Intraday Herding on a Cross-Border Exchange

Abstract

This study investigates intraday herding on the Euronext, the world's first cross-border consolidated exchange. Intraday herding is significant in the Euronext as a group and presents us with size, industry and country effects. Importantly, the trading dynamics of the group's member markets significantly affect each other and can, in the case of the Netherlands, promote herding formation. Intraday herding is found to be significant before, during and after the 2007-09 financial crisis period, with its presence appearing the least strong during the crisis. Overall, we demonstrate for the first time in the literature that cross-border exchanges harbour versatile herding dynamics at intraday level, a finding which reflects recent advances in financial technology and the ongoing financial integration in Europe.

JEL classification: G02; G15

Keywords: tick data; intraday herding; cross-border groups; Euronext

1. Introduction

Research interest in intraday herding has exhibited a notable surge during the past decade, motivated mainly by the fact that the daily or lower frequencies used by the bulk of herding studies preclude insight into the herding taking place within a trading session (Gleason et al., 2004; Henker et al., 2006). In the contemporary financial context, where advanced financial technology allows for increased trading, both in terms of size (Aggarwal and Dahiya, 2006) and frequency (Hasbrouck and Saar, 2013), establishing the presence of intraday herding is of key interest, more so considering the fact that herding itself tends to occur mostly within short horizons (Froot et al., 1992). Research on intraday herding (Gleason et al., 2004; Henker et al., 2006; Zhou and Lai, 2009; Blasco et al., 2011, 2012) has been conducted for a variety of national stock markets, with evidence to date appearing overall inconclusive. However, the onset of the globalization process since the 1990s has fomented cooperation among stock exchanges worldwide culminating in the formation of cross-border exchange groups, whose novel institutional settings offer a variety of services (trading; clearing; settlement) based on sophisticated technological infrastructure. It is interesting to note that no study to date has examined intraday herding (indeed, herding at any frequency) in such a group as a single entity (i.e. treating the group as a single market), despite the fact that cross-border exchange groups constitute notably appealing settings for the study of intraday herding for two reasons. On the one hand, their technological sophistication can give rise to unique intraday trading dynamics at the group level (i.e. spanning across their member markets), thus suggesting the possibility of these dynamics leading to intraday herding at that level. On the other hand, recent evidence (Andrikopoulos et al., 2014; Economou et al., 2015) has denoted that merging into a cross-border exchange group leads to an increase in a market's herding. Although these studies examine herding at lower frequencies (monthly and daily, respectively), the fact that joining a cross-border group constitutes an event capable of fostering herding in a market raises the question as to whether herding at the group level is also significant and what features it might entail.

Our study investigates this issue for the first time in the literature by examining intraday herding in the Euronext, one of the first cross-border groups ever launched using an extensive dataset of nine years of tick data (January 2002 – December 2010) for all firms trading on Euronext's four equity markets (Belgium, France, Netherlands and Portugal). We first investigate whether intraday herding is significant in the Euronext as a group and whether it is subject to the effect of established determinants (size, industry) of herding observed in earlier studies on individual stock markets. Secondly, we explore whether a country specific intraday herding effect is present (i.e. whether intraday herding within a cross-border group varies in its significance across its member markets) and whether this effect is robust when controlling for the trading dynamics of the group's other markets. Thirdly, we assess the effect of the 2007-09 global financial crisis, in view of evidence (Choe et al., 1999; Kim and Wei, 2002; Hwang and Salmon, 2004; Chiang and Zheng, 2010; Mobarek et al., 2014; Economou et al., 2015) suggesting that crisis episodes constitute turning points in herding.

From a theoretical perspective, herding relates to investors' sidelining their private signals (or fundamentals thereof) in favour of imitating the actions of their peers following interactive observation of these actions (or their payoffs: see Hirshleifer and Teoh, 2003). Herding is often motivated by the anticipation of informational payoffs (Devenow and Welch, 1996), whereby investors discard their private information and follow the actions of those they believe to be better informed instead (because they consider these actions as informative). If free riding on the information of others becomes a widespread practice among investors, this can render the public pool of information poorer and promote the evolution of informational cascades (Banerjee, 1992; Bikhchandani et al., 1992). It is also possible that herding is driven by professional reasons, something particularly relevant to fund managers, whose performance is assessed regularly on a relative basis (i.e. versus the performance of their peers). In this case, managers of inferior ability are tempted to mimic the trades of their better performing peers in order to improve their image when their assessment is due (Scharfstein and Stein, 1990). A factor capable of giving rise to high correlations in the actions of finance professionals is the relative homogeneity (De Bondt and The, 1997) in their environment. This homogeneity can involve similarities in their educational background, the financial indicators they examine and the regulatory framework governing their actions[1]. Characteristic trading (Bennett et al., 2003), namely trading strategies ("styles") basing the selection of stocks on specific characteristics (such as past performance, size and sector), is rather popular among fund managers and can also lead to similarities in their trades[2]. Recent research (Holmes et al., 2013; Gavriilidis et al., 2013) has grouped the above herding drivers into two

[1] Restrictions on performance and stock selection imposed by regulators over pension funds in emerging markets lead their managers to trade the same (normally, top capitalization) stocks (Voronkova and Bohl, 2005).

[2] Funds following a particular style are likely to exhibit correlation in their trades as a result of benchmarking their investments against the same stock characteristic. For example, momentum trading funds will go long (short) on recent winners (losers), rendering it likely that several of the stocks they buy/sell will be the same.

categories, contingent upon whether the herding they generate is intentional or spurious. According to this distinction, the herding generated due to informational and professional reasons is considered *intentional*, as it is motivated by the anticipation of a payoff in situations characterized by relative asymmetry (more versus less well informed investors; better versus less able managers). On the other hand, relative homogeneity and characteristic trading are taken to promote *spurious* herding, in the sense that they lead to correlated trades as a result of commonalities (such as analyzing the same indicators or employing the same investment style) triggering similar responses among market participants, without imitation being present.[3]

Empirical research on herding has been extensive during the past two decades, covering a multitude of stock exchanges across the world, with evidence produced from studies at both the micro level[4] (using data on investors' accounts/transactions) and at the market wide level[5] (using aggregate data, such as securities' prices) being inconclusive. Herding has been found to be, on average, of greater magnitude in emerging markets, a finding that has been ascribed to these markets' investors being less experienced and the informational environment being less transparent (Gelos and Wei, 2005). Size has also been found to be a determinant of herding, and in particular for stocks belonging to the two capitalization extremes, the largest[6]

[3] For further evidence on intentional and spurious herding see also Galariotis et al. (2015, 2016b).

[4] Micro level herding studies focus on institutional and retail traders. Evidence in favour of institutional herding has been documented in Germany (Walter and Weber, 2006; Kremer and Nautz, 2013), Poland (Voronkova and Bohl, 2005), Portugal (Holmes et al., 2013), South Korea (Choe et al., 1999) and Spain (Gavriilidis et al., 2013), while Wylie (2005) found little evidence of herding among UK funds. Regarding US funds, earlier studies (Lakonishok et al., 1992; Grinblatt et al., 1995; Wermers, 1999) reported limited herding among them, with later research (Sias, 2004; Choi and Sias, 2009; Singh, 2013) finding their herding to be of higher magnitude. Evidence (Kumar and Lee, 2006; Dorn et al., 2008; Kumar, 2009) shows that retail investors also herd significantly.

[5] Evidence from market-wide herding studies suggests either the absence of herding (Christie and Huang, 1995; Demirer and Kutan, 2006) or is inconclusive (Chang et al., 2000; Caparelli et al., 2004; Goodfellow et al., 2009; Chiang and Zheng, 2010; Economou et al., 2011; Mobarek et al., 2014; Galariotis et al., 2015; Bernales et al., 2016).

[6] The presence of herding for the largest capitalization stocks may be caused by either regulatory or structural reasons. An example of the former are the regulatory requirements for pension fund managers in emerging markets that restrict their opportunity set of stocks to their markets' blue chips (Voronkova and Bohl, 2005). The latter refer to cases where funds' performance is benchmarked to that of a market's main index, whose composition fund managers may replicate in their portfolios to avoid deviating from the index-performance, ending up holding the same stocks – the constituents of the index – in the process (Walter and Weber, 2006).

(Wylie, 2005; Walter and Weber, 2006; Galariotis et al., 2016a) and the smallest[7] (Lakonishok et al., 1992; Wermers, 1999; Chang et al., 2000; Dang and Lin, 2016) capitalization stocks. Herding has also been found to vary in significance across industries internationally (Voronkova and Bohl, 2005; Choi and Sias, 2009; Zhou and Lai, 2009; Demirer et al., 2010; Gebka and Wohar, 2013), with this significance also being a function of market and industry specific conditions (Gavriilidis et al., 2013).

