Herding Dynamics in Exchange Groups: Evidence from Euronext

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Abstract

This study investigates in the context of the Euronext, whether joining an exchange group affects herding in the group's member-markets and if this effect persists when accounting for various domestic and international market states, the dynamics of the group's member-markets and the outbreak of financial crises. We find that herding is significant post-merger in all four constituent equity markets (Belgium, France, the Netherlands and Portugal) of the Euronext, with herding in Portugal being significant (yet less strong) pre-merger as well. These results are robust when controlling for various domestic and international market states, as well as the dynamics of the group's markets. The period following the outbreak of the euro-zone sovereign debt crisis produces significant herding in Belgium, the Netherlands and Portugal, with this herding being motivated by the dynamics of the group's two largest markets (France and the Netherlands).

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1. Introduction

In the last decade, financial integration has prompted considerable cross-border co-operation among stock exchanges worldwide. Perhaps the most visible form of such co-operation is the forging of regional and global exchange groups, whereby the member-markets of any group share a common institutional framework in their regulatory design and a uniform trading protocol based on a single trading platform. Although this development has given rise to new trading dynamics by facilitating cross-market trading within each group (investors from any member-market can trade more easily in the group's other member-markets), the implications of this on investors' behaviour have been largely overlooked. In this study we primarily focus on the behavioural pattern of herding which has often been documented in investors' trades globally and has been found to impact on securities' returns[1]. An interesting issue arising in this context is whether membership in an exchange group produces an effect over investors' herding in the group's member-markets. A second issue is whether this effect persists when controlling for various domestic and international market conditions for each member-exchange, given the extant evidence in the literature suggest the sensitivity of herding to different domestic/international market states (Chang et al., 2000; Holmes et al., 2013; Gavriilidis et al., 2013). A third issue arising is whether our results are robust when controlled for the effect of the dynamics of the rest of the group's markets over each member-market's herding, in view of research suggesting that herding in a market can be affected by other markets' dynamics (Chiang and Zheng, 2010; Balcilar et al., 2013). Finally the fourth issue we examine is whether herding is significant following the outbreak of the recent sovereign debt crisis in the euro-zone, more so in view of research (Choe et al., 1999; Hwang and Salmon, 2004) denoting the role of crises as turning points in herding internationally. It is these four research questions this paper is addressing.

From a theoretical perspective, herding refers to individuals choosing to mimic the behaviour of others following observation of each other's actions and actions-payoffs (Hirshleifer and Teoh, 2003). Depending on the motives underlying imitation, herding can be classified into *intentional* and

[1] See the excellent survey study by Hirshleifer and Teoh (2003).

unintentional/spurious (Holmes et al., 2013; Gavriilidis et al., 2013). Intentional herding is reflected in correlated actions motivated through the anticipation of (mainly information- or career-related) payoffs in settings characterized by actual or perceived asymmetry. If an investor considers himself to be informationally disadvantaged relative to other investors due to the bad quality of his information or his inadequate information-processing skills, he has every reason to try to narrow the informational gap by copying the actions of those he considers better informed (Devenow and Welch, 1996). In the extreme, if the tendency to follow others instead of focusing on their own private signals becomes widespread among investors, this will give rise to cascades (Banerjee, 1992; Bikhchandani et al., 1992), leading the public pool of information to grow poorer. Career reasons can also motivate herding intent, something particularly relevant to finance professionals, such as fund managers. With fund managers' performance in the finance sector being assessed relative to their peers' (or the industry-average), bad-quality managers are tempted to mimic the trades of good-quality ones to improve their image and protect their career prospects (Scharfstein and Stein, 1990). Correlated actions can also emanate from commonalities in the background and trading conduct of market participants, thus leading to *unintentional* herding. Finance professionals, for example, can herd due to relative homogeneity (De Bondt and Teh, 1997) in their background (in terms of their education, the information they receive and its processing; Wermers, 1999) and the regulatory framework they are subject to (Voronkova and Bohl, 2005). Characteristic trading[2] also increases the correlation of investors' trades, thus generating a false impression of them imitating each other without imitation actually being present (their common strategy inevitably leads them to trade similar stocks).

From an empirical perspective, the presence of market herding has been tested internationally in both developed and emerging stock exchanges and for periods of various characteristics with overall evidence being mixed[3]. Christie and Huang (1995) report the absence of herding in the US during periods of extreme market returns, both at the aggregate market level and for different sectors. Chang

[2] Characteristic trading refers to strategies (e.g. momentum, value, etc., also known as "*styles*") basing stock-selection on particular characteristics (e.g. past performance, size, etc.) and is frequently employed by funds (Sias, 2004).

[3] Studies using transaction data also find mixed evidence on herding. Early studies (Lakonishok et al., 1992; Grinblatt et al., 1995; Wermers, 1999) found limited evidence of herding among US funds while subsequent studies reported significant institutional herding in the US at the aggregate (Sias, 2004) and sector (Choi and Sias, 2009) levels. Significant herding has been detected among institutional investors in Germany (Kremer and Nautz, 2013), Portugal (Holmes et al., 2013) and Spain (Gavriilidis et al., 2013), yet not to that extent in Poland (Goodfellow et al., 2009) and the UK (Wylie, 2005).

et al. (2000) find significant herding only for the emerging markets of their sample after controlling for market movement, size effects, daily price limits and market liberalization, while Hwang and Salmon (2004) report significant herding for the US and South Korean markets irrespective of market conditions and fundamental indicators. Caparelli et al. (2004) document mixed evidence for herding in the Italian market, while Gleason et al. (2004) document no evidence of intraday herding among US exchange-traded funds. Demirer and Kutan (2006) find no evidence of herding in the Shanghai and Shenzhen stock markets both at the aggregate market and the sector levels after controlling for extreme market returns, the Asian financial crisis and several regulatory changes; conversely, Tan et al. (2008) and Chiang et al. (2010) document the presence of significant herding for both A- and B-shares in Chinese markets[4]. Regarding the euro-zone's south European markets (Greece, Italy, Portugal, and Spain), Economou et al. (2011) find evidence of significant herding within and across all of them after controlling for periods of positive/negative market performance, high/low volatility/trading volume and the global financial crisis. Using an international sample of eighteen markets, Chiang and Zheng (2010) document strong evidence of herding in most of their sample markets (with the exception of Latin America and the US); their results suggest that herding is strong primarily during up-markets in Asian countries and that investors herd significantly towards the US market, aside from their domestic markets. Blasco et al. (2012) find that intraday herding rises with volatility in the Spanish market, while, Gebka and Wohar (2013) find limited evidence of herding at the aggregate market and sector levels across thirty-two markets.

Despite the above wealth of research on herding, very little attention has been devoted to its presence in the context of exchange groups, which are products of the global financial integration process underway during the past two decades. The liberalization of international portfolio flows and the proliferation of cross-listings in the 1990s changed the landscape for stock exchanges, which thereafter started vying internationally for more listings and higher volumes of trade in order to ensure their liquidity and profitability. To enable themselves to compete under these conditions, several exchanges

[4] Tan et al. (2008) find that B-shares' investors herd significantly during up/down market days, high/low volume days and high volatility days; A-shares' herding is found to be significant during up/down market days, high volume days and high volatility days. Chiang et al. (2010) report widespread herding among A-shares during up/down markets, with less herding being reported for B-shares.

opted for more flexible governance structures – demutualization (Aggarwal and Dahiya, 2006)[5]. The profit-seeking incentives of demutualized exchanges prompted them to commit more resources to advanced technologies and financial innovation in order to handle the increasing volumes of trade and attract more cross-listings (Nielsson, 2009). With the costs of these investments rising, many markets entered cross-border alliances with other exchanges in the pursuit of synergies (Hasan and Schmiedel, 2004), thus gradually giving rise to regional and global exchange groups[6] characterized by uniform regulatory frameworks and trading systems.

