LIMIT ORDER CLUSTERING AND PRICE BARRIERS ON FINANCIAL MARKETS: EMPIRICAL EVIDENCE FROM EURONEXT*

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Abstract

We investigate trade price and limit order price clustering on Euronext, a european stock market which is based on a computerized limit order book. We find evidence of widespread and pervasive trade price and limit order price clustering at increments of five and ten cents. Thus, investors appear to be naturally drawn to certain prominent numbers when placing limit orders. This tendency provides salient points in the order book where latent liquidity can accumulate. Thus, we show that limit order clustering at round numbers generates price barriers. This means that there are price levels (whole integers and halves) for which a given stock spends an inordinate amount of time, thus possibly hampering the market's ability to process information efficiently. Besides, we observe that the next price levels showing the strongest clustering effect are just above (beyond) dimes and nickels for the limit buy (sell) orders. It is consistent with a strategic undercutting behavior of some limit order traders who possibly anticipate clustering tendencies on dimes and nickels and try to step-ahead of the quotes and gain price priority.

EFM Classification Code: 360

Keywords: Price clustering; Order placement strategies; Price barriers

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1 Introduction

Price clustering - the tendency of prices to deviate from a uniform distribution, tending to center around certain prices and avoiding others – is observed in many markets of any kind (equities, forex, derivatives...). Nevertheless, it is inconsistent with market price following a simple random walk process. Indeed, if price discovery is uniform, realized trades should not cluster at certain prices. Numerous hypotheses have been proposed to explain such a pervasive pattern. For example, Shiller (2000) claims that market participants, in the absence of better knowledge, may use the nearest round number as a proxy for the fundamental value. More precisely, the "price resolution" hypothesis indicates that, if valuation is uncertain, traders may coordinate to restrict the price set so as to reduce search and cognitive costs (Harris, 1991). Nevertheless, this explanation is more likely to exist in pure dealer markets, where limit orders do not exist. In order driven markets, a limit order trader provides to other investors the ability to execute against his limit order. If a clustering pattern is obtained in this kind of market, it may stem from an intrinsic psychological preference for "prominent" numbers or, as suggested by Niederhoffer (1965), it may be the result of the tendency of stock markets participants to place their orders at "numbers with which they are accustomed to deal" (round numbers). It may also result from a complete rational behavior in order placement strategies.

To date, most of the literature on share price clustering has employed US Nyse and Nasdaq data[1]. In this paper, we investigate trade price and limit order price clustering on Euronext, a european stock market which is based on a computerized limit order market for which the tick size increases with the share price in a stepwise fashion.

Our first contribution is to show that transaction price clustering is in fact related to an important and pervasive clustering behavior in limit order prices, particularly beyond the best quotes. Thus, we observe an important order price clustering on prices ending with 00 and 50. Besides, limit order clustering on prices ending with X0 and X5 is not far from 40%. We also document a strategic undercutting behavior of some limit order traders who possibly anticipate clustering tendencies and place limit buy (sell) orders just above (beyond) round numbers.

Our second contribution to the literature is to make evidence that limit order clustering on round numbers can generate accumulation of depth at these numbers. This creates support and resistance levels which are difficult to penetrate. We make evidence that there are some "prominent" price levels (whole

[1] With some exceptions like Ball *et al.* (1985), Hameed & Terry (1994), Aitken *et al.* (1996), Brown *et al.* (2002) or Ahn *et al.* (2005).

integers and halves) for which a given stock spends an inordinate amount of time. Moreover, we show that, for stocks trading with a tick size of 1 cent and for our sample period, the proportion of daily highs and lows with price ending in X0 is quite 25%.

Finally, we notably illustrate the fact that, even if it seems inconsistent with the efficient markets hypothesis (there is no reason that the discounted value of future returns would be relatively often a round number), price clustering is not necessarily at odds with economic rationality. We suggest that "round numbers" could be recognised by numerous traders as "prominent"' numbers or "saliences" (i.e price levels having a quality that thrusts themselves into attention, see Schelling (1960)). On stock markets, if many limit orders tend to be placed at, just under or just beyond round numbers, thus creating support and resistance levels, these prices become "salient" prices for numerous traders. Therefore, and as mentioned by Osler (2003), the tendency to place orders at certain prominent prices could conceivably be creating the conditions necessary for that tendency to be conditionally rational.