Although the bulk of the above herding research has been conducted on the basis of data with a frequency ranging from daily to annual, recent studies have expanded the scope of herding research to the intraday level. This development is in line with the notion that herding often manifests itself as a short term phenomenon (Froot et al., 1992) and is part of a wider attempt to capture intraday trading dynamics (see the excellent review by Amini et al., 2013) in view of financial technology advances that have allowed for increased trading in terms of size (markets are able to absorb larger trading volumes) and frequency (latency has decreased immensely[8]). In this context, Gleason et al. (2004) found no evidence of significant intraday herding in a sample of US sector ETFs, while Henker et al. (2006) reported the near absence of intraday herding in Australia both at the market wide and the sector levels. Zhou and Lai (2009) found significant intraday herding in the Hong Kong market, whose significance was more pronounced among smaller stocks, during market downturns and on the sell side. Finally, Blasco et al. (2011) reported significant intraday herding for the Madrid Stock Exchange, with Blasco et al. (2012) documenting a strong contemporaneous linear relationship between intraday herding and volatility in that market.

Nevertheless, the above studies on intraday herding have all been undertaken in the context of national stock exchanges and no study to date exists on this issue for cross-border exchanges, which are the products of the ongoing process of global financial integration. The onset of globalization since the 1990s with (i) the liberalization of international capital flows, (ii) the surge in international portfolio investments and (iii) the proliferation of cross listings (Aggarwal and Dahiya 2006) prompted national stock markets to transform their governance

[7] Small capitalization stocks entail higher information risk, since their limited analyst coverage leads to less information being available about them. Investors focusing on such stocks could deem herding a viable option in order to counter this informational uncertainty (if they consider the trades of others to be informative).

[8] Latency is defined as the time lapsing between the submission of the order and its execution. As Hasbrouck and Saar (2013) note, contemporary financial technology allows for latencies as low as 2-3 milliseconds.

structures (demutualization)[9] and enter into alliances with other exchanges internationally in order to seek synergies in areas (particularly those of business development and technological infrastructure) key in ensuring global competitiveness. This consolidating trend has been gathering momentum since the late 1990s, culminating in the evolution of several regional (the Euronext, OMX and London Stock Exchange Group in Europe; the BRVM and BVMAC in Africa; the Eastern Caribbean Securities Exchange in the Caribbean) and global (NYSE-EURONEXT; NASDAQ-OMX) cross-border exchange groups. A key feature of each of these stock exchange groups is the presence of a single trading system which becomes operational via the group's common trading platform. All stocks of the group's members are traded on that platform based on a harmonized trading protocol whose design is outlined in the group's uniform regulatory framework. These platforms comprise sophisticated technological infrastructure aimed at unifying trading, settlement and clearing across the group's constituent markets in order to provide favourable trading conditions characterized by low transaction costs, higher trading volumes and increased liquidity (Arnold et al., 1999; Pagano and Padilla, 2005; Nielsson, 2009). As the sophisticated financial technology of these platforms tends to reduce both the frictions in the trading process and the latency in the execution of orders, this renders the practice of any trading strategy more feasible, since the likelihood of investors being able to trade as many times within a trading session as their strategy requires, increases.

Given that the above is expected to facilitate intraday trading, the issue arising is whether intraday herding exists in cross-border markets. From a theoretical perspective it is not altogether clear whether intraday herding in such markets should be significant or not, the more so given the lack of research evidence on this issue; to that end, we now turn to present possible theoretical justifications in favour and against the presence of intraday herding in cross-border groups.

[9] Demutualization involves the switch of stock exchanges' governance model from mutual-ownership towards for-profit. Mutual ownership involves the participation of brokers-dealers holding seats in an exchange in the exchange's shareholding-ownership with voting rights; in others words, trading rights and ownership are inseparable in this governance model. Demutualized exchanges are limited liability companies whose shareholders are not necessarily involved in trading. The first step towards its transformation from mutual-ownership to for-profit is for the exchange to become a privately owned corporation. This is usually accomplished through the issue of shares and their allocation to members of the exchange, followed by (or coupled with) a private placement (where the exchange raises capital from its members and outside investors). The second step is for the exchange-company to go public and list itself on an exchange (very often, its own).

The case in favour of intraday herding in cross-border exchanges is founded on the following arguments. To begin with, these groups' trading platforms are characterized by enhanced transparency, which can end up facilitating observation among investors, rendering it easier for them to imitate each other. At the intraday level, this will hold if some intraday traders learn to recognize the intraday trading patterns of other investors and use them as signals to herd on. It is also possible that intraday strategies generate correlated trades themselves, due to them either being programmed to focus on similar signals (those based on computer algorithms; see Sornette and von der Becke, 2011; Chaboud et al., 2014) or based on similar technical trading rules (the case of day trading). Also, as mentioned previously, earlier event studies (Andrikopoulos et al., 2014; Economou et al., 2015)[10] have demonstrated that joining a cross-border exchange group (more specifically, the Euronext) has led herding to grow in significance in the group's member markets. Although these studies examine herding at lower frequencies (monthly and daily, respectively), the significant herding documented in Euronext markets following their entry into the group suggests it is not unlikely that the group itself will also exhibit significant herding.

The case against intraday herding in cross-border exchanges can be justified on the following arguments. On the one hand, the sophisticated trading infrastructure of such group is bound to enhance the participation of other sophisticated (presumably institutional) investors both from

[10] Andrikopoulos et al., (2014) and Economou et al., (2015) compare herding in Euronext's four constituent equity markets prior to and after their merger into the group. Andrikopoulos et al., (2014) measure herding at the monthly frequency for the January 1993 – October 2009 period and show that herding in Belgium, France and the Netherlands is significant (insignificant) following (before) these markets' merger into the Euronext; no evidence of herding significance was detected for Portugal, be it before or after its entry into the group. Economou et al., (2015) measure herding at the daily frequency for the January 1990 – December 2012 period and show that herding in Belgium, France and the Netherlands is significant (insignificant) following (before) these markets' merger into the Euronext; evidence of herding significance was detected for Portugal both before and after its entry into the group. Aside from examining herding at intraday frequencies (compared to the monthly and daily ones of these studies) our work differs from the above studies, since, instead of investigating the effect of Euronext-membership over herding in each of these four markets individually, it investigates herding within the Euronext as *a group (i.e. treating the Euronext as a single market)*, given the lack of prior work on herding in cross-border exchange groups as single market entities. This does not only allow us to gauge whether herding is significant in the Euronext as a *group* (i.e. *a single market*), but also whether herding in the Euronext *at the group-level* is subject to a series of effects widely established in the herding literature (size; industry) for national stock markets, while also testing for the presence of a country-effect (given that the group encompasses equity markets from four different countries).

within and outside the group's member markets, thus enhancing the heterogeneity of its investors' base. Considering that the bulk of intraday trading is expected to be undertaken by institutional investors (as a result of the technological firepower and financial resources at their disposal), one would anticipate such sophisticated investors to trade based on their signals rather than imitate their peers. What is more, intraday strategies entail notable heterogeneity[11] themselves, thus suggesting that their interaction should theoretically reduce the potential for intraday herding. Furthermore, the high transparency characterizing cross-border exchanges should – again theoretically – encourage investors focusing on intraday signals to rely more on them and reduce their incentive to herd.

In view of the above discussion, our study investigates intraday herding for the first time in the literature in the context of the Euronext, one of the first ever cross-border exchanges established internationally, following the merger of the equity, derivatives and clearing segments of the Amsterdam, Brussels and Paris stock exchanges on September 22nd 2000. The group expanded to encompass LIFFE derivatives market and the Lisbon stock exchange in 2002, while in 2007 it entered into a merger with the New York Stock Exchange culminating in the creation of the NYSE-Euronext group, currently the world's largest exchange. In view of the research questions our study addresses that we outlined earlier in this section, our results indicate the presence of significant intraday herding in the Euronext as a group for the whole sample period and for both intraday frequencies (60-minute; 120-minute) used, thus demonstrating for the first time that, beyond national markets, intraday herding is also evident in cross-border exchanges. We produce evidence in support of a size effect for both frequencies, with herding in the Euronext being significant among the highest and lowest capitalization stocks, yet not among middle capitalization securities. This is in line with extant literature's evidence denoting that it is mainly the largest and the smallest stocks that are prone to herding. The presence of an industry effect is also documented, with herding being detected in specific sectors (Financials, Consumer Goods, Healthcare, Industrials, Oil and Gas, Technology, and Utilities), thus indicating that industry effects in herding are not only present in individual stock exchanges, but can be traced in cross-border platforms as well. We also present evidence of a country effect, showing that herding is significant in Belgium, France and Portugal, but not in the Netherlands, irrespective of the frequency

[11] Algorithmic/high frequency strategies employed by institutional investors can involve market-making, arbitrage, directional trading, structural trading and manipulation (Hagströmer and Nordén, 2013), while *day-trading* on behalf of retail investors based on technical rules further contributes to this heterogeneity.

employed to estimate it. These country-specific results are robust when controlling in each market for the effect of the remainder of the markets' trading dynamics, with our results further suggesting that the four markets' dynamics significantly affect each other. Perhaps more interestingly, we find that herding in a market can be motivated through the dynamics of other markets: this is the case with the Netherlands, where herding is motivated by the dynamics of the group's other three markets in almost all tests. Finally, the onset of the 2007-09 financial crisis appears to have had an adverse effect over herding, with the latter being the least strong during the crisis period (1st of June 2007 – 9th of March 2009) compared to before and after it, consistent with research (Choe et al., 1999; Hwang and Salmon, 2004) denoting a decrease in herding following the outbreak of financial crises.

