# Intraday Herding in Cross-Border Exchanges:

# Evidence from EURONEXT

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**Abstract**

We study herding in a cross-border group drawing on an extensive high frequency dataset containing all trades from Euronext's four constituent equity markets (Belgium, France, the Netherlands and Portugal). Herding is significant in the Euronext as a group and presents us with size- and industry-effects. Country-effects are also documented with herding being significant in Belgium, France and Portugal but not in the Netherlands. We also find that the trading dynamics of the group's member-markets significantly affect each other and can (in the case of the Netherlands) promote herding formation. Herding is found to be significant both during and outside the 2008 financial crisis period, with its magnitude found to be higher during the crisis. Overall, we demonstrate for the first time in the literature that cross-border exchanges harbour versatile herding dynamics, while the fact that these are detected at high frequencies suggests that a key part of them may be due to high-frequency trading.

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## 1. Introduction

Research interest in the behaviour of investors at the intraday level has exhibited a notable surge during the past decade as a result of the advances in financial technology that have enabled stock markets to handle large trading volumes (Aggarwal and Dahiya, 2006) and given investors the opportunity of trading at higher frequencies through low-latency in order-execution (Hasbrouck and Saar, 2013). In this context, a behavioural pattern that has been the focus of much recent research (Gleason et al, 2004; Henker et al, 2006; Zhou and Lai, 2009; Blasco et al, 2011, 2012) is intraday herding, with evidence to date on the significance of its presence being inconclusive. Although intraday herding has been investigated in a variety of national stock markets, it is interesting to note that no study to date has examined it in cross-border exchanges, despite the proliferation of the latter internationally since the onset of the globalization process in the 1990s. To that end, our study addresses for the first time in the literature whether intraday herding is significant in the context of a cross-border exchange by investigating its presence in the Euronext, one of the first cross-border groups to be launched.

The issue of cross-border herding in exchange groups poses several interesting questions. Firstly, we investigate whether established determinants (size, industry[1]) of herding in individual stock markets are relevant to herding in cross-border exchanges. Secondly, we explore whether a country-specific herding effect is present (i.e. whether herding within a cross-border group varies in its significance across its member-markets). Most importantly, in view of the role of cross-border exchanges as vehicles of financial integration, we investigate whether herding in one of the group's member-markets is affected by trading dynamics in the group's other markets. Finally, a fourth issue relates to the effect of the 2008 global financial crisis upon our results, in view of evidence (Choe et al, 1999; Kim and Wei, 2002; Hwang

[1] For more on the role of size and industry in herding see Lakonishok et al (1992), Wermers (1999), Voronkova and Bohl (2005), Choi and Sias (2009) and Gavriilidis et al (2013).

and Salmon, 2004; Chiang and Zheng, 2010; Mobarek et al, 2014) suggesting that crisis-episodes constitute turning points in herding.

Theoretically, 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 Teh, 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[2]. Characteristic trading (Bennett et al, 2003), namely trading strategies ("styles") basing stock-selection on specific stock-characteristics (such as past performance, size and sector), is rather popular among fund

[2] Evidence (Voronkova and Bohl, 2005) suggests that the restrictions imposed by regulatory authorities in terms of performance and stock-selection over pension funds in emerging markets lead their managers to trade similar stocks, normally those with the highest capitalization.

managers and can also lead to similarities in their trades[3]. Recent research (Holmes et al, 2013; Gavriilidis et al, 2013) has grouped the above herding drivers into two 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.

Empirically, research on the presence of herding has been extensive during the past two decades, covering a multitude of stock exchanges across the world, with evidence on herding presence 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'

[3] 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, funds that momentum-trade will tend to go long on recent winners and short on recent losers, which renders it likely that several of the stocks they buy/sell will be the same.

[4] Micro-level herding studies focus on specific investor-types, such as institutional and retail investors. 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. Earlier studies (Lakonishok et al, 1992; Grinblatt et al, 1995; Wermers, 1999) reported limited herding among US funds, with later research (Sias, 2004; Choi and Sias, 2009) finding higher levels of herding in the US institutional investors' community. As far as research on the non-institutional segment is concerned, recent studies (Kumar and Lee, 2006; Dorn et al, 2008; Kumar, 2009) have produced evidence in support of the presence of herding among retail investors.