The next section provides empirical evidence and theoretical explanations for price clustering. Our data and research methodology are outlined in section 3. In section 4, we present evidence of trade price and limit order price clustering on Euronext. We also show that limit order clustering can generate price barriers. Section 5 contains some conclusion and possible extensions.

2 Price Clustering: Empirical Evidences and Explanations

Empirical evidence indicates that round prices appear to be used significantly more often than non-round prices. This fact has been largely documented in equity markets, forex, gold markets, derivatives and even in IPO auctions and takeover bids[2]. In this section, we first document this widespread and persistent phenomenon observed for different financial instruments (2.1)and then consider the main theoretical explanations (2.2). Finally, we show that trade price clustering can largely be attributed to quote clustering (2.3).

2.1 Empirical Evidences

Research into price clustering started in the sixties with Osborne (1965), Niederhoffer (1965) and Niederhoffer & Osborne (1966) who found important evidence

[2]Niederhoffer (1965, 1966), Niederhoffer & Osborne (1966), Ball *et al.* (1985), Goodhart & Curcio (1991), Harris (1991), Christie & Schultz (1994), Aitken *et al.* (1996),Ap Gwilym *et al.* (1998), Kandel *et al.* (2001), Doucouliagos (2004), Sonnemans (2003).

of stickiness of prices at the integer and "congestion" in US share prices. Thus, before the decimalization reform in US[3], it was more common for stock prices to end with integers than with halves, which was more common than stock with odd-quarters, odd-eighths and other fractions. Harris (1991) found this phenomenon at the NYSE to have persisted, while Christie & Schultz (1994) found that NASDAQ market makers avoided odd-eight quotes. After the decimalization reform, clustering persisted and even increased significantly. Ikenberry & Weston (2003), found that over half of all trades on many stocks occur on price increments of five and ten cents. Moreover, they used the change to decimal prices in US markets as a natural experiment to distinguish whether the clustering phenomenon represent a rational response by investors to an arbitrary exchange regulation or whether it reflects a deeper psychological bias toward prominent numbers. The results suggest there may be only minor differences between the transaction prices that would prevail under a tick size of five cents relative to those observed under decimal pricing. Other papers confirmed the importance of clustering on a number of other competitive financial markets such as NYSE, AMEX and the London Stock Exchange. The same observations are also made for other decimal-pricing systems. Prices ending with whole dollars occur more frequently than half dollars which are more frequent than price multiples of 10 cents, 5 cents, even cents and odd cents (Aitken *et al.* (1996), on the Australian Stock Exchange and Hameed & Terry (1994) on the Stock Exchange of Singapore).

There is also strong evidence of price clustering on other markets.

Ball *et al.* (1985) found that price clustering on the London Gold market depended on the amount of information available to participants.

Goodhart & Curcio (1991) examining clustering in the bid and ask quotes for the DM/USD spot rate, concluded that that clustering in the final digit of the quotes depended on the desired degree of price resolution by traders[4]. This preference for round numbers is surprising. Indeed, clustering on an exchange rate ending or containing a zero or any other number should be irrelevant information as a quote can always be defined in two ways, a stated value and its inverse.

Ap Gwilym *et al.* (1998) found that 98% of quoted and traded prices for LIFFE stock index derivatives occur at even ticks (full index points) despite a minimum tick of 0.5 index points. Moreover, the FTSE250 futures and FTSE100 options also exhibit clustering at the decimals 0 and 5 for the final whole digit of price. This suggests that the market does not seem to require the addi-

[3]Early in 2001, US equity markets transitioned from trading in multiples of $1/16^{th}$ and $1/8^{th}$ of a dollar to a decimal format with a minimum tick size of one penny.

[4]On the contrary, the less volatile JPY-USD quotes exhibited expected less clustering.

tional price refinement of half index points, which support the price resolution hypothesis.

Finally, Kandel *et al.* (2001) showed evidence of round number clustering in orders submitted for IPO Israeli auctions. They found that investors submitting a limit order are twice as likely to use a round number for price.

2.2 Explanations of Price Clustering

Several explanations of price clustering are considered in the literature.