Our paper contributes significantly to the ongoing debate on herding, by providing evidence indicating for the first time that herding in a cross-border exchange group is a possibility and can entail qualitative features (such as size and industry effects) which have been to date widely reported for national stock exchanges in the literature. In view of the growing proliferation of such exchange groups internationally, our results point towards the need for herding research to devote more attention to them, in order to attain valuable insights into how herding manifests itself in these cross-border institutional settings. Furthermore, the fact that our evidence pertains to intraday frequencies contributes to our knowledge of intraday herding (particularly with respect to how the latter can be induced in a group's market via the trading dynamics of the group's other markets, as is the case of the Netherlands in our study), given the relatively limited research on this issue to date. These results are of particular relevance to the investment community, especially with regards to investors with a global investment outlook. On the one hand, the commonalities reported for the Euronext markets (considerable presence of herding; significant intra-group dynamics) render investing in a group's markets less beneficial in terms of international portfolio diversification. On the other hand, it is possible that the documented size, industry and country effects of herding can be utilized by investors for the purpose of formulating style strategies at the group level. These results are also of key interest to regulators in cross-border groups, since the latter's common trading platforms can allow the transmission of intraday herding incidents across their member markets with potentially destabilizing effects.

The rest of this paper is structured as follows. The next section provides an overview of the data and the methodology and presents some descriptive statistics. Section 3 presents and discusses the results and section 4 concludes by summarizing the paper's key findings and outlining their implications for investors and regulators.

2. Data and Methodology

2.1 Data

In this paper, we use an extensive intraday dataset of all trades reported on Euronext's four constituent markets (Amsterdam, Brussels, Lisbon and Paris) between January 2nd 2002 and December 31st 2010. The dataset has been obtained from Euronext N.V. and includes the following variables: exchange and instrument name, trade date and trade time in the nearest second, trade price, traded volume, currency and category type. The data on industry classifications are from the Thomson-Reuters Datastream database. We collect trades for all active, dead and suspended stocks to mitigate any survivorship bias in our results. We select equity trades only and drop trades that are not issued in the country that hosts the exchange and/or not denominated in Euros. We also delete half days and zero volume trades. Trading in the Euronext is conducted under the auspices of the French Nouvelle Système de Cotation (NSC), a hybrid trading platform and trading takes place between 09:00 and 17:25 (CET). In order to avoid any overnight and market closing effects, we drop the first 15 minutes and the last 10 minutes of the day which also allows us to create equal intervals during the trading day. We construct two intraday intervals: 60 minutes and 120 minutes. The choice of these two frequencies rests upon the fact that the number of stocks with observable trades decreases as one moves to higher frequencies and we wanted the number of securities included in our testing intervals to be from as wide a cross-section of stocks as possible in order for our herding estimations to be meaningful. Hence, for each stock and at each interval we select the first trade of the interval and estimate returns between two consecutive intervals. If there is no trade at an interval, we assign a return of zero.

2.2. Methodology

The notion of herding being detected through the clustering of stock returns around the market's consensus was first empirically formalized by Christie and Huang (1995), who proposed testing for herding using the following specification:

$$CSSD_{m,t} = \alpha_0 + \alpha_1 D^{UP} + \alpha_2 D^{DOWN} + e_t \quad (1)$$

In the above specification, D_t^{UP} (D_t^{DOWN}) assumes the value of one if market m's return falls in the extreme upper (lower) tail of the market return distribution[12], zero otherwise. CSSD is the cross-sectional standard deviation of returns and is calculated as:

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

In Equation (2), $r_{i,t}$ is the return of security *i* on interval *t*[13], $r_{m,t}$ is the average return of all securities (essentially, the average market return) during interval *t* and *n* is the total number of traded stocks in interval *t*. According to rational asset pricing (Black, 1972), the relationship between the cross-sectional dispersion of returns and the market's absolute return is positive given the different sensitivities of stocks to market movements, with the return dispersion increasing as market returns grow in absolute size. The latter is expected to be observed mostly during periods of extreme markets, suggesting that such periods would be characterized by higher values of cross-sectional return dispersion (hence, α_1 and α_2 would be expected in that case to be positive in the above model). If, however, investors were to discard their beliefs in favor of the consensus and resort to herding, stock returns should cluster more tightly around the market average, thus leading to lower values for the cross-sectional return dispersion; in that case, herding would be reflected in significantly negative values for α_1 and/or α_2.

A key issue with the above specification is that CSSD, as Economou et al. (2011) pointed out, is susceptible to the presence of outliers; another issue is that (1) assumes a strictly linear relationship between CSSD and market returns. In reality, however, returns in the market can be so extreme, that this relationship turns out to be nonlinear (instead of the anticipated linearly positive one described above). Chang et al. (2000) proposed the following specification to test for the possibility of nonlinearities in this relationship:

[12] Christie and Huang (1995) identified extreme up (low) returns with the 1% and 5% of the upper (lower) tail of the market return distribution.

[13] As noted, we employ 60- and 120-minute intervals for our herding estimations.

$$CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + e_t \quad (3)$$

The CSAD here is the cross-sectional absolute deviation of returns (used here instead of CSSD to mitigate the impact of outliers discussed above) and is calculated as follows:

$$CSAD_t = \frac{1}{n}\sum_{i=1}^{N}\left|r_{i,t} - r_{m,t}\right| \quad (4)$$

$r_{i,t}$ is the return of security *i* on interval *t*, while $r_{m,t}$ is the equal-weighted market return (i.e. the market's average[14]) during interval *t*. Equation (3) allows us to test for the significance of both the linear (reflected through $|r_{m,t}|$) and the nonlinear (reflected through the $r^2_{m,t}$) part of the relationship between the cross-sectional dispersion of returns and the absolute market returns. Under rational pricing assumptions, α_1 would be expected to be positive and α_2 insignificant; however, if herding grows in the market, α_2 should be significant and negative. Equation (3) is used to examine the significance of herding in the Euronext as a group and whether it is subject to size, industry and country effects.

Following Economou et al. (2015), we test whether the country effects are robust when controlling for the trading dynamics of the group's member markets by employing the following modified specification of (3) in line with Chiang and Zheng (2010):

$$CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + \alpha_3 r^2_{n,t} + e_t \quad (5)$$

In Equation (5), the squared return ($r^2_{n,t}$) of market n ($n \neq m$) is included in the right-hand side to test whether (i) it interacts significantly with market m's CSAD and (ii) its inclusion produces any effect over the herding of market m (i.e. whether it affects the significance of α_2). A significant value for α_3 would indicate an impact of market n's dynamics over market m and if its sign is negative, then this would indicate that market n is capable of inducing herding in market m (Chiang and Zheng, 2010).

Finally, to test for the effect of the 2007-09 global financial crisis on our results, we estimate equation (3) for each of the following three sub periods: pre crisis (2/1/2002 – 1/6/2007); in

[14] More formally, $r_{m,t}$ is calculated as $r_{m,t} = \frac{1}{n}\sum_{i=1}^{N} r_{i,t}$, where $r_{i,t}$ is the return of stock *i* during interval *t*. This is the equal-weighted average return of all *n* traded stocks in interval *t*.

crisis (4/6/2007 – 9/3/2009); and post crisis (10/3/2009 – 31/12/2010). Based on Andrikopoulos et al. (2012), we identify the financial crisis' window as the period between the peak of the Euronext 100 index on the 1st of June 2007 and its trough on the 9th of March 2009. Choosing this period allows us to cover all major financial events starting with the suspension of the three investment funds of BNP Paribas on the 9th of August 2007 and up to the G20 summit in London on the 2nd of April 2009.