[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;

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] (Wylie, 2005; Walter and Weber, 2006) and the smallest[7] (Lakonishok et al, 1992; Wermers, 1999; Chang et al, 2000) capitalization stocks. Finally, evidence indicates that herding varies in significance across different industries internationally (Voronkova and Bohl, 2005; Choi and Sias, 2009; Zhou and Lai, 2009; Demirer et al, 2010; Gebka and Wohar, 2013)[8], with this significance also being a function of market- and industry-specific conditions (Gavriilidis et al, 2013).

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Chiang and Zheng, 2010; Economou et al, 2011; Gebka and Wohar, 2013; Mobarek et al, 2014; Galariotis et al, 2014).

[6] The presence of herding for the largest capitalization stocks may be caused by either regulatory or structural reasons. The former relate to 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 those cases in which the performance of funds is benchmarked to that of a market's main index; in that case, fund managers may replicate the composition of the index 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).

[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 would, therefore, deem herding a viable option in order to counter this informational uncertainty (if they consider the trades of others to be informative). Also, the fact that small stocks enjoy lower volumes (i.e. they are subject to high liquidity risk) implies that investors can only trade in them when other investors do so (i.e. when the volume of trading picks up) and this inevitably increases the likelihood of herding.

[8] Voronkova and Bohl (2005) find that Polish pension funds herd significantly across stocks of various sectors on the Warsaw stock exchange (with their herding appearing to be highest for the Banking and Metals sectors), while Choi and Sias (2009) also present strong evidence of institutional industry herding for the US. Demirer et al (2010) find evidence of significant herding in almost all industries in the context of the Taiwanese market, while Zhou and Lai (2009) report significant herding among Financials and Construction and Property stocks in Hong Kong. Finally, Gebka and Wohar (2013) document evidence of herding significance internationally in specific sectors (Basic Materials, Consumer Services and Oil and Gas).

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 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, both in terms of size (markets are becoming more able to absorb larger trading volumes) and frequency (latency has decreased immensely leading to the proliferation of high frequency trading[9]). 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 exists for cross-border exchanges. 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 structures (demutualization)[10] and enter into alliances with other exchanges internationally in

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

[10] 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

order to seek synergies in areas (particularly those of business development and technological infrastructure) key in ensuring global competitiveness.[11] This consolidating trend has been gathering momentum since the late 1990s, culminating in the evolution of several cross-border exchange groups with regional (the Euronext in Western Europe; the OMX in Northern Europe; the BRVM in Western Africa; the BVMAC in Central Africa) and global (NYSE-EURONEXT; NASDAQ-OMX) dimensions. A key feature of each cross-border group is the presence of a single trading system which becomes operational via the group's common trading platform. All stocks of the group's member-markets 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). Such environments are particularly appealing to traders employing automated systems ("algorithms"[12]) as they allow them to make full use of their

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inseparable in this governance model. Conversely, demutualized exchanges are limited liability companies whose shareholders are not necessarily involved in trading. The first step towards the transformation from mutual-ownership to for-profit structures 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 (who now become legal owners), followed by (or coupled with) a private placement (where the exchange raises capital from its members as well as outside investors). The second step is for the exchange-company to go public and list itself on an exchange (very often, its own).

[11] Traditional stock exchanges had to face competition not only from other stock exchanges but also from non-exchange electronic trading venues. The latter came to be known as Alternative Trading Systems (ATS) and received regulatory treatment first in the US through The Regulation of ATS of 1998. Electronic Communications Networks (ECNs) are typical examples of ATS. ATS are also often referred to as "dark pools", in the sense that they aim to match blocks of buy and sell orders from traders anonymously, with the details (price, volume) of orders being invisible (hence "dark") prior to order-execution.