Negotiation/price resolution hypothesis: Ball *et al.* (1985) proposed that price clustering varies inversely with the degree to which the underlying value of the asset is known. If value is well known, trader will use a fine set of prices. If valuation is uncertain, investors may coordinate to restrict the price set (half or whole numbers) so as to reduce search and cognitive costs. Thus, the coarseness of the pricing grid used by investors depends on the willingness of traders to reduce the negotiation costs (Harris, 1991). Since the cost traders perceive from any rounding error decreases with price, clustering should also be more prevalent in high-price stocks. Moreover, traders will also use coarser price grids, when thin trading limits their incentive to make accurate asset. Harris (1991) found that stock price clustering increased with stock price and volatility and decreased with capitalization and trading frequency[5]. This result is consistent with the fact that clustering could result from imprecise beliefs ("haziness") about firm value and a less efficient price discovery process. Broom (2004) indicates that when sudden unexpected events heighten the uncertainty within the markets, thereby making the underlying value of stocks less known, one would expect clustering to increase. Analyzing the impact of the September 11, 2001 terrorist attacks on the NYSE and regional exchanges, Broom found that a large increase in clustering frequencies occurred on the first trading day after the attacks and was most prevalent over the first 5-day trading period after the attacks. Additionally, after the first post-attack week of trading, the clustering levels returned to its pre-attack level. While numerous results are consistent with the negotiation / price resolution hypothesis, they fail to explain the systematic and pervasive level of price clustering evident in all markets.

[5] Ikenberry & Weston (2003) confirm that price clustering increases with firm size, share price, volatility, bid-ask spreads and institutional ownership. Hameed & Terry (1994), examining factors affecting price clustering on the Stock Exchange of Singapore found that clustering increased with the price level and decreased with the stock's liquidity. Aitken *et al.* (1996) showed that stocks for which options were traded, and stocks for which short selling was allowed, exhibited less clustering. They indicate that clustering results from imprecise beliefs about firm value. Moreover, trade size clustering (for NYSE-listed stocks, orders and trades are often rounded at three size levels : multiple of 500, 1000 and 5000) tends to be heaviest during periods when price volatility is high (which often corresponds to a high degree of uncertainty in a stock's value).

Collusion hypothesis: Christie & Schultz (1994), found that dealers colluded to maintain artificially high spreads by posting quotes using only even-eighth quotes, thereby maintaining a spread of at least $.25 on every transaction. Numerous empirical studies thus indicate that bid-ask spreads on the NASDAQ were significantly broader than the ranges observed on stocks with closely related characteristics quoted on the NYSE, a clear acknowledgment of anti-competitive conduct on the part of those offering liquidity. Despite the fact that NASDAQ market makers stopped avoiding odd-eighth quotes after the revealings of Christie & Schultz (1994) and the decimalization reform in early 2001, prices for NASDAQ stocks are still not uniformly distributed over the grid of possible prices. Indeed, Ikenberry & Weston (2003), using daily closing prices for all NYSE and NASDAQ stocks from May to October 2001, found that nearly half of all trades occur at only 20 percent of the available price intervals.

Aspiration level hypothesis: when investors buy an asset, they have a target price in mind for which they are willing to sell in the future. It seems that these target prices are typical round numbers. Sonnemans (2003), using data from the Dutch stock market during 1990-2001, focuses on the tendency of prices to cluster at round number. After January 1, 1999 stock prices were listed in euros, while guilders were still the currency of daily life until 2002. Stocks bought before but hold after January 1, 1999 will have target prices that are still round numbered in guilders but not so in euros[6]. Therefore, the aspiration level hypothesis predicts that a round number effect in guilders will only slowly disappear after the transition to the euro. The result show an abrupt change in clustering effects on round numbers for stock prices converted from euros to guilders after January 1, 1999, thus rejecting the aspiration level hypothesis[7].

Attraction hypothesis: investors have a basic attraction to certain integers like zero or five. The number zero is a stronger attractor than 5, which is stronger than 2 and 8 (two places removed from the strongest attractor and three places removed from 5), then $3 = 7$, $4 = 6$. The least common will be 1 and 9. Goodhart & Curcio (1991) found that the clustering in the bid-ask spread on Forex was consistent with the attraction hypothesis, and Aitken *et al.* (1996) argue that investors seems to have a basic "attraction" to certain

[6] Sonnemans explains that there is no reason to change a target price to a round number in euros because, when the stock is sold, guilders will be received and consumed during the years 1999-2001.