We now turn to discuss the possible effects of a market's merger into an exchange group over that market's herding; the salient point here is whether the merger leads herding-related factors to grow more (in which case, the incentive to herd should increase) or less (in which case, herding would be expected to decrease) important. Exchange groups operate common trading platforms whose technological sophistication enhances transparency, promotes ease of trading across the group's member markets (Andrikopoulos et al., 2014), leads to reduced transaction costs (Pagano and Padilla, 2005) and can allow for higher volumes/frequencies of trading (Hagströmer and Nordén, 2013), thus leading to higher liquidity (Nielsson, 2009). These features are notably appealing, in particular, to foreign institutional investors[7] and if a market's merger into a group with such highly sophisticated structures leads to a rise in the participation of this investor-type in its trading activity[8], this will, in turn, increase its investors-heterogeneity, and improve the quality of its public information-pool[9]. Under these conditions, it is reasonable to expect that the significance of herding will decline, as investors will be able to rely more on publicly available information (thus feeling less informationally disadvantaged) and any herding tendencies can quickly be arbitraged away by informed investors.

[5] Namely the transformation of exchanges from mutual ownership structures to for-profit corporations. Under mutual ownership structures, trading and ownership are inseparable i.e. brokers command shares of the exchange and voting rights. Demutualized exchanges are limited liability companies, whose owners are not necessarily involved in their trading process.
[6] Examples of regional exchange groups include the Euronext and OMX in Europe and the BRVM in Western Africa; NYSE-Euronext and NASDAQ-OMX are examples of global exchange groups.
[7] Institutional investors internationally are increasingly relying on automated trading systems ("algorithms"; see Hasbrouck and Saar, 2013), which can allow them substantial trading firepower in settings characterized by advanced financial technology (like those of an exchange group).
[8] Foreign investors have been found (Gelos and Wei, 2005) to be attracted to markets typified by greater transparency. Transparency aside, diversification is another factor that can encourage foreign funds to enter a market that has just merged into an exchange group (this is the case, for example, of those funds whose investment scope targets the specific group).
[9] This is because foreign institutional investors are normally regarded as informed, sophisticated traders (Grinblatt and Keloharju, 2000; Froot and Ramadorai, 2008).

However, it is possible that the merger of a market into a group may actually amplify herding tendencies. A possibility here is that a group's greater transparency can facilitate observation among investors, leading the uninformed to track the trades of the informed ones (Holmes et al., 2013); less skilled or less experienced local fund managers in that market, for example, may begin tracking the trades of newly attracted overseas funds in an effort to improve their professional prospects[10]. The feasibility of herding in this case would be further boosted in view of the anticipated lower transaction costs in a group's context. Moreover, contingent upon the incentives driving their decision-making, institutional investors can also lead herding in a market to be affected by the dynamics of the group's other markets. If managers, for example, are risk-averse and at the same time treat the group as a single market in their portfolio, then a negative announcement regarding one of the group's markets can lead them to reduce their exposure to the group as a whole since they might anticipate the announcement to cast a negative effect over other member-markets of the group.[11] Similarly, if managers invest in only one of the group's markets (market A) and their information about that market is imperfect, then a negative announcement regarding another member-market of that group (market B) can prompt them to reduce their exposure to market A, if they consider signals from the group's other member-markets to be informative for their decisions regarding market A.[12]

The above discussion denotes that the effect of exchange group membership over a market's herding constitutes a controversial issue and our paper aims at investigating it in the context of the Euronext, one of the first-ever cross-border exchange-groups established, which is comprised of the equity markets of Belgium, France, the Netherlands and Portugal. Given the mixed evidence in the literature on the effect of different market states on herding, we also examine how herding varies in each Euronext-market pre- versus post-merger with various domestic and international market conditions; the latter include (as we shall discuss in more detail in section 3) the daily (up and down) movement of each market's average return and trading volume, the return of the CAC40 (the blue chip index of

[10] According to Menkhoff et al. (2006) less experienced fund managers are more likely to herd. Moreover, even though, local fund managers are expected to have more correlated investment behavior (e.g. due to shared local information and informal communication, social interaction, performance-based appraisal with their domestic peers etc.), local fund managers can also be tempted to observe and imitate their cross-border peers (Parwada and Yang, 2009).

[11] A manager whose investments cover a whole group may behave like this due to information costs – the larger the number of markets in a group, the higher the cost of obtaining information for each.

[12] Such behaviour may be rational if acquiring information regarding market A comes at a high cost.

France, Euronext's lead market), the return of the S&P500 and the US VIX values. In view of our discussion in the previous paragraph, we also explore whether controlling for the dynamics of the rest of Euronext's markets confers an effect over each member-market's herding before and after its merger in the group. Finally, we also analyse whether herding is significant following the outbreak of the European sovereign debt crisis, in view of research (Choe et al., 1999; Hwang and Salmon, 2004) suggesting that financial crises constitute turning points in herding.

Our results show that Belgium, France and the Netherlands are characterized by significant herding only in the aftermath of their merger into the Euronext, with herding in Portugal appearing significant both pre- and post-merger. These results are relatively robust when controlled for the effect of various domestic and international market states as well as for the dynamics of the group's other member-markets. A very interesting observation is that these dynamics give rise themselves to significant herding in all four markets post-merger, thus leading each market to present itself with evidence of herding motivated by both its domestic and the group's dynamics following its merger in the group. The outbreak of the European sovereign debt crisis brings about significant herding in three of the group's markets (with the exception of France); however, in this case, any evidence of herding is exclusively motivated by the dynamics of the group's two largest markets (France; Netherlands).

Our study contributes to the herding literature[13] by providing novel insights into the effect of exchange group membership over herding dynamics. The results reported here are of interest to regulators and policymakers alike, given the ongoing consolidating activity among stock markets internationally and

[13] Andrikopoulos et al. (2014) tested whether herding grows more or less significant for the same four markets following their merger into the Euronext and whether controlling for various domestic conditions conferred an effect over their results. Our study differs from theirs in several ways:
a) their study tested for herding using the model of Hwang and Salmon (2004) which extracts herding from the cross-sectional dispersion of monthly equity betas; in other words, herding is estimated in this framework at the monthly frequency. Conversely, we test for herding using the Chang et al. (2000) approach which entails two distinct advantages compared to Hwang and Salmon (2004). On the one hand, it allows us to examine herding at the daily frequency (as opposed to the monthly one of Hwang and Salmon, 2004), thus allowing us to capture short-term herding dynamics, something particularly important, given that herding normally occurs at short horizons (Froot et al., 1992). On the other hand, by employing returns and their dispersions, it bypasses the issue of potential biases in herding estimations in the Hwang and Salmon (2004) framework due to beta-estimation biases which have been extensively documented in the literature (see e.g. Brooks et al., 2005).
b) we test for the effect of international, as well as domestic, market conditions over herding pre- versus post-merger, whereas their work focuses exclusively on the effect of domestic variables.
c) our study tests for the impact of the dynamics of the group's markets over each member-market's herding, which their paper does not.

the relation of herding to systemic risk within, and contagion across, capital markets (Dornbusch et al., 2000). The evidence presented is also of interest to investors with a global investment outlook in view of the negative impact of herding over diversification (Chang et al., 2000). The next section presents an overview of the Euronext; section 3 presents the data and methodology employed alongside some descriptive statistics. Section 4 presents and discusses the results and section 5 concludes.

2. The Euronext

The birth of the Euronext can be traced back to March 2000, when the merger of the Amsterdam, Brussels and Paris stock exchanges was announced with the merger of their equity, derivatives and clearing segments coming into effect from September 22nd of that year. The group expanded shortly thereafter when the LIFFE (London International Financial Futures and Options Exchange) and the Lisbon exchange joined it in 2002,[14] while 2007 saw it merging with the New York Stock Exchange to create the first intercontinental exchange in history. With its share in Euronext's total equity turnover and capitalization hovering around 65 percent, France clearly emerges as the group's dominant market, followed by the Netherlands, Belgium and Portugal[15].