[12] Algorithmic trading involves the execution of orders based on a set of pre-defined parameters (regarding execution-time, price, volume or holding-time among others) encoded in a computer algorithm. It is primarily used by financial intermediaries (e.g. brokers) for non-proprietary trading purposes and involves trade horizons

computational/technological firepower to trade at very high frequencies.[13] The growing participation of high-frequency traders in equity volumes worldwide[14] and the fact that the world's two largest exchanges (NYSE-EURONEXT; NASDAQ-OMX) are cross-border suggests the presence of intraday trading dynamics in these groups and we now turn to discussing how these dynamics can promote or inhibit intraday herding.

To begin with, an increased presence of high-frequency trading in a cross-border group allows for greater heterogeneity in each of the member-markets and the group as a whole due to both the multiple classes of high-frequency strategies[15] and the fact that high-frequency traders ("fast" traders) have to interact in the group's markets with other investors trading at lower frequencies ("slow" traders). This should lead to new intraday dynamics while enhancing the diversity in trading activity for the group as well as its constituent markets and it would be reasonable to assume that this would imply a reduced potential for herding at the

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of a day or more. For more detail, see Norges Bank Investment Management (NBIM) Discussion Note #1 (2013).

[13] High-frequency trading is a form of algorithmic trading relying on high-speed computer algorithms ensuring very low latency and is undertaken for proprietary reasons primarily by investment banks and hedge funds. High-frequency traders aim at capturing ultra-short market movements (their horizon is often measured in seconds or fractions of a second), which often leads them to maintain a very high order-to-transaction ratio (most orders are cancelled/updated in view of rapidly – given these traders' very short trading horizons – changing market conditions). An example of this is presented in Hagströmer and Nordén (2013) who showed that high-frequency traders on the Stockholm stock exchange had order-to-transaction (also known as quote-to-trade) ratios in the 10-15 region, implying that, for every 10-15 orders placed, only one resulted in an actual trade; conversely, non-high-frequency trading investors had order-to-transaction ratios that did not exceed 3.

[14] The US Security Exchange Commission's Concept Release on Equity Market Structure (Securities Exchange Act Release No. 34-61358, 75 FR 3594, 3606, January 21st 2010) shows that high-frequency trading accounts for over 50% of total US equity trading. According to the Netherlands Authority for Financial Markets 2010 report on high-frequency trading, the corresponding percentages for European markets hover between 20-40%, while high-frequency traders make up around half of all equity trading on the Tokyo stock exchange (*U.S. High-Frequency Trading Firms Look Eastward, http://www.wallstreetandtech.com/infrastructure/us-high-frequency-trading-firms-look-eastward/a/d-id/1264813?*, May 11th 2011).

[15] High-frequency trading strategies can involve market-making, arbitrage, directional trading, structural trading and manipulation, to mention but a few. For more on these strategies, see Hagströmer and Nordén (2013).

intraday level. This is further supported by the fact that in high-frequency trading it is the algorithm rather than the human that is empowered with the decision to trade, which renders the intentional herding drivers noted previously (informational and professional) less relevant in this context.

However, an increased presence of high-frequency trading in a cross-border group is also capable of amplifying intraday herding in at least two ways. On the one hand, it is possible that the algorithms themselves generate correlated trades, due perhaps to them being programmed to focus on similar signals (Sornette and von der Becke, 2011; Chaboud et al, 2014) and this can obviously boost herding at high frequencies. At the extreme, it can also lead to short-lived episodes, the most typical case being the mini flash crash of May 2010 in the US.[16] In view of our earlier discussion, the herding generated in such a fashion would be classified as spurious, motivated by the relative homogeneity of high-frequency traders (or their algorithms).[17] On the other hand, intraday herding can arise through the interaction between "fast" and "slow" traders. The technological superiority of high-frequency traders

[16] On May 6th 2010 around 14:32, the algorithm of a US mutual fund entered an order involving the sale of 75,000 shares of the E-mini S&P500 futures contract, with the value of the order estimated at $4.1 billion. The order triggered massive sales on behalf of high-frequency traders' algorithms, which started trading amongst themselves in an effort to sell their shares in the contract. The downward loop created in the contract's price is clearly reflected in the fact that between 14:45:13 and 14:45:27 high-frequency traders traded well over 27,000 contracts, around 49 per cent of the contract's total trading volume. By 14:45:28, the market's system paused for five seconds (the phenomenal slump led to a stop-logic functionality of the trading system), following which prices reverted to normal. During the crash – which lasted a few minutes – the Dow Jones Industrials index lost around 600 points which it recouped a few minutes later.