[7] According to the author, this result is in line with is the odd pricing hypothesis : odd pricing is the tendency of investors to consider an odd price like 19.95 for example as significant lower than the round price 20 (a tendency well documented in the marketing of consumer goods). A stock price of 20 will therefore been considered much higher than a price of 19.95. A seller will be happy to sell at 20 and a buyer will be reluctant to pay a price that is in the 30s.

integers like zero or five. Nevertheless, Harris (1991) rejected the attraction hypothesis because he found the frequencies of odd-eighths (1,3,7 and 9) were approximately the same.

Preference for round numbers: while the tendency to cluster is consistent with various theories, the high degree of clustering appears indicative of a general attraction by investors to trade in prominent numbers. von Neumann & Morgenstern (1953) indicated that the average person does not make economic decisions with exact prediction, but instead acts in a "sphere of considerable haziness". Butler & Loomes (1988) precise that to deal with their limited cognitive abilities, individuals "choose and develop rules and heuristics" based on previous decisions and their consequences. A set of rules, like trading at prices ending with 0 or 5, emerge and are used in subsequent decision making. This suggests that investors could have a "psychological bias" for trading in round numbers, particularly when price levels and uncertainty increase (Ikenberry & Weston, 2003). Kandel *et al.* (2001) examine prices in limit orders submitted in auctions for newly issued stocks. Since the orders are directly submitted to the stock issuers by thousands of investors and neither market makers specify the prices of the orders, negotiation / resolution price hypothesis and collusion hypothesis cannot explain the use of round prices. They also concluded that the clustering effect reflects nothing but investor tendency to trade in round number[8].

The numerous empirical results are such that it seems difficult to gauge if the price clustering arise from strategic behavior, bias in decision making caused by behavioral factors or intrinsic conscious specific importance assigned to certain prominent numbers. In the following section, we show that trade price clustering can often be attributed to quote clustering and suggest evidence of rationale for round number clustering in financial decision making.

2.3 Quote and limit Order Clustering

Niederhoffer (1965) documented clustering of limit orders taken from the order book of a specialist on the NYSE. He suggested that there is a strong tendency for limit orders to be placed at familiar whole numbers like 10, 25, 50, 75 and 100[9] leading to congestion (existence of "price ranges in which a given stock price spends an inordinate amount of time"). Examining the distribution of limit orders for a representative corporation, he found that 78 per cent of all

[8] This result is also consistent with the attraction hypothesis.

[9] Harris (1991) mentioned that his data suggests round integer clustering at any five integers starting at 5.

the limit orders were accumulated at the integer (0)[10]. Therefore, if clustering of individual stock prices is caused by relatively many limit orders at round numbers, this would cause the emergence of resistance points at these numbers[11]. Indeed, depth clustering could generate price barriers which are difficult to penetrate. What we call here a "price barrier" can result from the tendency of agents to attach some special importance to the last digits of the price of an asset, but is not inevitably joined with what newspapers and other mass media identify as "psychological barriers" (for example, when stock indexes pass trough some important reference points supposed to influence market sentiments). De Grauwe & Decupere (1992) find that price barriers exist and are significant in the dollar-yen market. For example, market exchange rates tend to resist movements toward numbers such as 130, 140,. . . yen per dollar etc. In addition, once these barriers have been crossed, exchange rates accelerate away from them.