Trading in the Euronext is based on a common platform modelled after the French Nouvelle Système de Cotation (NSC) – a hybrid system with a limit-order book emphasis. The harmonization of the four constituent equity markets (Amsterdam, Brussels, Lisbon and Paris) with that system came about rather easily, since all four of them shared rather similar trading systems (order-driven, electronic system for continuous trading with market-makers assigned to illiquid stocks) prior to their merger into the group (Nielsson, 2009). Stock trading on Euronext is continuous with a double-auction in place and lasts from 09:00 to 17:25 Central European Time. The first auction (*"start-of-day"*) takes place before continuous trading commences and leads to opening prices being set while the second auction (*"end-of-day"*) takes place at day-close between 17:25 and 17:30 followed by a 10-minute window of trading to allow traders to transact at the *"end-of-day"* auction's prices (Beltran et al., 2004). The system allows the placement

[14] Portuguese stocks were first included in Euronext indices in April 2002.
[15] The figures reported in Andrikopoulos et al. (2014) indicate the following average percentage shares in the Euronext's total equity turnover (capitalization) for the 2003-2008 window: Belgium 4% (10%); France 64% (66%); the Netherlands 30% (22%) and Portugal 2% (3%).

of traditional *(limit/market)* and more sophisticated *(fill-or-kill*[16]*; must-be-filled*[17]*; iceberg*[18]*)* orders. Block trading is allowed for large-volume orders within price-limits set by the market (Beltran et al., 2004). Details on all orders/trades are available to traders pre- and post-trade, with trader-anonymity being ensured (Andrikopoulos et al., 2014).

3. Methodology and Data

From a methodological perspective, the first attempt at estimating herding at the market level was that by Christie and Huang (1995) who used to that end the cross-sectional standard deviation of returns, formally calculated as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{n}(r_{i,t} - r_{m,t})^2}{n-1}} \quad (1)$$

Here $r_{i,t}$ is security *i's* return on day *t*, $r_{m,t}$ is the market's average return on day *t* (calculated by averaging the returns of all securities for day *t*) and *n* is the total number of listed stocks on day *t*. Next, herding is estimated using the following linear regression model:

$$CSSD_t = \alpha_0 + \alpha_1 D_t^U + \alpha_2 D_t^L + \varepsilon_t \quad (2)$$

D_t^U (D_t^L) equals one if the market return lies in the extreme upper (lower) tail of the market return distribution, otherwise it is zero. Rational asset pricing models (Black, 1972) predict that the dispersion of returns is an increasing function of the market's absolute return, given each stock's different sensitivity to market movements. This would suggest that extreme periods, which accommodate returns of high absolute value, should witness an increase in the values of CSSD; if, however, extreme periods are characterized by herding, securities' returns would be expected to cluster tightly around the market-average (a proxy for the market's consensus), thus leading to a reduction in the values of CSSD. As a result, herding would be reflected in equation (2) through significantly negative values of α_1 and/or α_2, as this would denote that CSSD decreases during extreme market periods.

[16] These are limit orders that are either to be fully executed or cancelled.
[17] These are market orders whose execution must take place irrespective of the price.
[18] They are "hidden" limit orders whose total size is not displayed in the order book but is split into equal-sized tranches where the execution of each tranche is conditional upon the execution of the previous one.

The above model has few drawbacks, the first one being that the CSSD is susceptible to the impact of outliers (Economou et al., 2011). The second one relates to the fact that in the presence of herding during extreme periods the linearly positive relationship between returns' dispersion and market returns does not hold, becoming non-linear instead. To address these issues, Chang et al. (2000) proposed a modified approach over the Christie and Huang (1995) one which is based on the detection of herding through the relationship of the market returns and the cross-sectional absolute deviation (CSAD) of returns, formally calculated as:

$$CSAD_t = \frac{1}{n}\sum_{i=1}^{N}\left|r_{i,t} - r_{m,t}\right| \quad (3)$$

The notation is the same as for equation (1) above. Chang et al. (2000) estimated herding utilizing the following specification:

$$CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + \varepsilon_t \quad (4)$$

Controlling for market returns (through $|r_{m,t}|$, in order to capture the linear part of the relationship between CSAD and market returns), equation (4) accounts for the non-linear part of this relationship through the inclusion of the squared market return; in view of the above, herding is identified through significantly negative values for the α_2 coefficient. For the purposes of this study, we assess the effect of the merger into the Euronext on herding using the following specification of equation (4):

$$CSAD_{m,t} = \alpha_0 + \alpha_1 D^{Euronext}|r_{m,t}| + \alpha_2(1-D^{Euronext})|r_{m,t}| + \alpha_3 D^{Euronext} r^2_{m,t} + \alpha_4(1-D^{Euronext})\, r^2_{m,t} + \varepsilon_t \quad (5)$$

Equation (5) is a modified version of equation (4) and is used to assess the presence of herding in each of the four markets before and after its merger into the Euronext for the December 31st, 1989 – October 31st, 2009 period (in order to avoid including the European sovereign debt crisis period that ensued after October 2009). Significantly negative values of α_3 (α_4) would indicate the presence of herding following (before) the merger of that market into the Euronext. The Euronext-dummy ($D^{Euronext}$) equals one from October 2000 onwards for Belgium, France and the Netherlands and April 2002 onwards for Portugal and zero before that.

To assess the robustness of the results to various domestic and international market states, we parameterize equation (5) on the directional movement (up and down) of the following variables[19]:

a) **Domestic average market return**. This is $r_{m,t}$ used in the calculation of CSAD for each market and is utilized here to gauge whether herding significance is a function of a market's performance. Down-markets can be conducive to herding as they prompt market participants to unload their position in order to avoid suffering further losses in case the downturn becomes prolonged; this is particularly the case with institutional investors, given the adverse effect that losses can bear over their periodic performance evaluation[20]. On the other hand, up-markets can also boost herding, since they can lead investors to ride on what they believe to be an upward trend (De Long et al., 1990). Empirical research on the link between herding and market performance is rather extensive, yet characterized by mixed evidence to date[21].

b) **Domestic market trading volume**. It is calculated for each market as the sum of the daily volumes of all listed stocks in that market. Rising volumes tend to attract more informed investors (they allow them to trade on their information) and make it easier for uninformed investors to mimic them (high liquidity implies less frictions in trading, thus rendering it easier for investors to herd if they choose to do so (Gavriilidis et al., 2013). On the other hand, low volume can also promote herding, since it prompts investors to focus their trades on those stocks with sufficient volume, essentially leading to a clustering of trading activity. Again here, the role of volume in herding has been denoted by several studies, with the evidence produced being mixed[22].

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[19] The conditioning of equation (5) upon the different states of variables a) – e) mentioned here follows Chang et al. (2000) (e.g. they estimate herding for up-market days as $CSAD^{UP}_t = \alpha^{UP}_0 + \alpha^{UP}_1|r_{m,t}| + \alpha^{UP}_2 r^2_{m,t} + \varepsilon_t$ by utitlizing only trading days with positive market returns).

[20] Lesser-quality fund managers would have an obvious incentive to mimic their better-able counterparts during down-market periods, since they could ascribe their losses to the overall adverse market conditions, despite them having made the "right" investment decisions (i.e. those they copied from their "good" peers). For more on this, see Holmes et al. (2013).

[21] Chen (2013), Philippas et al. (2013) and Mobarek et al. (2014) reported significant herding during market slumps. Chiang et al. (2010) found significant herding in both up- and down- markets for Chinese A-shares; conversely, herding was significant only in downside markets for B-shares. Tan et al. (2008) reported stronger herding during up- markets in Shanghai A-shares, with no such asymmetry surfacing in the Shenzhen market (or the B-shares' segment of Shanghai thereof). From the perspective of institutional investors, Holmes et al. (2013) and Gavriilidis et al. (2013) documented significant herding among Portuguese and Spanish funds respectively, during periods of negative market/sector returns.