2.3 Descriptive statistics

Table 1 presents a series of descriptive statistics regarding our database. Panel A outlines some key statistical measures for both CSAD and $r_{m,t}$ for the Euronext as a whole and for each of its constituent markets for both frequencies (60-/120-minute) employed here covering the entire sample period (January 2nd 2002 – December 31st 2010). Table 1 shows that the average CSAD is higher for the 120-minute interval, a finding that is confirmed for all markets individually and the Euronext as a whole. Moreover, the volatility of CSAD increases as the trading frequency decreases. The highest values for CSAD are reported for the Netherlands, followed by France, Belgium and Portugal, indicating the presence of variability in the dispersion of returns across the group's four markets. Panel B introduces the correlation matrix for the four markets' CSADs for both frequencies and Panel C the equivalent matrix for all four markets' $r_{m,t}$. The matrices presented demonstrate that there exists some positive correlation among the CSADs ($r_{m,t}$, respectively) of all four markets which tends to increase progressively as the frequency decreases (i.e. as we move from the 60- to the 120-minute frequency), while the smallest correlations in both matrices overall are observed for Portugal, the group's smallest market. Panel D presents the number of firms corresponding to each market and sector (details on the construction of sector portfolios are included in the next section).

Insert Table 1 around here

3. Empirical Evidence

3.1 Is herding significant in the Euronext as a group?

We begin our empirical analysis by assessing whether herding is significant at the group level in the Euronext. Table 2 presents the results from Equation (3) using Newey-West consistent estimators for frequencies of 60 and 120 minutes for the January 2002 – December 2010 period for the group as a whole. As the table shows, the values of the coefficient α_1 are significantly (1% level) positive for both frequencies, indicating that the cross-sectional absolute dispersion (CSAD) of returns increases with the magnitude of the market's return, a finding that is in line with the predictions of rational asset pricing models (Black, 1972). According to Chang et al. (2000), if herding ensues in the market, the relationship between the CSAD and the market's return will become nonlinear and the presence of herding itself will be reflected through a significantly negative α_2 coefficient. As Table 2 illustrates, this is indeed the case, since α_2 appears significantly (at the 1% level) negative in all tests, suggesting that there exists significant intraday herding in the Euronext as a group.[15] In view of the above, the results presented in Table 2 provide an affirmative answer to our first research question (i.e. whether herding is significant in the Euronext as a group), producing evidence for the first time of the existence of herding in cross-border groups.

Insert Table 2 around here

3.2 Is herding in the Euronext subject to the size effect?

We next test for the possibility that herding in the Euronext is subject to the size effect. To that end (and in line with Chang et al., 2000), we sort the universe of listed stocks (i.e. from all four constituent markets) each year according to their market capitalization at December 31st of the immediately preceding year[16], split them into five equal-sized quintiles (quintile 1 is the smallest, quintile 5 the largest) and estimate Equation (3) for each quintile. Results are reported in Table 3 and indicate that intraday herding is robustly significant (α_2 appears significantly negative at the 1% level) for quintiles 1, 4 and 5 for both frequencies (see Panels A and B) and for the 120-minute frequency only for quintile 2 (α_2 is significantly negative at the 5% level in Panel B for that quintile); no evidence of herding is found for quintile 3.[17] These results point towards the presence of a size effect in our findings, as they denote that intraday herding in the Euronext is detected among stocks of high- and low- (but not mid-) capitalization. These findings are in line with the aforementioned international evidence

[15] For robustness purposes, we repeated our tests using the following modified specification of equation (3): $CSAD_{m,t} = \alpha_0 + \alpha_1 r_{m,t} + \alpha_2|r_{m,t}| + \alpha_3 r^2_{m,t} + e_t$ (Chiang and Zheng 2010) with results confirming those reported in Table 2. Results are not included here in the interest of brevity, but are available upon request.

[16] Data on year-end market capitalizations was obtained from the Thomson Reuters Datastream database.

[17] We have also repeated our tests using the following modified specification of equation (3): $CSAD_{m,t} = \alpha_0 + \alpha_1 r_{m,t} + \alpha_2|r_{m,t}| + \alpha_3 r^2_{m,t} + e_t$ (Chiang and Zheng 2010) with results confirming those reported in Table 3. Results are not reported here in the interest of brevity, but are available upon request.

(Lakonishok et al., 1992; Wermers, 1999; Chang et al., 2000; Wylie, 2005; Walter and Weber, 2006) demonstrating that herding is most evident in extreme capitalization stocks. It is possible that our findings are related to the behaviour of different investor types when trading at the intraday level. For example, as high capitalization stocks are mainly held by institutional investors, who tend to employ intraday trading strategies, the presence of significant intraday herding for quintiles 4 and 5 can be attributed to the fact that these intraday strategies are often built around similar parameters in terms of indicators and signals (a reflection of the aforementioned relative homogeneity typifying the institutional trading segment), prompting those pursuing these strategies to exhibit correlation in their trades (spurious herding). Regarding quintile 1, which accommodates small capitalization stocks, typically held by retail investors, these market participants are often drawn to day trading motivated by behavioural factors (e.g. overconfidence), despite extant evidence indicating that excessive day trading proves detrimental to their wealth (Barber et al., 2014). With day trading strategies based predominantly on technical rules it is reasonable to assume that retail investors' day trading relies on similar indicators, thus giving rise to the significant intraday herding documented for this quintile. Another possibility is that part of this herding is due to fund managers copying their peers when trading small stocks mainly due to informational reasons (see e.g. Lakonishok et al., 1992; Wermers, 1999). Whatever the case, the relatively low volumes of small stocks would be expected to allow for a reduced expression of herding (they allow for fewer trades to be executed) compared to large stocks. Our results confirm this, with the values of α_2 always being smaller (in absolute terms) for quintile 1 compared to quintiles 4 and 5, indicating that herding is stronger for large stocks as opposed to the smallest ones.

Insert Table 3 around here

3.3 Is herding in the Euronext subject to industry effects?

To test whether herding in the Euronext presents us with industry effects, we split all stocks listed in the group's four constituent markets into ten industries[18] and estimate Equation (3) for each sector for both frequencies. The significant herding reported in Table 3 for stocks in quintiles 1, 4 and 5, prompts us to expect that herding would also appear significant for those

[18] The industries are: Basic Materials, Consumer Goods, Consumer Services, Financials, Healthcare, Industrials, Oil and Gas, Technology, Telecommunications and Utilities. The classification was based on the FTSE Industry Classification Benchmark (ICB) categories.

industries accommodating primarily stocks of the largest and smallest capitalisations. Results are reported in Table 4 (Panels A and B) and indicate the presence of significant herding (α_2 appears significantly negative at the 5% level) for the 60- and 120-minute frequencies (Panels A and B) in Consumer Goods, Healthcare, Industrials and Utilities and only for the 120-minute frequency (Panel B) in Financials, Oil and Gas and Technology.[19] No evidence of herding is detected in any of our tests for Basic Materials, Consumer Services and Telecommunications. Taken together, these results confirm the presence of industry effects in herding in the Euronext as a group. The fact that herding is significant in industries whose firms are traditionally ranked among the largest in capitalization terms (Financials, Oil & Gas, Healthcare and Utilities) is in line with the evidence presented in Table 3 on herding significance for the largest capitalization quintiles 4 and 5. As for the Technology sector, a possible explanation for the significant herding detected there is that the sector is characterized by higher perceived risk, as it comprises mainly of growth stocks of rather moderate or small size (Gavriilidis et al., 2013). It is interesting to note that some of the sectors for which we have found herding to be significant have been identified as being susceptible to herding in other markets as well. This is the case with Financials in Hong Kong (Zhou and Lai, 2009) and Spain (Gavriilidis et al., 2013), Technology, Industrials and Consumer Goods in Spain (Gavriilidis et al., 2013) and Oil and Gas globally (Gebka and Wohar, 2013).

