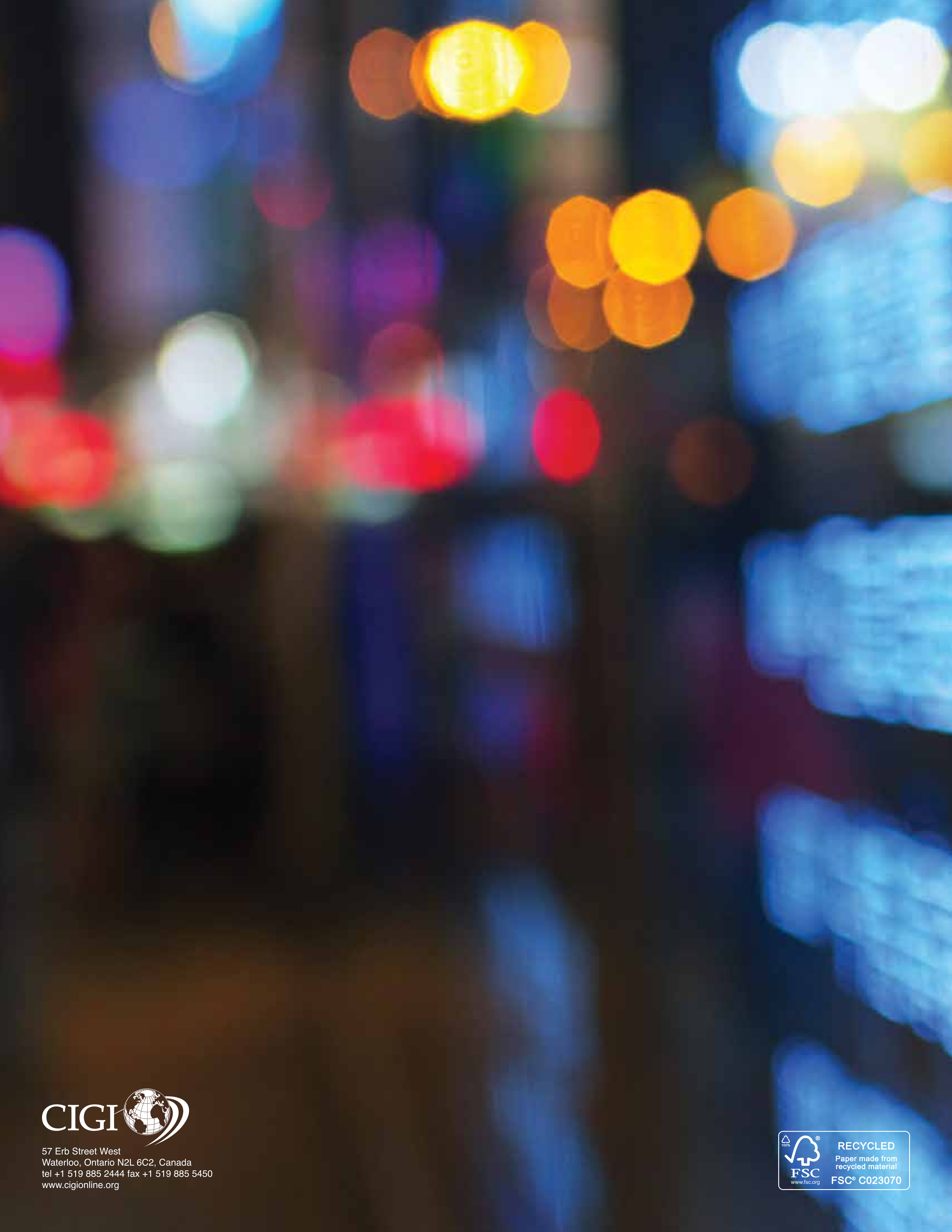


Are Short Sellers Positive Feedback Traders? Evidence from the Global Financial Crisis

CIGI Paper No. 15

Martin T. Bohl, Arne C. Klein and Pierre L. Siklos

This paper examines bans on selected financial stocks in six countries during the 2008-2009 global financial crisis. These provided a setting to analyze the impact of short-sale restrictions on feedback trading. The findings suggest that, in the majority of markets examined, restrictions of this kind amplify positive feedback trading during periods of high volatility and, hence, contribute to stock market downturns. On balance, therefore, short-selling bans do not contribute to enhancing financial stability.



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