[22] Tan et al. (2008) report significant herd behavior for A-share markets in China during high-volume days, while B-shares' investors herd significantly during both high- and low- volume days. Moreover, Economou et al. (2011) provide evidence of an asymmetric volume effect for the Spanish and the Portuguese markets with herding being higher there during high trading volume days, while no such asymmetry is reported for the Greek and the Italian stock markets. Gavriilidis et al. (2013) found that Spanish fund managers tended to herd more at the industry level during periods characterized by rising/high market/sector volume.

c) **CAC40**. France's blue chip index comprised of the forty largest stocks listed on the Paris market. With France being Euronext's largest market, we use it as a control variable to test whether the group's lead market affects herding in the group's other markets.

d) **S&P500**. The US main market index, comprised of the 500 largest stocks listed on the US market. We use the S&P500 here as a control variable to test whether the world's largest market affects herding dynamics in our estimations, more so in view of evidence (Chiang and Zheng, 2010) indicating that US market conditions prompt investors' herding worldwide.

e) **CBOE VIX**. A proxy of US investors' sentiment, calculated as an implied volatility index based on S&P500 options, expressing the next 30 calendar days expected future market volatility. The CBOE VIX index was introduced in 1993 and is widely considered to be the "investors' fear gauge" (Whaley, 2000). As a result, higher VIX levels indicate higher uncertainty and fear in the market. The US sentiment is a factor affecting international markets (Verma and Soydemir, 2006), with evidence (Chiang et al., 2013; Philippas et al., 2013) suggesting the presence of a significant relationship between herding and the VIX-index internationally.

It is also possible that the significance of herding in an exchange group's member-market is affected by the dynamics in the group's other markets. To account for this possibility, we modify equation (4) as follows:

$$CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + \alpha_3 CSAD_{n,t} + \alpha_4 r^2_{n,t} + \varepsilon_t \quad (6)$$

In equation (6), the cross-sectional absolute deviation and the squared return of market n ($n \neq m$) are included as independent variables, in line with Balcilar et al. (2013), Lee et al. (2013) and Chiang and Zheng (2010); to assess whether the effect from other member-markets' dynamics changes pre- versus post-merger into the Euronext, we modify equation (5) as follows:

$$CSAD_{m,t} = \alpha_0 + \alpha_1 D^{Euronext}|r_{m,t}| + \alpha_2(1-D^{Euronext})|r_{m,t}| + \alpha_3 D^{Euronext} r^2_{m,t} + \alpha_4(1-D^{Euronext})\, r^2_{m,t} + \alpha_5 D^{Euronext} r^2_{n,t} + \alpha_6(1-D^{Euronext})\, r^2_{n,t} + \alpha_7 D^{Euronext}|CSAD_{n,t}| + \alpha_8(1-D^{Euronext})|CSAD_{n,t}| + \varepsilon_t \quad (7)$$

Given that the Euronext includes four markets, the equation is run three times for each market (to account for the effect of each of the other three markets' dynamics separately). Again here, all tests are performed for the December 31st, 1989 – October 31st, 2009 period.

Financial crises have been shown to constitute turning points for herding in capital markets, with a series of studies (Choe et al., 1999; Hwang and Salmon, 2004) showing that the onset of a crisis leads to changes in herding. With the Euronext involving European markets and in view of the ongoing euro-zone sovereign debt crisis, we assess the presence of herding during the crisis (November 1st, 2009 – December 31st, 2012) by estimating equations (4) and (6) for each market during that period.[23]

Our data was obtained from the Thomson-Reuters DataStream database and contains daily observations of closing prices, market capitalization and trading volume for all ordinary stocks listed on the Euronext's four equity markets commencing from December 31st, 1989 until December 31st, 2012. Our study consists of up to 534 firms for Belgium, 2470 firms for France, 361 firms for the Netherlands and 270 firms for Portugal. In order to account for survivorship bias, we incorporate all active, dead and suspended stocks over the sample period. Panel A in Table 1 presents descriptive statistics for each market's CSAD and average daily returns, while Panel B contains the correlation matrices for our markets' average daily returns and CSADs. Overall, the correlations documented are high, with their lowest values reported for Portugal, the group's smallest (and as these figures indicate least integrated) market.

4. Results-discussion

4.1 Merging of the exchanges and herding

Tables 2-5 present the estimates (using Newey-West (1987) consistent estimators) and associated p-values (in brackets) from the tests of equation (5) for each of our four sample markets and for each of the (domestic and international) market states from 31/12/1989 to 31/10/2009. As tables 2-4 illustrate, Belgium, France and the Netherlands present us with very little evidence of herding pre-merger, with

[23] In order to define the breakpoint i.e. the outbreak of the euro-zone debt crisis, we have performed a series of structural break tests. To begin with, we employed Bai and Perron's (2003) breakpoint test in equation (4) for the whole sample during the post-merger period (since April 2002). In this way, we endogenously identified October 2009 as a breakpoint; we confirmed this break point for each individual stock market using Chow's (1960) breakpoint test. Moreover, Hui and Chung (2011) and Ahmad et al. (2014) place the outbreak of the European sovereign debt crisis in late 2009 (October 2009), while Kalbaska and Gątkowski (2012) provide empirical findings based on which the crisis' start-point can be identified with November 2009. Therefore, in line with the structural breaks tests as well as the relevant literature we employ November 2009 as the starting point of the euro-zone crisis for our analysis.

α_4 almost never assuming significantly negative values for any of these three markets[24]; conversely, all three markets accommodate significant herding post-merger, as indicated by the consistently negative and significant (1 percent level) values of α_3 across all the tests. Portugal, on the other hand, appears to maintain a relatively consistent presence of herding both before and after its merger into the Euronext, with both α_3 and α_4 being significantly (10 percent level) negative for almost all tests (see table 5), indicating the presence of significant herding in that market throughout our sample period[25]. A closer inspection of the results from the Portuguese market reveals that for the tests where α_3 and α_4 are jointly significant, the absolute value of α_3 is larger than that of α_4 (with the single exception of the test for up CAC40 days), suggesting that the magnitude of herding has increased in the Portuguese market post-merger. The difference between the α_3 and α_4 estimates is significant (1 percent level) in all cases for Belgium, France and the Netherlands, and in most cases for Portugal[26]. Overall, these results show that herding is significant in all four constituent equity markets (Belgium, France, the Netherlands and Portugal) of the Euronext post-merger only, with herding in Portugal being significant (yet less strong) pre-merger as well. A possible explanation for this, in line with Holmes et al. (2013), is that herding is promoted in the Euronext as a result of the group's sophisticated structures that facilitate the observation (through the group's enhanced transparency) and imitation (rendered feasible through the group's enhanced liquidity) of the actions of informed investors by their uninformed counterparts.

We also performed tests of the difference for each of α_3 and α_4 between each control variable's up versus down periods and reported their results in tables 2-5[27]. Regarding α_4, it differs significantly between up and down periods of any single variable (all but one[28] of the relevant test-statistics are significant at the 10 percent level), yet, as mentioned above, it presents us with limited evidence in favor of herding overall. With regards to α_3, we observe that α_3 is larger in absolute value during up

[24] The coefficient a_4 is significantly (5 percent level) negative only during days of up CAC40-movements in Belgium and up domestic market days in France.
[25] Herding in Portugal is absent pre-merger during days of down S&P500-movements and up VIX-movements; and post-merger during days of down domestic volume-movements.
[26] The exceptions in the case of Portugal arise for the tests performed for days of down domestic market-movements and up CAC40-movements.
[27] What we are doing here is testing whether for each pair of tests related to a variable's two possible conditions (e.g. herding test for Belgium during up and during down volume days) the hypotheses $\alpha_{3,UP} = \alpha_{3,DOWN}$ and $\alpha_{4,UP} = \alpha_{4,DOWN}$ hold.
[28] This is the case of the test between up versus down VIX-days for France.

domestic/CAC40/S&P500 days (as opposed to down ones) in almost all cases for all markets[29], with the difference in α_3 between up versus down domestic/CAC40/S&P500 days being statistically significant in most cases[30]; comparing α_3 between up versus down days for the VIX or domestic volume across all markets furnishes us with mixed results.

The presence of stronger herding during up-market days can be due to investors' optimism leading them to ride on upward trends. It is further possible that rising prices encourage the entry of unsophisticated investors in the market, in line with evidence from Grinblatt and Keloharju (2001) and Lamont and Thaler (2003), thus rendering it more likely for herding to surface during up-market periods. The fact that this herding asymmetry is observed for both domestic and non-domestic (CAC40; S&P500) up-market days during the post-merger period is an indication that joining the Euronext has rendered these markets more sensitive to international market movements (more specifically, those of France - Euronext's lead market - and the US – the world's largest market).