Insert Table 4 around here

3.4 Is herding in the Euronext subject to country effects?

In the context of a cross-border group it is possible that herding varies in its significance across the group's markets and that herding in each of the group's markets is dissimilar to the herding witnessed at the group level; in other words, it is possible that there exists a country effect in the group's estimated herding. To explore this possibility, we estimate Equation (3) separately for each of Euronext's four equity markets (Belgium, France, the Netherlands and Portugal) and report our results in Table 5. As the estimates in Table 5 indicate, herding is significant (α_2 appears significantly negative at the 1% level) in all tests using both

[19] These results are robust when employing the following modified specification of equation (3): $CSAD_{m,t} = \alpha_0 + \alpha_1 r_{m,t} + \alpha_2|r_{m,t}| + \alpha_3 r^2_{m,t} + e_t$ (Chiang and Zheng 2010). Results are not reported here in the interest of brevity, but are available upon request.

frequencies for Belgium, France and Portugal, yet not for the Netherlands.[20] In view of the results in Table 2 denoting the presence of significant herding in the Euronext as a group, this suggests the presence of a country effect in the group's herding, with herding being significant in some markets (Belgium, France and Portugal), but not others (the Netherlands).[21] A possible explanation underlying this is the distinctively enhanced presence of overseas investors in the Dutch market compared to the group's other three markets. As Figure 1 illustrates, whereas the participation of foreign investors in Belgium, France and Portugal hovered around 28-46% during the 2002-2007[22] period, the corresponding figures for the Netherlands were in the 67-80% range (FESE Share Ownership Structure in Europe 2007 Survey). With foreign investors being institutional in nature, it is likely that the absence of herding in the Dutch market is due to it being dominated by sophisticated investors. It may also be the case that the global outlook characterizing the investments of foreign investors leads them to base their trades in any individual market on international asset allocation/diversification considerations, rather than herding towards that market's consensus.

Insert Table 5 and Figure 1 around here

3.5 Is herding in each market member affected by the trading dynamics of the other markets?

Membership in a cross-border group can lead to herding in one market being affected by the trading dynamics of the group's other constituent markets, more so given the common platform linking all the markets together; this raises the issue of whether the previously

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[20] As before, we have assessed the robustness of these results using the modified specification of Equation (3) ($CSAD_{m,t} = \alpha_0 + \alpha_1 r_{m,t} + \alpha_2|r_{m,t}| + \alpha_3 r^2_{m,t} + e_t$) proposed by Chiang and Zheng (2010). Results are essentially identical and are available upon request from the authors.

[21] These results are rather different to those reported by Andrikopoulos et al. (2014) and Economou et al. (2015) who found herding to be significant in the four Euronext constituent markets following their entry into the Euronext (with the exception of Portugal for Andrikopoulos et al. (2014), who detected no herding for that market after its inclusion in the Euronext). Of course, it is useful to keep in mind that, compared to our work, herding post-Euronext entry for each market was tested for sample windows ending in different time-points (October 2009 for Andrikopoulos et al. and December 2012 for Economou et al.) for these studies; what is more, the latter measured herding using lower frequencies (monthly and daily, respectively).

[22] We have not been able to trace data on investors' composition in these markets post-2007. However, it is highly unlikely that the notably high figures of foreign shareholder-ownership changed in the Netherlands post-2007, more so given the historically high participation of foreign investors in that market (see, for example, Nielsson (2009), who provided evidence denoting that foreign investors controlled around two-thirds of the equity volume of the Amsterdam market since the 1990s).

documented country effect is robust when taking these dynamics into account. Following Economou et al. (2015), we explore this issue using Equation (5), which is a modified specification of the Chang et al. (2000) herding model, incorporating the squared return of the group's other member markets in a market's herding estimations (Chiang and Zheng, 2010). Equation (5) is estimated for each of the four markets separately, for all possible combinations of markets.[23] Results are presented in Table 6 and by and large confirm the evidence on the country effect previously reported in Table 5. Herding is again significant (α_2 appears significantly negative at the 1% level) in Belgium, France and Portugal for all tests while once more insignificant in the Netherlands for all tests. The α_3 coefficient accounting for the effect of other markets' dynamics on each market's herding presents us with notably interesting results. As can be seen from Table 6, the values for almost[24] all tests relating to the Belgian, French and Portuguese markets are positive and significant (α_3 appears significantly positive at the 10% level), indicating that these three markets are significantly affected by the trading dynamics of their counterparts in the Euronext (without their herding significance being affected though, as discussed above). However, it is the results from the Netherlands that are most interesting in this regard, since, as Table 6 illustrates, almost all[25] α_2 values are significantly (5%) positive, while the α_3 values are almost all[26] significantly (at the 10% level) negative. In line with Chiang and Zheng (2010), this suggests that herding formation in the Netherlands is not a function of the market's domestic conditions (we found no such evidence in Table 5 either), but rather those of its peers in the Euronext.[27] This is probably not irrelevant to the previous discussion, since the dominance of foreign investors in

[23] Equation (5) is estimated for each market including the squared return of each of the other three markets in turn (i.e. it is run three times for each market). For example, in the case of Belgium, we estimate this equation first by including the squared return of the French market only on the right-hand side, then by including the squared return of the Dutch market only and then that of the Portuguese market only.

[24] The sole exception here is observed for the Portuguese market when controlling for the dynamics of the Dutch market at the 60-minute frequency, where α_3 is insignificant.

[25] The sole exception here is the test at the 120-minute frequency controlling for the Portuguese market's dynamics, for which α_2 is insignificantly negative.

[26] The sole exception here is the test at the 120-minute frequency controlling for the Portuguese market's dynamics, for which α_3 is insignificantly negative.

[27] According to the Chang et al. (2000) approach, herding in a market is reflected in the nonlinear relationship between the CSAD and the market's return. If by adding the squared market return of other markets in a market's herding equation we obtain significantly negative coefficients for that variable, then this suggests that herding in that market is induced by other markets' dynamics as well.

the Dutch market would be expected to render their investment decisions in the Netherlands more dependent on international market conditions (as opposed to domestic factors alone).[28]

Insert Table 6 around here

3.6 Does herding in the Euronext vary before, during and after the outbreak of the 2007-09 global financial crisis?

We finally turn to testing whether herding in the Euronext was affected by the global financial crisis in 2007-09. To that end, we estimate Equation (3) for the group as a whole before, during and after the financial crisis, in line with the sub periods defined in the previous section. Results are presented in Table 7 and they denote the presence of significant (α_2 appears significantly negative at the 5% level) herding for all tests performed (before, during and after the crisis) for both frequencies tested. It is interesting to note that, in absolute terms, α_2 presents us with the highest values prior to the crisis' outbreak and its smallest values during the crisis' period. These results suggest that herding, albeit significant throughout the 2002-2010 period, appears less strong during the 2007-2009 crisis period. A possible explanation for this is that the outbreak of the crisis led to the unearthing of novel fundamentals for the global economy, prompting investors to rely more on them to inform their trading and less on the pre-crisis consensus (upon which the heavy pre crisis herding was founded). In view of the previously discussed differences in herding significance among the Euronext markets, we also estimate Equation (3) for each market for each of the three sub periods (before; during; after the crisis) and report the results in Table 8. Herding in France exhibits significance irrespective of the sub period examined, with α_2 presenting us with its

[28] Whereas we find evidence of herding being induced in the Netherlands only by the trading dynamics of the other three Euronext-markets, Economou et al. (2015) document this to be the case for all four Euronext-markets. Aside from the differences in sample window and frequency between our study and theirs, it is also worth noting that they tested for the effect of other member markets' dynamics over each Euronext-market's herding using the following specification $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + \alpha_3 r^2_{n,t} + \alpha_4 CSAD_{n,t} + \varepsilon_t$ (equation 6, p 234). Essentially the difference between the two approaches hinges on the other markets' CSAD on the right-hand-side which we chose not to employ, as we wanted to focus on the interaction between market m's CSAD with the squared return of market n (since this would indicate to us whether herding in market m is induced by the trading dynamics of market n). Nevertheless, for robustness purposes, we have repeated our estimations in Table 6 using their specification and find qualitatively similar results to the ones presented here, which are not reported for brevity reasons and are available upon request.

highest (smallest) values in absolute terms after (during) the crisis' outbreak. Herding in Belgium is significant before and during the crisis only, with α_2 presenting us with higher values (in absolute terms) before the crisis' outbreak. Investors in Portugal herded significantly during and after the crisis' outbreak, with their herding appearing stronger in the post crisis period (α_2 bears higher values in absolute terms following the crisis' outbreak). The results for Belgium, France and Portugal hold for both frequencies tested; it is also interesting to note that the Dutch market furnished us with evidence of herding significance during the crisis' period for both frequencies. Overall, our results confirm the evidence presented so far on herding at the group level (significant herding in the Euronext as a group) and for each individual market (significant herding in Belgium, France and Portugal; near absence of herding in the Netherlands), while also indicating that the outbreak of the recent global financial crisis culminated in a reduction in intraday herding in the Euronext, a result consistent with research (Choe et al., 1999; Hwang and Salmon, 2004) denoting a decrease in herding following the outbreak of financial crises[29].