[17] A relevant issue here is that the high-frequency trading community is rather narrow in terms of numbers, consisting mainly of large algorithmic institutional investors and investment banks trading for proprietary reasons (Netherlands Authority for Financial Markets 2010 report on high-frequency trading). An interesting description of the community in the US is provided by Sornette and von der Becke (2011): "Some sources suggest that HFTs make up 2% of approximately 20,000 trading firms in the U.S. and account for about 60-70% of equity trading volume. These are suggested to include a small number of investment banks, less than 100 hedge funds and hundreds of specialist prop shops" (Sornette and von der Becke, 2011, p. 9).

allows them the opportunity to be among the very first to observe signals in the market and trade on them before "slow" investors (those who either do not use algorithms or whose algorithms operate at lower frequencies). This means that the trades from the high-frequency segment of market participants will shape the market's initial reaction to a signal, raising the possibility that "slow" investors will follow up by herding in the direction of high-frequency trades[18]. Although the above two possibilities can theoretically lead to intraday herding in any individual market with a significant presence of high-frequency traders, they would be expected to be stronger in cross-border groups, since the presence of a common trading platform in a group can give rise to group-wide (i.e. across the group's member-markets) intraday herding dynamics.

In view of the above discussion, our study investigates intraday herding in cross-border exchange groups for the first time in the literature. We use nine years of tick data (January 2002 – December 2010) for all firms trading on the Euronext, one of the first-ever cross-border exchanges established internationally, comprising of the stock exchanges of Amsterdam, Brussels, Lisbon and Paris[19]. We address the following research questions:

(i) Is there significant intraday herding in the Euronext as a group?

(ii) Is the significance of intraday herding in the Euronext robust when controlling for the effects of size, industry and country?

[18] The possibility of this occurring for manipulative reasons has not escaped the attention of regulatory authorities; see, for example, the Economic and Financial Newsletter of the French Financial Regulatory Authority (Autorité des Marchés Financiers – AMF), issue 1 (2013-14).

[19] Euronext came to life on September 22nd 2000 following the merger of the equity, derivatives and clearing segments of the Amsterdam, Brussels and Paris stock exchanges although the official announcement of the merger had already been made in March 2000. The group soon expanded to encompass LIFFE 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).

(iii) Is the significance of intraday herding in any single member-market affected by trading dynamics in the other member-markets?

(iv) Did the significance of intraday herding in the Euronext vary with the onset of the global financial crisis in 2008?

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, 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 the aforementioned 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 also 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 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 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 2008 financial crisis appears to have had little effect on the prevalence of herding, with the latter being significant both during (August – December 2008) and outside the crisis-period. It is worth noting, however, that the magnitude of herding is considerably higher during the crisis-period, compared to before and after it, consistent with prior research (Kim and Wei, 2002; Chiang and Zheng, 2010; Mobarek et al, 2014) which found an increase in herding following the outbreak of financial crises.

Our paper produces two distinct contributions to the ongoing debate on herding. Firstly, it demonstrates that cross-border exchanges are capable of generating significant herding at high frequencies, with this herding found to exhibit properties (effects of size, industry and crises) widely documented in the literature for individual capital markets. Secondly, it shows that trading dynamics among a group's markets are significantly interrelated and can, occasionally, give rise to herding within a group's member-markets (the case of the Netherlands). 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, however, 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. What is more, these results are also of key interest to regulators, since the fact that the herding documented here occurs at high frequencies suggests that a substantial part of it is probably due to high-frequency trading. Combining the dominant position of high-frequency traders in international equity investments, their potential for inciting destabilizing episodes (such as the May 2010 flash-crash in the US) and the fact that we found evidence of stronger herding during the 2008 crisis suggest that it is necessary for regulators to equip themselves with sophisticated technological tools to monitor high-frequency trading activity. This is particularly important in the context of cross-border groups, whose common trading platforms can allow the transmission of 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 2$^{nd}$ 2002 and December 31$^{st}$ 2010. The dataset includes the following variables: exchange and instrument name, trade date and trade time, 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 on the premises 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 on the premise of the following specification:

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

In the above specification, $D_t^U$ ($D_t^L$) assumes the value of one if the market's return falls in the extreme upper (lower) tail of the market return distribution, zero otherwise. CSSD is the cross-sectional standard deviation of returns and is calculated as:

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

In Equation (2), $r_{i,t}$ is the return of security *i* on interval *t*[20], $r_{m,t}$ is the average return of all securities (essentially, the average market return) during interval *t* and *n* is the total number of

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

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, $\alpha_1$ and $\alpha_2$ 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 $\alpha_1$ and/or $\alpha_2$.

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 non-linear (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:

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

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:

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

$r_{i,t}$ 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) during interval *t*. Equation (3) allows us to test for the significance of both the linear (reflected through $|r_{m,t}|$) and the non-linear (reflected through the $r^2_{m,t}$) part of the relationship between the cross-sectional return-dispersion and absolute market returns. Under rational pricing assumptions, $\alpha_1$ would be expected to be positive and $\alpha_2$ insignificant; however, if herding grows in the market, $\alpha_2$ should be significant and negative. Equation (3) is used to address questions (i) and (ii) outlined in the previous section.

To test for the effect of member-markets' trading dynamics (research question (iii)) over each market's herding, we employ the following modified specification of (3) in line with Chiang and Zheng (2010):

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

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 $\alpha_2$). A significant value for $\alpha_3$ 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 2008 global financial crisis on our results (research question (iv)), we employ the following specification:

$$CSAD_{m,t} = \alpha_0 + \alpha_1 D^{CRISIS}|r_{m,t}| + \alpha_2(1-D^{CRISIS})|r_{m,t}| + \alpha_3 D^{CRISIS} r^2_{m,t} + \alpha_4(1-D^{CRISIS})\, r^2_{m,t} + e_t \qquad (6)$$

In the above equation, $D^{crisis}$ assumes the value of one during the August – December 2008 period, zero otherwise.

*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 $\alpha_1$ 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 non-linear and the presence of herding itself will be reflected through a significantly negative $\alpha_2$ coefficient. As Table 2 illustrates, this is indeed the case, since $\alpha_2$ appears significantly (at the 1% level) negative in all tests, suggesting that there exists significant intraday herding in the Euronext as a group.[21] 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

[21] 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 interests of brevity, but are available upon request.

all four constituent markets) each year according to their market capitalization at December 31st of the immediately preceding year, 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 ($\alpha_2$ 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 ($\alpha_2$ is significantly negative at the 5% level in Panel B for that quintile); no evidence of herding is found for quintile 3.[22] 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 (Lakonishok et al, 1992; Wermers, 1999; Chang et al, 2000; Wylie, 2005; Walter and Weber, 2006) demonstrating that herding is most evident in capitalization-extremes. The presence of significant intraday herding for the top two capitalization quintiles may be attributable to high frequency traders (due e.g. to correlations in their algorithms' parameters), who would be expected to be attracted to these stocks, since the latter's high liquidity facilitates the implementation of low-latency strategies. As for the herding observed in quintile 1, it is less likely to be driven by high frequency traders, since small stocks' relatively low liquidity is not conducive to low latencies of trading. Small capitalization stocks are mainly held by retail investors and one possibility is that herding among these stocks in this case is due to behavioural factors to which retail investors have been found to be particularly susceptible (Barber et al, 2009). Another possibility is that part of this herding is due to fund managers who have been found (see e.g. Lakonishok et al, 1992; Wermers, 1999) to copy their peers when trading small stocks mainly due to information reasons. Whatever the case, the

[22] 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 interests of brevity, but are available upon request.