4.2 Herding across member-markets

We now turn to assess whether controlling for the dynamics of the group's other member-markets over each market's herding produces an effect over our herding estimates. Equation (7) is estimated for each market for all possible combinations of markets as described in the previous section and results are reported in table 6. Results presented are by and large similar to those reported in tables 2-5, with herding being significant (1 percent level) in Belgium, France and the Netherlands[31] post-merger only; its significance (1 percent level) is documented both pre- and post-merger for Portugal, while the difference between the α_3 and α_4 estimates is significant at the 5 percent level for all four markets in all tests. The estimates for coefficients α_7 and α_8 are almost always significantly positive[32], indicating that the cross-sectional dispersions of returns of all markets in our sample are significantly related to each other, in line with the high correlation coefficients among the CSADs presented in table 1, panel B. The values of α_5 are significantly (10 percent level) negative for all markets[33], whereas those of α_6 are

[29] The sole exception here is the up versus down days' pair for the CAC40 for the Portuguese market.
[30] This is not the case between up-down S&P500 days for France, the Netherlands and Portugal and up-down domestic market returns' days for Portugal.
[31] Herding is absent post-merger in the Netherlands when controlling for the French market.
[32] The single exception here is detected in the Belgian market when controlling for Portugal.
[33] The exception here is Portugal, when controlling for the Belgian market.

significantly (1 percent level) positive for all tests. These results suggest that the merger into Euronext has led not only to the evolution of significant domestic herding in the group's markets, but also allowed for herding in each market to be induced through the dynamics of the other member-markets, indicating that financial integration within the context of an exchange group can affect investors' behavior in a market.

4.3 Financial crisis and herding

Table 7 presents the results from equations (4) (panel A) and (6) (panel B) for the period following the outbreak of the sovereign debt crisis in the euro-zone. Results from panel A suggest that Euronext-markets exhibit no evidence of domestic herding during the crisis, as the coefficient α_2 is insignificant in all cases. Controlling for the effect of other member-markets confirms (panel B) the absence of domestic herding in all markets, yet we also notice that α_3 assumes significantly negative values for Belgium, the Netherlands and Portugal for several tests (this is the case for Belgium and Portugal when controlling for the effect of the French and the Dutch markets, and for the Netherlands when controlling for the effect of the French market). These results are notably interesting, as they suggest that the sovereign debt crisis promoted herding in the Euronext; however, this herding was not domestically motivated, but rather stemmed from the group's largest markets, France (for the rest three markets) and the Netherlands (for Belgium and Portugal). A possible explanation for this is that the outbreak of the crisis led to the collapse of the pre-crisis consensus in the euro-zone (hence, the lack of "domestic" herding in all markets post-outbreak) by revealing groundbreaking macroeconomic fundamentals for several European nations. Amid such uncertainty, euro-zone's largest markets grew in importance as indicators of the investment community's views on the ongoing crisis, affecting the decisions of investors in euro-zone's smaller markets and (considering the fact that all Euronext-markets are also members of the euro-zone) this is what our results reveal in terms of the specific investment pattern of herding for Euronext's markets.

In summary, our findings show that herding is significant in all four constituent equity markets (Belgium, France, the Netherlands and Portugal) of the Euronext post-merger only, with herding in Portugal being significant (yet less strong) pre-merger as well. These findings are robust when controlled for various domestic and international market states[34], with results also indicating that herding post-merger grows stronger during days of positive performance of the domestic market, the Euronext's lead market (France) and the US market. The robustness of our results is further confirmed when accounting for the dynamics of the group's markets, while an interesting finding in this context is that herding in each market post-merger is not only domestically motivated but can also be induced via the dynamics of the group's other member-markets. The outbreak of the euro-zone sovereign debt crisis has given rise to significant herding in Belgium, the Netherlands and Portugal, with herding post-outbreak being, however, exclusively motivated by the dynamics of the group's two largest markets (France and the Netherlands).

5. Conclusion

The current study explores the effect of membership in cross-border exchange groups over herding dynamics in a group's member-markets and whether this effect persists when controlling for different domestic and international market states, the dynamics of the group's markets as well as the outbreak of financial crises. We investigate these issues in the context of the Euronext, one of the first-ever launched exchange groups, which encompasses four European equity markets (Belgium, France, the Netherlands and Portugal). Herding is significant in all four markets post-merger only, with herding in Portugal being significant (yet less strong) pre-merger as well. The robustness of these results is confirmed when controlling for various domestic and international market states, with herding appearing stronger during days of positive performance for the domestic market, Euronext's lead market (France) and the US market. Controlling for the dynamics of the group's markets further confirms the robustness of our results, with each market post-merger presenting us with significant herding motivated both domestically and by the dynamics of the rest three markets. The outbreak of the euro-zone

[34] To account for the possibility that the time-difference between Europe and the US affects our estimates from the tests controlling for US variables (S&P500/VIX), we repeated all tests controlling for these variables, this time conditioning herding upon their lagged values; results overall confirm the patterns reported in tables 2-5. We also tested for the possibility of the size-effect in our findings by performing all unconditional herding tests (i.e. those whose estimates are presented in tables 2-5 under the title "total") using value-weighted CSADs; results from these tests confirmed overall the findings presented in tables 2-5. Finally, as regards trading volume, we also employed an alternative specification, conditioning herding upon whether volume is above or below its 30-day moving average value, in line with Economou et al. (2011), with results confirming those documented in tables 2-5 from estimations using up-down volume days. Results from the above tests are not reported here in the interest of brevity and are available upon request from the authors.

sovereign debt crisis produces significant herding in Belgium, the Netherlands and Portugal, with this herding, however, being not domestic but rather motivated by the dynamics of the group's two largest markets (France and the Netherlands).

Our findings are of particular interest to the investment community and regulatory authorities in light of the ongoing global integration of capital markets. From an investor's perspective, the significance of herding post-merger in all four Euronext-markets coupled with the finding that much of it is due to intra-Euronext dynamics (aside from each market's domestic ones) raises questions as to whether investing in markets that are integrated in common institutional settings (such as exchange groups) is beneficial in terms of portfolio diversification. As far as regulators are concerned, the fact that intra-Euronext dynamics can promote herding in each member-market alongside the increased levels of herding during both domestic and international up-market days post-merger suggests that the integration of a capital market in an exchange group enhances the market's exposure to non-domestic factors. Given the increased frequency with which global financial episodes have affected capital markets during the past decades and the destabilizing potential of herding, these results suggest that such exposure can amplify investors' herding tendencies during global crises, thus increasing a market's systemic risk as well as the possibility of contagion within an exchange group.

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Table 1: Statistical properties of the average returns and cross sectional absolute deviations of returns

Panel A: Descriptive statistics

	$r_{m,t}$				CSAD			
	Belgium	France	Netherlands	Portugal	Belgium	France	Netherlands	Portugal
Mean	0.0001	0.0001	-0.0002	0.0003	0.0168	0.0157	0.0155	0.0140
Median	0.0005	0.0007	0.0005	0.0006	0.0163	0.0146	0.0141	0.0127
Standard Deviation	0.0083	0.0068	0.0090	0.0094	0.0072	0.0049	0.0065	0.0060
Minimum	-0.0658	-0.0578	-0.0955	-0.1115	0.0000	0.0000	0.0000	0.0000
Maximum	0.0793	0.0498	0.0804	0.0877	0.0778	0.0567	0.0685	0.1069

Panel B: Correlation matrices

	Belgium $r_{m,t}$	France $r_{m,t}$	Netherlands $r_{m,t}$	Portugal $r_{m,t}$
Belgium $r_{m,t}$	1.0000			
France $r_{m,t}$	0.6976	1.0000		
Netherlands $r_{m,t}$	0.6864	0.8279	1.0000	
Portugal $r_{m,t}$	0.4812	0.5902	0.5818	1.0000

	Belgium CSAD	France CSAD	Netherlands CSAD	Portugal CSAD
Belgium CSAD	1.0000			
France CSAD	0.5910	1.0000		
Netherlands CSAD	0.5617	0.7475	1.0000	
Portugal CSAD	0.2641	0.3228	0.3306	1.0000

Notes: Panel A presents statistics on the mean, median, standard deviation, minimum and maximum values for the daily observations of the cross-sectional absolute deviation of returns (CSAD) and average returns ($r_{m,t}$) for each of Euronext's four constituent equity markets. $r_{m,t}$ is calculated by averaging all daily securities' returns each day, whereas the CSAD is calculated as $CSAD_t = \frac{1}{n}\sum_{i=1}^{N}\left|r_{i,t} - r_{m,t}\right|$, where $r_{i,t}$ is security's i return on day t, $r_{m,t}$ is the market's average return on day t (calculated by averaging all securities' returns on day t) and n is the total number of listed stocks. Panel B presents the pairwise correlation coefficients of the CSAD and $r_{m,t}$ for each of Euronext's four constituent equity markets. The sample window is December 31st, 1989 – December 31st, 2012.