Insert Tables 7 and 8 around here

4. Conclusion

This paper investigates for the first time in the literature the presence of herding in a cross-border market group on the premises of the Euronext, one of the first ever such groups formed internationally. Drawing on tick data from Euronext's Trade-and-Quote database (TAQ) covering all trades conducted on all four Euronext constituent equity markets (Brussels, Paris, Amsterdam and Lisbon) between January 2002 and December 2010, we produce evidence showing that herding is significant in the Euronext as a group. Additional tests reveal that herding in the Euronext presents itself mainly for stocks of high and low capitalization and across several sectors, thus confirming the existence of size and industry effects. We also report evidence of a country effect, with herding being significant in Belgium, France and Portugal, but not in the Netherlands. This effect is robust when controlling for the impact of each market's trading dynamics over the remaining three markets, with the exception of the Netherlands, for which we find the other three markets' dynamics motivating herding. We attribute this finding to the fact that the Dutch market is

[29] For Tables 3 – 5 and 7, we have performed an F-test to test for the equality of α_2 across size quintiles, industries, countries and before/during/after the crisis period, respectively. Results uniformly reject the null hypothesis of the equality of coefficients across regressions (these results are available upon request).

overwhelmingly dominated by foreign investors, whose sophistication coupled with their global outlook would be expected to render their investment decisions in the Netherlands more dependent on international market conditions (as opposed to domestic factors). Finally, herding in the Euronext is found to be significant before, during and after the 2007-09 financial crisis period, with its presence being the least strong during the crisis.

Our findings present important implications for the investment community, particularly with regards to investors with a global investment outlook aiming to harness the benefits of international portfolio diversification. This is because the significant herding reported in this study for the Euronext suggests the presence of commonalities in trading dynamics within and across a cross-border group's markets. Assuming an investor wishes to invest in markets belonging to the same group, these commonalities would be expected to reduce the diversification benefits from such an investment. On the other hand, however, it is possible that the documented size, industry and country effects of intraday herding can be utilized by investors for the purpose of formulating intraday style strategies at the group level. From a regulatory perspective, these results are also of key interest in the context of cross-border groups, since the latter's common trading platforms can allow the transmission of intraday herding incidents across their member markets with potentially destabilizing effects.

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Table 1: Descriptive statistics

Panel A: Statistics for CSAD and $R_{m,t}$ for each of Euronext's constituent markets and Euronext as a whole

	Mean		Standard deviation		Maximum		Minimum		Skewness		Kurtosis		Number of observations
	CSAD	$r_{m,t}$	CSAD	$r_{m,t}$	CSAD	$r_{m,t}$	CSAD	$r_{m,t}$	CSAD	$r_{m,t}$	CSAD	$r_{m,t}$	
Belgium													
60 minutes	0.390	-0.013	0.222	0.168	3.447	2.443	0.017	-3.643	2.187	-1.108	10.425	21.462	18,196
120 minutes	0.497	-0.022	0.271	0.214	3.459	2.007	0.017	-2.913	2.012	-0.910	7.417	12.996	9,100
France													
60 minutes	0.512	-0.014	0.234	0.182	3.081	2.633	0.001	-2.191	1.872	-0.857	6.839	13.598	18,181
120 minutes	0.676	-0.025	0.319	0.247	3.563	2.869	0.155	-2.726	1.866	-1.191	6.209	13.294	9,092
Netherlands													
60 minutes	0.603	-0.034	0.717	0.472	14.718	4.653	0.081	-8.014	6.799	-3.334	69.148	38.419	18,173
120 minutes	0.826	-0.054	0.788	0.564	11.672	4.023	0.136	-6.626	4.932	-2.185	35.724	17.559	9,088
Portugal													
60 minutes	0.414	-0.005	0.297	0.290	3.376	4.148	0.010	-3.477	2.473	-0.086	10.140	16.673	14,291
120 minutes	0.577	-0.007	0.370	0.389	3.324	4.199	0.036	-3.768	1.908	0.017	5.669	12.935	7,150
Total EURONEXT													
60 minutes	0.495	-0.016	0.232	0.177	2.999	2.540	0.014	-2.418	1.931	-0.933	7.043	15.064	18,357
120 minutes	0.656	-0.027	0.315	0.241	3.232	2.863	0.167	-2.453	1.885	-1.172	5.960	13.424	9,180

Panel B: Correlation Matrix (CSAD)

	Belgium		France		Netherlands		Portugal	
	60m	120m	60m	120m	60m	120m	60m	120m
Belgium	-	-	0.791	0.837	0.472	0.567	0.474	0.535
France	0.791	0.837	-	-	0.494	0.583	0.490	0.535
Netherlands	0.472	0.567	0.494	0.583	-	-	0.325	0.414
Portugal	0.474	0.535	0.490	0.535	0.325	0.414	-	-

Panel C: Correlation Matrix ($r_{m,t}$)

	Belgium		France		Netherlands		Portugal	
	60m	120m	60m	120m	60m	120m	60m	120m
Belgium	-	-	0.632	0.715	0.511	0.603	0.411	0.498
France	0.632	0.715	-	-	0.633	0.697	0.499	0.553
Netherlands	0.511	0.603	0.633	0.697	-	-	0.420	0.477
Portugal	0.411	0.498	0.499	0.553	0.420	0.477	-	-

Panel D: Number of firms per country/sector

Sector	Basic Materials	Consumer Goods	Consumer Services	Financials	Healthcare	Industrials	Oil and Gas	Technology	Telecommunications	Utilities
Number of firms	85	280	294	334	97	405	32	309	25	36
Countries	Belgium	France	Netherlands	Portugal						
Number of firms	324	1,340	161	77						

Table 1 contains information on the descriptive statistics of our database. Panel A details statistics on the mean, standard deviation, maximum values, minimum values, skewness, kurtosis and number of observations for CSAD and $r_{m,t}$ for the Euronext as a group and for each of its constituent markets for two frequencies (60-/120- minutes) for the period January 2nd 2002 – December 31st 2010. Panels B and C contain the correlation matrices for CSAD and $r_{m,t}$ for the two frequencies and the four constituent markets. Panel D includes the number of firms for each country and sector.

Table 2: Herding in the Euronext as a group

	60-minute frequency	120-minute frequency
Constant	0.347	0.458
	(167.38)***	(128.32)***
$r_{m,t}$	1.406	1.415
	(56.99)***	(47.53)***
$r^2_{m,t}$	-0.238	-0.214
	(-6.54)***	(-7.38)***
R^2	0.548	0.538

The table presents Newey-West consistent estimates from the equation $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + e_t$ drawing upon the universe of listed stocks on the Euronext's equity segment (comprised of the equity markets of Belgium, France, the Netherlands and Portugal). Estimations are run for two frequencies (60-/120-minutes) for the January 2002 – December 2010 sample period. T-statistics are reported in brackets. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

Table 3: Herding and the size effect in the Euronext

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Panel A: 60-minute frequency results					
Constant	0.162	0.317	0.348	0.328	0.290
	(14.73)***	(68.33)***	(113.35)***	(165.22)***	(183.64)***
$r_{m,t}$	1.703	1.700	1.506	1.392	0.864
	(63.05)***	(69.48)***	(68.35)***	(65.35)***	(67.15)***
$r^2_{m,t}$	-0.0119	-0.00120	0.0722	-0.156	-0.0846
	(-6.87)***	(-0.10)	(6.59)***	(-5.30)***	(-7.55)***
R^2	0.925	0.797	0.763	0.500	0.560
Panel B: 120-minute frequency results					
Constant	0.289	0.422	0.456	0.438	0.397
	(31.33)***	(43.20)***	(94.80)***	(122.37)***	(137.07)***
$r_{m,t}$	1.769	1.857	1.528	1.355	0.822
	(72.99)***	(29.38)***	(45.53)***	(41.95)***	(45.48)***
$r^2_{m,t}$	-0.00926	-0.0927	0.0342	-0.186	-0.0585
	(-3.87)***	(-2.16)**	(2.39)**	(-5.13)***	(-4.70)***
R^2	0.898	0.688	0.648	0.520	0.576

The table presents Newey-West consistent estimates from the equation $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + e_t$ drawing upon the universe of listed stocks on the Euronext's equity segment (comprised of the equity markets of Belgium, France, the Netherlands and Portugal) split into five equal-sized quintiles. The quintile-construction process has followed the methodology proposed by Chang et al. (2000), according to which, we sort the universe of listed stocks (i.e. from all four constituent markets) each year according to their market capitalization at December 31st of the immediately preceding year and then split them into five equal-sized quintiles (quintile 1 is the smallest; quintile 5 the largest). Estimations are run for two frequencies (60-/120-minutes) for the January 2002 – December 2010 sample period for each quintile (Panels A-B). T-statistics are reported in brackets. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