relatively low volumes of small stocks would be expected to allow for a reduced expression of herding (they allow for less trades to be executed) compared to large stocks. Our results confirm this, with the values of $\alpha_2$ 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[23] and estimate Equation (3) for each sector for both frequencies. Results are reported in Table 4 (Panels A-B) and indicate the presence of significant herding ($\alpha_2$ 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.[24] 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. The fact that herding is significant for sectors whose firms are traditionally ranked among the largest in capitalization terms (Financials, Oil and Gas and Utilities) is in line with the evidence presented in Table 3 on herding significance for the two largest capitalization quintiles. As for the Technology sector, a possible explanation for the significant herding detected there is that the sector is

[23] 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.

[24] 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.

characterized by higher perceived risk, as it comprises mainly of growth stocks of rather moderate 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 ($\alpha_2$ appears significantly negative at the 1% level) in all tests using both frequencies for Belgium, France and Portugal, yet not for the Netherlands.[25] 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). 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. Whereas the participation of foreign investors in Belgium, France and Portugal hovered around 28-46%

[25] 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.

during the 2002-2007[26] period, the corresponding figures for the Netherlands were in the 67-80% range (FESE Share Ownership Structure in Europe 2007 Survey).[27] 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 around here***

*3.5 Is herding in each member-market 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. 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[28]. Results are presented in Table 6 and by and large confirm the estimates previously reported in Table 5. Herding is again significant ($\alpha_2$ appears

[26] We have not been able to trace data on investors' composition in these markets post-2007.

[27] The percentages of foreign investors' participation in shareholder ownership in each of the four markets is given for each year as follows: Belgium (2002 = 28.3; 2003 = 30.4; 2004 = 28.8; 2005 = 36.2; 2006 = 37.8; 2007 = 38.7); France (2002 = 38.5; 2003 = 37.5; 2004 = 40.0; 2005 = 40.5; 2006 = 40.7; 2007 = 41.1); Netherlands (2002 = 67.0; 2003 = 69.0; 2004 = N/A; 2005 = 80.0; 2006 = 79.0; 2007 = 71.0); Portugal (2002 = 45.9; 2003 = 41.8; 2004 = 40.0; 2005 = 39.8; 2006 = 42.8; 2007 = 44.8).

[28] 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.

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 $\alpha_3$ 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[29] all tests relating to the Belgian, French and Portuguese markets are positive and significant ($\alpha_3$ 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[30] $\alpha_2$ values are significantly (5%) positive, while the $\alpha_3$ values are almost all[31] 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.[32] This is probably not irrelevant to the previous discussion, since the dominance of foreign investors in 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).

***Insert Table 6 around here***

[29] 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 $\alpha_3$ is insignificant.

[30] The sole exception here is the test at the 120-minute frequency controlling for the Portuguese market's dynamics, for which $\alpha_2$ is insignificantly negative.

[31] The sole exception here is the test at the 120-minute frequency controlling for the Portuguese market's dynamics, for which $\alpha_3$ is insignificantly negative.

[32] 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.

*3.6 Does herding in the Euronext vary within versus outside the 2008 global financial crisis?*

We finally turn to testing whether herding in the Euronext was affected by the global financial crisis in 2008. To that end, we use Equation (6) for the group as a whole, in order to test whether herding was stronger during or outside the financial crisis period (defined here as the window between August and December 2008[33]). Results are presented in Table 7 and they denote the presence of significant ($\alpha_3$ and $\alpha_4$ appear significantly negative at the 5% level) herding for all tests performed both during and outside the crisis. It is interesting to note that the values of $\alpha_3$ are notably higher in absolute terms than those of $\alpha_4$, suggesting that herding grew stronger during the crisis. In view of the previously discussed differences in herding significance among the Euronext markets, we also estimate Equation (6) for each market and report the results in Table 8. As the Table suggests, herding is significant ($\alpha_3$ and $\alpha_4$ appear significantly negative at the 1% level) both during and outside the crisis for all tests in Belgium, France and Portugal, with the values of $\alpha_3$ being again higher in absolute terms than those of $a_4$ in all cases. Regarding the Netherlands, we noted the lack of herding outside the crisis period, yet the findings indicate the presence of significant herding during the crisis ($\alpha_3$ is significantly negative at the 1% level). Overall, our results confirm the evidence presented so far on herding at the group level and for each individual market, while also indicating that the outbreak of the global financial crisis culminated in a severe rise in intraday herding in the Euronext, a result consistent with research (Kim and Wei, 2002;