Table 2: Estimates of herding in Belgium pre- versus post-merger in the Euronext

Estimated parameters	TOTAL	DOMESTIC RETURN UP	DOMESTIC RETURN DOWN	CAC40 UP	CAC40 DOWN	S&P500 UP	S&P500 DOWN	VIX UP	VIX DOWN	DOMESTIC VOLUME UP	DOMESTIC VOLUME DOWN
α_0	0.0127	0.0126	0.01356	0.0123	0.01356	0.0130	0.01268	0.0124	0.0133	0.0125	0.0131
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	1.1166	1.1967	0.9894	1.1884	0.9851	1.0786	1.1081	1.1172	1.0587	1.0518	1.1578
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2	0.3329	0.4169	-0.0405	0.4627	-0.1118	0.0339	0.4459	0.4323	-0.0045	0.3035	0.1447
	(0.0000)	(0.1440)	(0.4480)	(0.0000)	(0.0300)	(0.4970)	(0.0000)	(0.0000)	(0.9301)	(0.0000)	(0.0085)
α_3	-10.6987	-13.1080	-8.0668	-12.8277	-7.9902	-10.6186	-10.0442	-10.2720	-9.9828	-9.2727	-11.0756
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_4	4.8361	-0.7360	24.3611	-2.9013	26.6295	19.9813	-0.9636	-0.4495	23.1339	2.7294	25.9564
	(0.0000)	(0.5119)	(0.0000)	(0.0105)	(0.0000)	(0.0000)	(0.4132)	(0.6993)	(0.0000)	(0.0173)	(0.0000)
t-stat$_1$	-22.9468	-15.8298	-19.9006	-14.5877	-22.0163	-20.9264	-13.7440	-14.4247	-21.0284	-16.5676	-18.0925
(H_0:$\alpha_1 = \alpha_2$)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
t-stat$_2$	12.2919	6.0042	15.7639	4.8194	17.9021	14.3228	5.7156	6.1411	15.2073	7.9881	13.1616
(H_0:$\alpha_3 = \alpha_4$)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
t-test		4.2341		4.0941		-15.9397		0.1862		-0.8130	
(H_0:$\alpha_{3,UP} = \alpha_{3,DOWN}$)		(0.0000)		(0.0000)		(0.0000)		(0.8523)		(0.4163)	
t-test		13.0282		16.5024		-17.7903		12.6359		10.4793	
(H_0:$\alpha_{4,UP} = \alpha_{4,DOWN}$)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
R^2	0.3976	0.3713	0.4578	0.3759	0.4658	0.4274	0.3916	0.3788	0.4472	0.3879	0.4591

Notes: Table 2 presents the estimates from the following equation:

$$CSAD_{m,t} = \alpha_0 + \alpha_1 D^{Euronext}|r_{m,t}| + \alpha_2(1-D^{Euronext})|r_{m,t}| + \alpha_3 D^{Euronext} r^2_{m,t} + \alpha_4(1-D^{Euronext})\, r^2_{m,t} + \varepsilon_t$$

The equation is estimated for the 31/12/1989 - 31/10/2009 period both unconditionally (column headed "total") and conditionally upon the daily movement (up/down) of the following variables: domestic market average return; domestic market trading volume; CAC40; S&P500; and the VIX. All estimates' p-values are reported in parentheses; the difference in significance between the pre- versus post-merger values of each coefficient is tested using t-test statistics; t-statistics are also used to test for the difference in significance for a_3 and a_4 between up and down states of each variable. $r_{m,t}$ refers to the Belgian market's average return; $CSAD_{m,t}$ refers to the cross-sectional absolute deviation of returns for the Belgian market. $D^{Euronext}$ is a dummy equalling one following Belgium's merger into the Euronext (October 2000), zero otherwise.

Table 3: Estimates of herding in France pre- versus post-merger in the Euronext

Estimated parameters	TOTAL	DOMESTIC RETURN UP	DOMESTIC RETURN DOWN	VIX UP	VIX DOWN	DOMESTIC VOLUME UP	DOMESTIC VOLUME DOWN	S&P500 UP	S&P500 DOWN
α_0	0.0129	0.0125	0.0132	0.0129	0.0129	0.0127	0.0131	0.0127	0.0133
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.9435	1.0820	0.8450	0.9112	0.9772	0.9281	0.9570	0.9724	0.8955
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2	0.3859	0.6181	0.2085	0.4031	0.3880	0.3315	0.4538	0.4599	0.2343
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2301)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_3	-9.3840	-13.0100	-6.9918	-9.0638	-9.2698	-9.9760	-4.8958	-9.8645	-8.3996
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0000)	(0.0000)
α_4	1.2131	-8.1099	6.9573	1.2820	0.0025	0.1206	5.8831	-2.0032	9.3237
	(0.3063)	(0.0000)	(0.0000)	(0.3561)	(0.9991)	(0.9379)	(0.0024)	(0.1645)	(0.0000)
t-stat$_1$	-19.2150	-11.1761	-15.3054	-13.3558	-12.7413	-14.7247	-12.2731	-13.0650	-14.8196
(H_0:$\alpha_1 = \alpha_2$)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
t-stat$_2$	7.9949	2.1096	8.2169	6.5144	3.7990	5.8418	4.9473	4.7021	7.7248
(H_0:$\alpha_3 = \alpha_4$)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
t-test		5.6698		-0.1447		3.6330		1.1618	
(H_0:$\alpha_{3,UP} = \alpha_{3,DOWN}$)		(0.0000)		(0.8849)		(0.0003)		(0.2454)	
t-test		9.9450		-0.5595		2.9814		5.1806	
(H_0:$\alpha_{4,UP} = \alpha_{4,DOWN}$)		(0.0000)		(0.5758)		(0.0029)		(0.0000)	
R^2	0.4240	0.3956	0.4663	0.4451	0.4069	0.4119	0.4862	0.4032	0.4529

Notes: Table 3 presents the estimates from the following equation:

$$CSAD_{m,t} = \alpha_0 + \alpha_1 D^{Euronext}|r_{m,t}| + \alpha_2(1-D^{Euronext})|r_{m,t}| + \alpha_3 D^{Euronext} r^2_{m,t} + \alpha_4(1-D^{Euronext})\, r^2_{m,t} + \varepsilon_t$$

The equation is estimated for the 31/12/1989 - 31/10/2009 period both unconditionally (column headed "total") and conditionally upon the daily movement (up/down) of the following variables: domestic market average return; domestic market trading volume; S&P500; and the VIX. All estimates' p-values are reported in parentheses; the difference in significance between the pre- versus post-merger values of each coefficient is tested using t-test statistics; t-statistics are also used to test for the difference in significance for a_3 and a_4 between up and down states of each variable. $r_{m,t}$ refers to the French market's average return; $CSAD_{m,t}$ refers to the cross-sectional absolute deviation of returns for the French market. $D^{Euronext}$ is a dummy equalling one following France's merger into the Euronext (October 2000), zero otherwise.