Table 4: Herding and industry effects in the Euronext

	Basic Materials	Consumer Goods	Consumer Services	Financials	Healthcare	Industrials	Oil and Gas	Technology	Telecommunications	Utilities
Panel A: 60-minute frequency results										
Constant	0.263	0.278	0.343	0.210	0.339	0.303	0.218	0.439	0.161	0.182
	(58.26)***	(48.53)***	(133.09)***	(72.27)***	(129.70)***	(152.80)***	(90.43)***	(120.41)***	(25.78)***	(51.70)***
$r_{m,t}$	0.932	1.446	1.055	1.507	1.100	1.216	0.664	1.313	0.986	0.955
	(20.92)***	(20.64)***	(48.46)***	(43.86)***	(52.54)***	(65.83)***	(39.96)***	(45.62)***	(27.38)***	(29.84)***
$r^2_{m,t}$	0.0933	-0.238	0.158	0.0933	-0.0851	-0.141	0.0244	0.119	0.0888	-0.0764
	(1.76)*	(-2.54)**	(4.82)***	(2.68)***	(-3.48)***	(-6.02)***	(1.42)	(4.91)***	(4.14)***	(-2.18)**
R^2	0.586	0.549	0.552	0.805	0.456	0.548	0.447	0.650	0.706	0.481
Panel B: 120-minute frequency results										
Constant	0.355	0.380	0.451	0.274	0.476	0.406	0.284	0.587	0.245	0.229
	(73.59)***	(89.38)***	(106.92)***	(74.89)***	(108.58)***	(110.27)***	(74.15)***	(91.67)***	(35.96)***	(47.98)***
$r_{m,t}$	0.983	1.384	1.163	1.614	1.052	1.249	0.725	1.407	0.991	1.001
	(29.73)***	(39.03)***	(52.76)***	(47.90)***	(41.19)***	(46.92)***	(39.03)***	(37.08)***	(32.07)***	(31.59)***
$r^2_{m,t}$	0.0147	-0.132	0.00443	-0.0951	-0.111	-0.149	-0.0175	-0.0474	0.0714	-0.0843
	(0.45)	(-3.23)***	(0.37)	(-2.66)***	(-5.69)***	(-6.03)***	(-2.29)**	(-2.12)**	(4.40)***	(-3.21)***
R^2	0.571	0.553	0.519	0.737	0.439	0.540	0.474	0.570	0.703	0.522

The table presents Newey-West consistent estimates from the equation $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + e_t$ drawing upon the universe of listed stocks on the Euronext's equity segment (comprised of the equity markets of Belgium, France, the Netherlands and Portugal) split into ten industries in line with the FTSE ICB classification. Estimations are run for two frequencies (60-/120-minutes) for the January 2002 – December 2010 sample period for each industry (Panels A-B). T-statistics are reported in brackets. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

Table 5: Herding and country effects in the Euronext

	Belgium	France	Netherlands	Portugal
Panel A: 60-minute frequency results				
Constant	0.246	0.362	0.0961	0.202
	(133.02)***	(167.88)***	(7.86)***	(73.10)***
$r_{m,t}$	1.358	1.352	1.338	1.255
	(80.19)***	(56.89)***	(41.42)***	(60.48)***
$r^2_{m,t}$	-0.144	-0.197	0.261	-0.173
	(-9.85)***	(-5.72)***	(53.28)***	(-10.62)***
R^2	0.529	0.53	0.858	0.635
Panel B: 120-minute frequency results				
Constant	0.32	0.473	0.409	0.304
	(92.32)***	(125.21)***	(52.51)***	(60.31)***
$r_{m,t}$	1.361	1.386	1.184	1.194
	(39.12)***	(44.39)***	(28.22)***	(43.28)***
$r^2_{m,t}$	-0.156	-0.19	0.112	-0.157
	(-3.57)***	(-5.89)***	(6.22)***	(-8.75)***
R^2	0.566	0.532	0.78	0.599

The table presents Newey-West consistent estimates from the equation $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + e_t$ for each of Euronext's equity markets (Belgium, France, the Netherlands and Portugal). Estimations are run for two frequencies (60-/120-minutes) for the January 2002 – December 2010 sample period for each country (Panels A-B). T-statistics are reported in brackets. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

Table 6: The effect of member' trading dynamics over each market's herding

Market m:	Belgium			France			Netherlands			Portugal		
Control market n:	France	Netherlands	Portugal	Belgium	Netherlands	Portugal	Belgium	France	Portugal	Belgium	France	Netherlands
Panel A: 60-minute frequency results												
Constant	0.247	0.246	0.246	0.359	0.361	0.349	0.262	0.260	0.294	0.201	0.201	0.201
	(122.00)***	(131.61)***	(107.39)***	(128.23)***	(165.17)***	(158.40)***	(54.63)***	(58.74)***	(50.55)***	(71.53)***	(75.16)***	(72.50)***
$r_{m,t}$	1.324	1.350	1.303	1.374	1.345	1.267	1.374	1.445	1.006	1.253	1.256	1.255
	(62.35)***	(79.00)***	(51.70)***	(35.43)***	(55.61)***	(56.02)***	(41.65)***	(46.18)***	(17.54)***	(58.36)***	(64.10)***	(58.66)***
$r^2_{m,t}$	-0.209	-0.147	-0.154	-0.319	-0.208	-0.248	0.0909	0.0796	0.128	-0.184	-0.186	-0.179
	(-7.02)***	(-9.59)***	(-4.70)***	(-5.20)***	(-5.95)***	(-6.38)***	(7.47)***	(7.02)***	(2.49)**	(-10.50)***	(-11.05)***	(-10.11)***
$r^2_{n,t}$	0.156	0.00648	0.0489	0.166	0.00998	0.0598	-0.293	-0.598	-0.0831	0.0799	0.0550	0.0106
	(4.60)***	(5.07)***	(4.47)***	(2.52)**	(5.45)***	(4.85)***	(-3.08)***	(-8.40)***	(-5.03)***	(3.16)***	(1.83)*	(1.46)
R^2	0.535	0.532	0.540	0.537	0.535	0.541	0.861	0.868	0.660	0.636	0.636	0.635
Panel B: 120-minute frequency results												
Constant	0.320	0.319	0.315	0.472	0.471	0.453	0.408	0.404	0.408	0.302	0.303	0.300
	(74.17)***	(86.05)***	(74.87)***	(117.58)***	(121.92)***	(114.12)***	(53.43)***	(51.86)***	(58.01)***	(63.09)***	(63.72)***	(62.88)***
$r_{m,t}$	1.344	1.345	1.312	1.362	1.362	1.283	1.234	1.279	1.074	1.186	1.194	1.191
	(28.58)***	(34.91)***	(30.41)***	(38.06)***	(41.30)***	(37.29)***	(24.74)***	(28.12)***	(22.78)***	(47.69)***	(50.23)***	(47.81)***
$r^2_{m,t}$	-0.208	-0.166	-0.166	-0.272	-0.210	-0.261	0.106	0.103	-0.0403	-0.176	-0.179	-0.179
	(-2.80)***	(-3.33)***	(-2.85)***	(-5.82)***	(-5.83)***	(-6.52)***	(5.96)***	(6.01)***	(-1.11)	(-11.26)***	(-11.97)***	(-12.02)***
$r^2_{n,t}$	0.0770	0.0128	0.0324	0.215	0.0220	0.0468	-0.300	-0.357	-0.0114	0.147	0.0987	0.0428
	(3.04)***	(4.88)***	(3.92)***	(4.23)***	(6.73)***	(3.89)***	(-1.89)*	(-5.44)***	(-0.74)	(4.07)***	(3.36)***	(4.85)***
R^2	0.569	0.571	0.593	0.541	0.541	0.535	0.784	0.790	0.588	0.603	0.601	0.602

The table presents Newey-West consistent estimates from the equation $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + \alpha_3 r^2_{n,t} + e_t$ for each of Euronext's equity markets (Belgium, France, the Netherlands and Portugal), controlling for the trading dynamics of each of the other three markets (reflected here through $r^2_{n,t}$ in the right-hand side). Estimations are run for two frequencies (60-/120-minutes) for the January 2002 – December 2010 sample period for each country (Panels A-B). T-statistics are reported in brackets. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

Table 7: The effect of the 2007-2009 global financial crisis on herding in the Euronext as a group