[33] This period is considered to be the peak of the global financial crisis characterised mainly by widespread panic on the part of investors following the collapse of the US IndyMac Bankcorp Inc. on July 31st 2008. In the subsequent months, August to October, a number of other financial institutions were either taken over, filed for bankruptcy or bailed out by their governments, such as Lehman Brothers, Merrill Lynch, AIG, and Citigroup among others. From November 2008 onwards, most central banks, including the European Central Bank (ECB), instigated a series of interest rate cuts aimed at boosting economic growth and restoring confidence in the financial markets.

Chiang and Zheng, 2010; Mobarek et al, 2014) denoting an increase in herding following the outbreak of financial crises.

***Insert Table 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 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 at the group-level. 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 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 both during and outside the 2008 financial crisis period, with its predominance being stronger 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 herding can be utilized by investors for the purpose of formulating style strategies at the group-level. Of key interest to regulators is the fact that the herding documented here occurs at high frequencies, thereby suggesting that a substantial part of it is probably due to high-frequency trading. Given recent incidents (such as the 2010 flash-crash) involving herding on behalf of high-frequency traders and the current dominant position of this trading segment in equity-investments, these results suggest that the development of sophisticated technological tools for regulators to monitor high-frequency trading activity is necessary. Such necessity is especially pertinent in cross-border groups, whose common trading platforms can allow the transmission of 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 two frequencies and 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 |
|---|---|---|
| $\alpha_0$ | 0.347 | 0.458 |
| | (167.38)*** | (128.32)*** |
| $\alpha_1$ | 1.406 | 1.415 |
| | (56.99)*** | (47.53)*** |
| $\alpha_2$ | -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 | | | | | |
| $\alpha_0$ | 0.162 | 0.317 | 0.348 | 0.328 | 0.290 |
| | (14.73)*** | (68.33)*** | (113.35)*** | (165.22)*** | (183.64)*** |
| $\alpha_1$ | 1.703 | 1.700 | 1.506 | 1.392 | 0.864 |
| | (63.05)*** | (69.48)*** | (68.35)*** | (65.35)*** | (67.15)*** |
| $\alpha_2$ | -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 | | | | | |
| $\alpha_0$ | 0.289 | 0.422 | 0.456 | 0.438 | 0.397 |
| | (31.33)*** | (43.20)*** | (94.80)*** | (122.37)*** | (137.07)*** |
| $\alpha_1$ | 1.769 | 1.857 | 1.528 | 1.355 | 0.822 |
| | (72.99)*** | (29.38)*** | (45.53)*** | (41.95)*** | (45.48)*** |
| $\alpha_2$ | -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 | | | | | | | | | | |
| $\alpha_0$ | 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)*** |
| $\alpha_1$ | 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)*** |
| $\alpha_2$ | 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 | | | | | | | | | | |
| $\alpha_0$ | 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)*** |
| $\alpha_1$ | 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)*** |
| $\alpha_2$ | 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 | | | | |
| $\alpha_0$ | 0.246 | 0.362 | 0.0961 | 0.202 |
| | (133.02)*** | (167.88)*** | (7.86)*** | (73.10)*** |
| $\alpha_1$ | 1.358 | 1.352 | 1.338 | 1.255 |
| | (80.19)*** | (56.89)*** | (41.42)*** | (60.48)*** |
| $\alpha_2$ | -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 | | | | |
| $\alpha_0$ | 0.32 | 0.473 | 0.409 | 0.304 |
| | (92.32)*** | (125.21)*** | (52.51)*** | (60.31)*** |
| $\alpha_1$ | 1.361 | 1.386 | 1.184 | 1.194 |
| | (39.12)*** | (44.39)*** | (28.22)*** | (43.28)*** |
| $\alpha_2$ | -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-markets' 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 | | | | | | | | | | | | |
| $\alpha_0$ | 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)*** |
| $\alpha_1$ | 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)*** |
| $\alpha_2$ | -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)*** |
| $\alpha_3$ | 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 | | | | | | | | | | | | |
| $\alpha_0$ | 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)*** |
| $\alpha_1$ | 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)*** |
| $\alpha_2$ | -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)*** |
| $\alpha_3$ | 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 2008 global financial crisis on herding in the Euronext as a group