Table 4: Estimates of herding in Netherlands pre- versus post-merger in the Euronext

Estimated parameters	TOTAL	DOMESTIC RETURN UP	DOMESTIC RETURN DOWN	CAC40 UP	CAC40 DOWN	S&P500 UP	S&P500 DOWN	VIX UP	VIX DOWN	DOMESTIC VOLUME UP	DOMESTIC VOLUME DOWN
α_0	0.0113	0.0110	0.0115	0.0109	0.0116	0.0111	0.0116	0.0114	0.0112	0.0113	0.0112
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.9454	1.0707	0.8474	1.0609	0.8554	0.9880	0.9016	0.8932	1.0011	0.8692	1.0582
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2	0.3956	0.5541	0.2764	0.5531	0.2813	0.4072	0.3902	0.3466	0.4539	0.4185	0.3431
	(0.1304)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.4928)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_3	-6.8335	-7.3770	-5.8157	-7.2739	-5.9353	-7.0600	-6.4167	-6.3740	-6.9131	-5.9345	-7.5755
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_4	3.9620	-2.1948	7.8397	-3.3789	8.4132	5.7280	2.0145	6.2882	1.1862	0.4937	13.2304
	(0.0036)	(0.3594)	(0.0000)	(0.1239)	(0.0000)	(0.0017)	(0.3221)	(0.0008)	(0.5501)	(0.7699)	(0.0000)
t-stat_1	-17.3989	-11.1736	-13.1195	-11.2861	-12.9019	-13.5611	-10.8598	-12.4939	-11.9495	-10.9390	-14.5976
$(H_0: \alpha_1 = \alpha_2)$	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
t-stat_2	7.9562	2.1644	8.0603	1.7673	8.1021	6.8807	4.1892	6.8407	4.0320	3.8359	8.7842
$(H_0: \alpha_3 = \alpha_4)$	(0.0000)	(0.0305)	(0.0000)	(0.0773)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
t-test		2.7373		2.2781		1.0639		-0.6384		-1.9510	
$(H_0: \alpha_{3,UP} = \alpha_{3,DOWN})$		(0.0062)		(0.0228)		(0.2875)		(0.5233)		(0.0512)	
t-test		5.9041		6.6345		-1.8254		-2.5707		5.3976	
$(H_0: \alpha_{4,UP} = \alpha_{4,DOWN})$		(0.0000)		(0.0000)		(0.0681)		(0.0102)		(0.0000)	
R^2	0.5002	0.4812	0.5369	0.4983	0.5141	0.4985	0.5035	0.5102	0.4943	0.5035	0.5153

Notes: Table 4 presents the estimates from the following equation:

$$CSAD_{m,t} = \alpha_0 + \alpha_1 D^{Euronext}|r_{m,t}| + \alpha_2(1-D^{Euronext})|r_{m,t}| + \alpha_3 D^{Euronext} r^2_{m,t} + \alpha_4(1-D^{Euronext})\, r^2_{m,t} + \varepsilon_t$$

The equation is estimated for the 31/12/1989 - 31/10/2009 period both unconditionally (column headed "total") and conditionally upon the daily movement (up/down) of the following variables: domestic market average return; domestic market trading volume; CAC40; S&P500; and the VIX. All estimates' p-values are reported in parentheses; the difference in significance between the pre- versus post-merger values of each coefficient is tested using t-test statistics; t-statistics are also used to test for the difference in significance for a_3 and a_4 between up and down states of each variable. $r_{m,t}$ refers to the Dutch market's average return; $CSAD_{m,t}$ refers to the cross-sectional absolute deviation of returns for the Dutch market. $D^{Euronext}$ is a dummy equalling one following Netherlands's merger into the Euronext (October 2000), zero otherwise.

Table 5: Estimates of herding in Portugal pre versus post-merger in the Euronext

Estimated parameters	TOTAL	DOMESTIC RETURN UP	DOMESTIC RETURN DOWN	CAC40 UP	CAC40 DOWN	S&P500 UP	S&P500 DOWN	VIX UP	VIX DOWN	DOMESTIC VOLUME UP	DOMESTIC VOLUME DOWN
α_0	0.0097	0.0096	0.0098	0.0097	0.0098	0.0097	0.0101	0.0102	0.0096	0.0097	0.0101
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.6302	0.6718	0.5909	0.6455	0.6042	0.6195	0.5825	0.5686	0.6439	0.6559	0.5453
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2	0.7301	0.8029	0.6313	0.6797	0.7176	0.7163	0.5158	0.5411	0.7450	0.7216	0.4950
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_3	-4.8815	-4.9480	-4.0804	-1.1660	-6.1680	-6.6453	-2.9140	-2.9156	-6.6210	-6.2735	8.4459
	(0.0000)	(0.0000)	(0.0000)	(0.0741)	(0.0000)	(0.0000)	(0.0028)	(0.0003)	(0.0000)	(0.0000)	(0.0000)
α_4	-3.2309	-2.6640	-3.4246	-2.2709	-3.7289	-2.8092	5.7647	3.0325	-2.7425	-4.1820	-1.4644
	(0.0000)	(0.0002)	(0.0000)	(0.0015)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0241)
t-stat$_1$	-4.6264	4.4019	1.2656	1.1138	3.7176	3.4952	-1.9011	-0.8291	3.5205	2.1243	-1.6516
(H_0:$\alpha_1 = \alpha_2$)	(0.0000)	(0.0000)	(0.2058)	(0.2655)	(0.0002)	(0.0005)	(0.0574)	(0.4071)	(0.0004)	(0.0337)	(0.0987)
t-stat$_2$	-2.8030	-2.4816	-0.7970	1.2356	-3.0262	-5.7349	7.4781	5.8086	-5.3561	-2.5198	9.8026
(H_0:$\alpha_3 = \alpha_4$)	(0.0051)	(0.0131)	(0.4255)	(0.2167)	(0.0025)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0118)	(0.0000)
t-test		-0.9920		-1.9491		-0.1078		0.2625		4.1881	
(H_0:$\alpha_{3,UP} = \alpha_{3,DOWN}$)		(0.3213)		(0.0514)		(0.9142)		(0.7929)		(0.0000)	
t-test		1.9742		-11.4535		14.8801		-23.8966		16.7722	
(H_0:$\alpha_{4,UP} = \alpha_{4,DOWN}$)		(0.0485)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
R^2	0.4125	0.4417	0.3914	0.4499	0.3922	0.3849	0.4981	0.4564	0.3993	0.4037	0.4900

Notes: Table 5 presents the estimates from the following equation:

$$CSAD_{m,t} = \alpha_0 + \alpha_1 D^{Euronext}|r_{m,t}| + \alpha_2(1-D^{Euronext})|r_{m,t}| + \alpha_3 D^{Euronext} r^2_{m,t} + \alpha_4(1-D^{Euronext})\, r^2_{m,t} + \varepsilon_t$$

The equation is estimated for the 31/12/1989 - 31/10/2009 period both unconditionally (column headed "total") and conditionally upon the daily movement (up/down) of the following variables: domestic market average return; domestic market trading volume; CAC40; S&P500; and the VIX. All estimates' p-values are reported in parentheses; the difference in significance between the pre- versus post-merger values of each coefficient is tested using t-test statistics; t-statistics are also used to test for the difference in significance for a_3 and a_4 between up and down states of each variable. $r_{m,t}$ refers to the Portuguese market's average return; $CSAD_{m,t}$ refers to the cross-sectional absolute deviation of returns for the Portuguese market. $D^{Euronext}$ is a dummy equalling one following Portugal's merger into the Euronext (April 2002), zero otherwise.