	60-minute frequency			120-minute frequency		
	Before the crisis	During the crisis	After the crisis	Before the crisis	During the crisis	After the crisis
Constant	0.312	0.417	0.376	0.417	0.533	0.510
	(154.95)***	(95.30)***	(87.79)***	(101.47)***	(66.99)***	(70.00)***
$r_{m,t}$	1.785	1.110	1.130	1.762	1.152	1.007
	(77.64)***	(41.22)***	(28.56)***	(55.40)***	(29.72)***	(18.55)***
$r^2_{m,t}$	-0.503	-0.0621	-0.295	-0.367	-0.0924	-0.151
	(-15.20)***	(-2.89)***	(-4.81)***	(-13.35)***	(-3.50)***	(-2.26)**
R^2	0.567	0.579	0.430	0.541	0.598	0.436

The table presents Newey-West consistent estimates from the equation $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + e_t$ drawing upon the universe of listed stocks on the Euronext's equity segment (comprised of the equity markets of Belgium, France, the Netherlands and Portugal). Estimations are run for two frequencies (60-/120-minutes) for the following three sub periods: pre crisis (2/1/2002 – 1/6/2007); in crisis (4/6/2007 – 9/3/2009); and post crisis (10/3/2009 – 31/12/2010). T-statistics are reported in brackets. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

Table 8: The effect of the 2007-2009 global financial crisis on herding in Euronext's constituent markets

Panel A: 60-minute frequency results

	Belgium			France			Netherlands			Portugal		
	Before	During	After	Before	During	After	Before	During	After	Before	During	After
Constant	0.209	0.335	0.307	0.336	0.432	0.369	0.215	0.382	0.356	0.152	0.302	0.255
	(105.09)***	(72.09)***	(79.66)***	(161.15)***	(93.19)***	(77.91)***	(76.71)***	(71.18)***	(50.75)***	(68.30)***	(53.94)***	(49.73)***
$r_{m,t}$	1.434	1.237	0.995	1.586	1.113	1.256	1.684	0.809	0.776	1.286	1.090	1.037
	(56.70)***	(47.49)***	(29.62)***	(71.78)***	(38.94)***	(28.88)***	(171.12)***	(39.20)***	(26.50)***	(68.22)***	(49.45)***	(44.29)***
$r^2_{m,t}$	-0.193	-0.103	0.0322	-0.356	-0.0556	-0.358	0.0314	-0.0209	0.411	0.0734	-0.123	-0.124
	(-4.05)***	(-6.05)***	(0.73)	(-12.16)***	(-2.37)**	(-5.22)***	(12.46)***	(-1.94)*	(23.84)***	(3.55)***	(-11.00)***	(-7.67)***
R^2	0.517	0.532	0.475	0.530	0.558	0.441	0.215	0.382	0.356	0.694	0.598	0.567

Panel B: 120-minute frequency results

	Belgium			France			Netherlands			Portugal		
	Before	During	After	Before	During	After	Before	During	After	Before	During	After
Constant	0.277	0.418	0.387	0.440	0.551	0.497	0.333	0.513	0.556	0.236	0.432	0.375
	(82.49)***	(56.34)***	(60.91)***	(104.39)***	(65.88)***	(63.21)***	(54.77)***	(49.49)***	(38.71)***	(49.86)***	(40.97)***	(38.19)***
$r_{m,t}$	1.500	1.223	1.011	1.626	1.168	1.172	1.588	0.863	0.611	1.272	1.008	1.015
	(47.87)***	(32.00)***	(21.61)***	(53.81)***	(28.30)***	(20.36)***	(82.99)***	(29.02)***	(11.49)***	(36.96)***	(31.65)***	(30.71)***
$r^2_{m,t}$	-0.317	-0.0645	-0.0507	-0.281	-0.0965	-0.300	0.0429	-0.0575	0.380	-0.0233	-0.0920	-0.144
	(-8.59)***	(-2.31)**	(-0.94)	(-11.78)***	(-3.35)***	(-4.24)***	(7.71)***	(-4.65)***	(11.80)***	(-0.60)	(-6.92)***	(-8.10)***
R^2	0.500	0.632	0.512	0.538	0.572	0.429	0.869	0.567	0.624	0.590	0.566	0.538

The table presents Newey-West consistent estimates from the equation $CSAD_{m,t} = \alpha_0 + \alpha_1|r_{m,t}| + \alpha_2 r^2_{m,t} + e_t$ for each of Euronext's four equity markets (Belgium, France, the Netherlands and Portugal). Estimations are run for two frequencies (60-/120-minutes) for the following three sub periods: pre crisis (2/1/2002 – 1/6/2007); in crisis (4/6/2007 – 9/3/2009); and post crisis (10/3/2009 – 31/12/2010). T-statistics are reported in brackets. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.

Figure 1: Foreign investors' participation in shareholding ownership in Euronext's four constituent equity markets

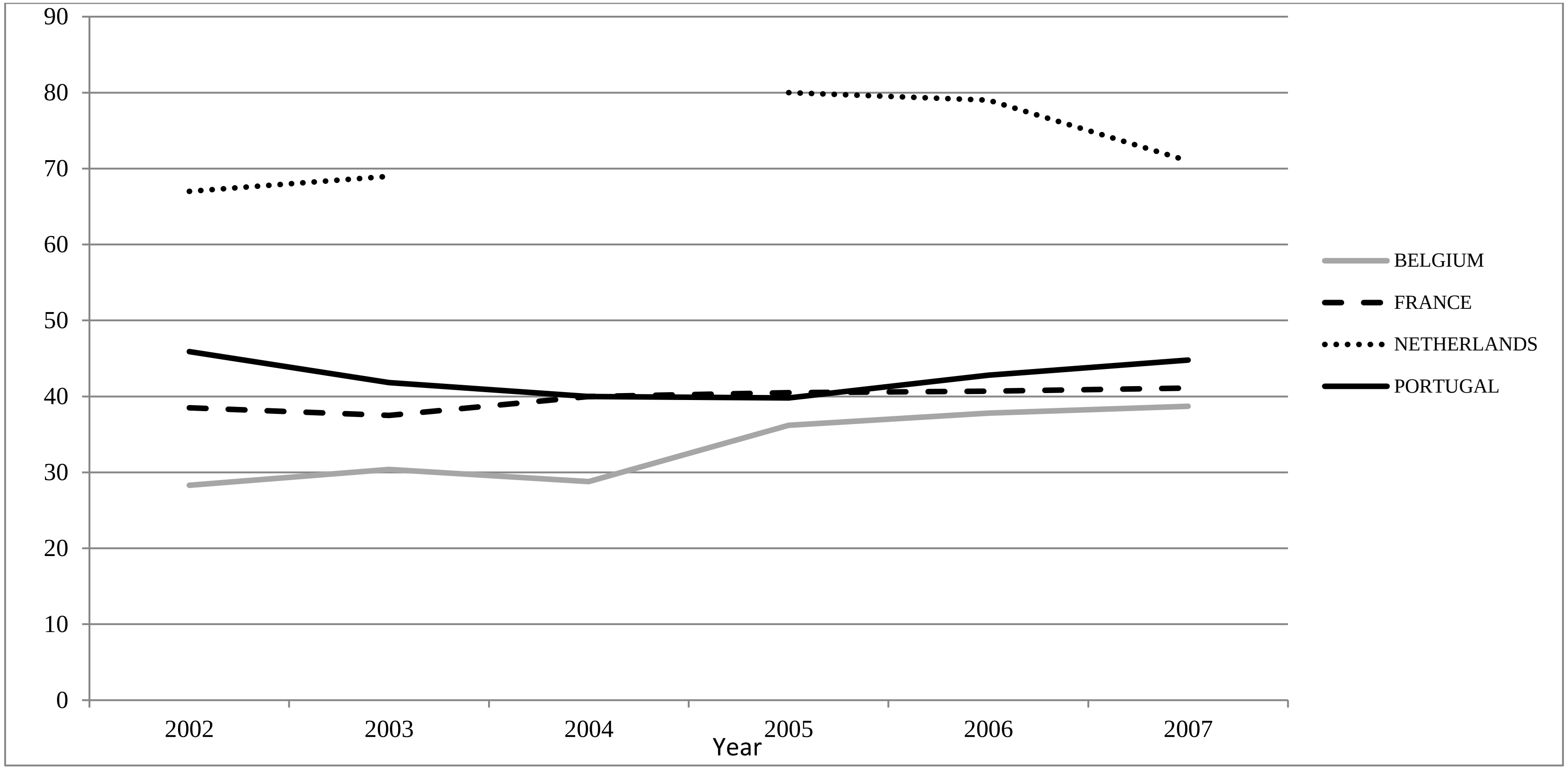

Figure 1 presents the percentage participation of foreign investors in the shareholding ownership in each of Euronext's four constituent markets. Data is available for the 2002-2007 period and was obtained from the Federation of European Securities Exchanges (FESE) Share Ownership Structure in Europe 2007 Survey. No data exists for the Netherlands for year 2004, hence the break in its line on that year.