| | 60-minute frequency | 120-minute frequency |
|---|---|---|
| $\alpha_0$ | 0.349 | 0.461 |
| | (134.42)*** | (128.39)*** |
| $\alpha_1$ | 1.694 | 1.785 |
| | (33.15)*** | (25.27)*** |
| $\alpha_2$ | 1.371 | 1.352 |
| | (35.39)*** | (43.42)*** |
| $\alpha_3$ | -0.371 | -0.418 |
| | (-7.13)*** | (-7.06)*** |
| $\alpha_4$ | -0.256 | -0.187 |
| | (-3.73)*** | (-5.54)*** |
| $R^2$ | 0.553 | 0.543 |

The table presents Newey-West consistent estimates from the equation

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

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. $D^{crisis}$ equals one for the August – December 2008 period, zero otherwise. 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 2008 global financial crisis on herding in Euronext's constituent markets

| | Belgium | France | Netherlands | Portugal |
|---|---|---|---|---|
| Panel A: 60-minute frequency results | | | | |
| $a_0$ | 0.252 | 0.365 | 0.255 | 0.206 |
| | (111.85)*** | (151.15)*** | (52.36)*** | (76.71)*** |
| $a_1$ | 1.761 | 1.700 | 1.320 | 1.557 |
| | (35.15)*** | (34.58)*** | (26.37)*** | (43.21)*** |
| $a_2$ | 1.246 | 1.301 | 1.394 | 1.192 |
| | (40.91)*** | (42.00)*** | (41.12)*** | (58.07)*** |
| $a_3$ | -0.287 | -0.392 | -0.189 | -0.299 |
| | (-6.36)*** | (-8.01)*** | (-5.11)*** | (-16.68)*** |
| $a_4$ | -0.0766 | -0.188 | 0.0912 | -0.149 |
| | (-2.67)*** | (-3.60)*** | (6.98)*** | (-8.42)*** |
| $R^2$ | 0.541 | 0.536 | 0.868 | 0.642 |
| Panel B: 120-minute frequency results | | | | |
| $a_0$ | 0.324 | 0.477 | 0.405 | 0.308 |
| | (92.63)*** | (128.75)*** | (49.50)*** | (57.83)*** |
| $a_1$ | 1.842 | 1.840 | 1.347 | 1.419 |
| | (22.90)*** | (24.94)*** | (25.89)*** | (28.56)*** |
| $a_2$ | 1.294 | 1.320 | 1.200 | 1.150 |
| | (35.87)*** | (43.08)*** | (26.36)*** | (36.35)*** |
| $a_3$ | -0.343 | -0.480 | -0.191 | -0.217 |
| | (-4.23)*** | (-7.50)*** | (-8.03)*** | (-7.95)*** |
| $a_4$ | -0.187 | -0.156 | 0.127 | -0.151 |
| | (-3.59)*** | (-4.70)*** | (7.12)*** | (-6.63)*** |
| $R^2$ | 0.582 | 0.538 | 0.796 | 0.604 |

The table presents Newey-West consistent estimates from the equation

$CSAD_{m,t} = a_0 + a_1D^{crisis}|r_{m,t}| + a_2(1\text{-}D^{crisis})|r_{m,t}| + a_3D^{crisis}r^2_{m,t} + a_4(1\text{-}D^{crisis})\ r^2_{m,t} + e_t$

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). $D^{crisis}$ equals one for the August – December 2008 period, zero otherwise. T-statistics are reported in brackets. * = significance at the 10% level; ** = significance at the 5% level; *** = significance at the 1% level.