Table 6: Estimates of herding in Euronext's four markets controlling for the dynamics of the group's markets pre- versus post-merger in the Euronext

Market for which herding is estimated→		BELGIUM			FRANCE			NETHERLANDS			PORTUGAL		
Estimated parameters ↓	Control markets →	France	Netherlands	Portugal	Belgium	Netherlands	Portugal	Belgium	France	Portugal	Belgium	France	Netherlands
α_0		0.0092	0.0116	0.0118	0.0117	0.0113	0.0124	0.0097	0.0073	0.0108	0.0091	0.0083	0.0089
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1		0.7422	0.8602	0.9309	0.7265	0.5901	0.8068	0.7268	0.4022	0.8036	0.5018	0.5500	0.5825
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2		0.3299	-0.0450	0.4940	0.5421	0.3447	0.4575	0.5239	0.3799	0.4439	0.7554	0.6944	0.7018
		(0.0000)	(0.2388)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.4903)	(0.0000)	(0.0885)
α_3		-4.0615	-7.1730	-9.8495	-4.2611	-2.9227	-6.6115	-4.1086	0.4786	-4.8117	-5.5214	-4.4406	-4.8732
		(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.2827)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_4		5.5227	24.6049	3.2993	-1.4659	2.8433	2.8229	7.2215	7.1700	5.0738	-2.2642	-2.1705	-2.4902
		(0.0000)	(0.0000)	(0.0004)	(0.1676)	(0.0086)	(0.0159)	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)
α_5		-13.1427	-2.4481	-1.2899	-4.2513	-3.2860	-1.7856	-5.9431	-16.8259	-2.9401	-0.3733	-3.1085	-0.7637
		(0.0000)	(0.0000)	(0.0144)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5329)	(0.0004)	(0.0556)
α_6		7.1227	9.0255	0.4209	6.3374	8.1596	1.3706	12.4299	11.0187	0.2475	1.8644	6.8750	4.3375
		(0.0000)	(0.0000)	(0.2138)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.00000	(0.0000)
α_7		18.8031	7.5819	11.6506	6.2100	9.4019	6.5571	8.7128	25.8449	8.8338	3.5798	6.4237	2.9013
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_8		15.5882	11.6427	0.5792	4.3255	12.0210	1.6150	5.4541	17.4486	0.8500	1.6809	7.0395	4.9070
		(0.0000)	(0.0000)	(0.1043)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0047)	(0.0000)	(0.0000)	(0.0000)
t-stat$_1$		-9.1812	-20.6310	-11.3735	-5.6692	-8.1803	-10.8564	-5.5384	-0.6630	-9.9073	8.8811	4.7507	4.3731
(H_0:$\alpha_1 = \alpha_2$)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5073)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
t-stat$_2$		6.6619	19.2371	10.0452	2.0809	4.3172	6.8372	7.6385	4.8142	6.5444	-4.2483	-2.4789	-2.3479
(H_0:$\alpha_3 = \alpha_4$)		(0.0000)	(0.0000)	(0.0000)	(0.0375)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0132)	(0.0189)
t-stat$_3$		3.9773	-5.2448	1.3912	-3.0882	-5.6577	0.9651	-5.8740	4.7286	4.5982	-1.9200	-3.2931	-4.0334
(H_0:$\alpha_5 = \alpha_6$)		(0.0001)	(0.0000)	(0.1642)	(0.0020)	(0.0000)	(0.3345)	(0.0000)	(0.0000)	(0.0000)	(0.0549)	(0.0010)	(0.0000)
t-stat$_4$		4.0031	5.4624	-15.5966	-5.8598	6.0216	-10.5249	7.1702	-14.9502	174.5251	-4.6189	1.0146	3.8991
(H_0:$\alpha_7 = \alpha_8$)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0762)	(0.0000)	(0.0025)	(0.0000)	(0.3103)	(0.0001)
R^2		0.5153	0.5052	0.4607	0.5446	0.6425	0.5010	0.5839	0.7374	0.5348	0.4285	0.4454	0.4349

Notes: Table 6 presents the estimates from the following equation:

$$CSAD_{m,t} = \alpha_0 + \alpha_1 D^{Euronext}|r_{m,t}| + \alpha_2(1-D^{Euronext})|r_{m,t}| + \alpha_3 D^{Euronext} r^2_{m,t} + \alpha_4(1-D^{Euronext})\, r^2_{m,t} + \alpha_5 D^{Euronext} r^2_{n,t} + \alpha_6(1-D^{Euronext})\, r^2_{n,t} + \alpha_7 D^{Euronext}|CSAD_{n,t}| + \alpha_8(1-D^{Euronext})|CSAD_{n,t}| + \varepsilon_t$$

The equation is estimated for the 31/12/1989 - 31/10/2009 period for each Euronext-market and all estimates' p-values are reported in parentheses. The difference in significance between the pre- versus post-merger values of each coefficient is tested using t-test statistics. $r_{m,t}$ and $CSAD_{m,t}$ refer to the average return and the cross-sectional absolute deviation of returns for the market for which herding is estimated each time. $r_{n,t}$ and $CSAD_{n,t}$ refer to the average return and the cross-sectional absolute deviation of returns for the control market used for each test. $D^{Euronext}$ is a dummy equalling one following the merger of each market for which herding is estimated into the Euronext, zero otherwise.

Table 7: Estimates of herding in Euronext's four markets following the outbreak of the euro-zone's sovereign debt crisis

Panel A: Herding estimates without controlling for the other member-markets' effect

	Belgium	France	Netherlands	Portugal
α_0	0.0151	0.0130	0.0145	0.0134
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.4754	0.4610	0.4386	0.4720
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2	-1.3306	-0.4110	-1.6311	-1.8232
	(0.5276)	(0.6751)	(0.2390)	(0.1178)
R^2	0.2897	0.6213	0.3481	0.2236

Panel B: Herding estimates controlling for the effect of the other member-markets

Market for which herding is estimated→		Belgium			France			Netherlands			Portugal		
Estimated parameters↓	Control markets →	France	Netherlands	Portugal	Belgium	Netherlands	Portugal	Belgium	France	Portugal	Belgium	France	Netherlands
α_0		0.0128	0.0147	0.0152	0.0122	0.0118	0.0127	0.0137	0.0103	0.0137	0.0136	0.0107	0.0114
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1		0.3880	0.4576	0.4977	0.4471	0.3715	0.4465	0.4381	0.3509	0.4248	0.4670	0.4341	0.4467
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_2		3.9902	0.3728	-2.7631	-0.5957	-0.8865	-0.4960	-1.7071	-3.1032	-1.8489	-2.2653	-1.8003	-1.8301
		(0.1426)	(0.8762)	(0.2165)	(0.5916)	(0.3901)	(0.6143)	(0.2750)	(0.1806)	(0.1858)	(0.1572)	(0.1227)	(0.1122)
α_3		-10.6523	-1.8589	0.9537	-0.5040	0.4455	0.0678	-1.1440	-6.9350	-0.3298	3.4109	-5.4225	-1.9864
		(0.0000)	(0.0479)	(0.0431)	(0.5076)	(0.4003)	(0.7501)	(0.4071)	(0.0002)	(0.4490)	(0.0549)	(0.0185)	(0.0915)
α_4		12.4380	1.9646	-0.7320	2.6234	4.6449	1.0069	2.4183	21.8996	2.5430	-0.7930	13.7206	7.5182
		(0.0000)	(0.0331)	(0.1528)	(0.0000)	(0.0000)	(0.0000)	(0.0034)	(0.0000)	(0.0000)	(0.5486)	(0.0000)	(0.0000)
R^2		0.3281	0.2949	0.2939	0.6438	0.6834	0.6314	0.3552	0.4435	0.3711	0.2273	0.2436	0.2525

Notes: Table 7 presents the estimates from the following equations:

Panel A: $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + \varepsilon_t$

Panel B: $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + \alpha_3 CSAD_{n,t} + \alpha_4 r^2_{n,t} + \varepsilon_t$

The equation is estimated for the 1/11/2009 - 31/12/2012 period for each Euronext-market and all estimates' p-values are reported in parentheses. $r_{m,t}$ and $CSAD_{m,t}$ refer to the average return and the cross-sectional absolute deviation of returns for the market for which herding is estimated each time. $r_{n,t}$ and $CSAD_{n,t}$ in panel B refer to the average return and the cross-sectional absolute deviation of returns for the control market used for each test.