This fact has been largely documented by Osler (2003) when examining order clustering in currency markets using data on stop-loss and take-profit orders. A stop-loss buy (sell) order instructs the dealer to purchase (sell) currency once the market rates rises (falls) to a certain level. A take-profit buy (sell) order instructs the dealer to purchase (sell) currency once the market rates falls (rises) to a certain level. Analyzing orders placed at a large dealing bank from August 1, 1999 to April 11, 2000, she shows that they cluster strongly at round numbers. Moreover, she shows that executed take-profit orders cluster more strongly at round numbers ending in 00 than do stop-loss orders. Therefore, trends would be likely to reverse when they hit take-profit dominated order clusters at round numbers. This first result is consistent with a widely used prediction of technical analysis, that is, down trends (up trends) tend to reverse course at support (resistance) levels which are often round numbers[12]. The second result is that stop-loss buy orders have a pronounced tendency to be placed at rates just beyond the round numbers (for example 1.6605, rather than 1.6600 or 1.6595), and stop-loss sell orders tend to be clustered just below round numbers (1.6595, rather than 1.6600 or 1.6605). Thus, clusters just beyond round numbers dominated by stop-loss orders could propagate existing trends. This is in line with a second widely prediction rule of technical analysis indicating that trend tend to be unusually rapid after rates cross support or resistance levels.Empirical results demonstrate that exchange tend to reverse course at round numbers and trend rapidly after crossing these round numbers. Currency stop-loss orders gener-

[10] Moreover, the ratio of limits at the even eighths (0, 2, 4, 6) to limits at the odd eighths (1, 3, 5, 7) was 8,8 / 1.

[11] An example indicates that for a well-known corporation then trading at 79, 40% of the limit orders to purchase a total of 500 round lots rested at the attractive number 75, and 26,5% of 337 round lots to sell were placed at 80 (Niederhoffer, 1965).

[12] A support (resistance) level is defined by technician as a concentration of demand (supply).

ate positive feedback trading and contribute to self-reinforcing price cascades. Osler (2005) adds that this pattern may be self-reinforcing even in the presence of rational fundamental-based traders, because price-contingent orders are not observable to anyone.

Osler (2003) indicates that the round number clustering is consistent with the fact that agents choose round numbers to minimize time and error in their communication with dealers, or that agents prefer certain numbers for behavioral reasons. Thus, even if passing a round number gives no information about underlying fundamentals, it may be rationale to take into account the possibility that some irrational investors trade based upon these round number signals. Therefore, there may be a self-fulfilling element to the order placement strategy because given that some agents cluster their orders at round numbers, it may be rational for others to do so, as well.

However, instead of presupposing that investors share a common bias toward certain prominent prices identified as cluster points, an alternative hypothesis would be that people rationally select numbers that they believe others recognize as saliences. A salience is a focal point for each person's expectation of what the other expects him to be expected to do. According to Schelling (1960), focal points or "saliences" are a possible medium by which coordination may be possible[13]. If people are more likely to believe that the others will also choose a feature that they find to be salient, such features become a focal point to their actions. The theory of focal points brings evidence of rationale for clustering in financial decision making. It is possible that, on financial markets, some numbers are more salient than others within the range of possible values, price clustering on those prominent prices could be here considered as an example of coordination by focal points.

Interestingly, Brown *et al.* (2002) focused on cultural bias aspect of price clustering. They found that prices observed on Asian financial markets are influenced by Chinese superstition. They document price clustering in six Asia-Pacific stock markets, using daily closing stock prices over the period from 1994 to 1998. Consistent with results observed on Western financial markets, prices are found to cluster at 0, 5 and the even integers. Moreover, Chinese culture is found to have some influence on price clustering in the Honk Kong market, because of the avoidance of the unlucky number 4 during the Chine New Year and other auspicious festivals[14]. This phenomenon is not as pervasive in the

[13] A well known example is that if you are asked to meet up with someone in New York on a particular day but cannot communicate, when and where would you go? The salient answer is supposed to be Grand Station at midday. Salience is some kind of cultural focal point that presents itself in the mind of an individual (Mehta *et al.*, 1994*a*,*b*; Sugden, 1995, for instance).

[14] Many Chinese believe some numbers are unlucky. The number 4 have to be avoided because of the cantonese pronunciation of 4 is similar to the phrase "to die".

other predominantly ethnic Chinese countries of Singapore and Taiwan. This suggests that cultural factors may influence the salience of numbers and thereby price clustering.

3 Data and Methodology

This study investigates trade price and limit order clustering at Euronext Paris, which is based on a computerized limit-order trading system. On such an order driven market, buy and sell orders are prioritized for execution in terms of price and time: orders for each security are ranked by price limit as they enter the system. For example, buy orders specifying a higher limit are executed before orders with lower limits. Secondly, orders are ranked in chronological order: two buy or sell orders at the same price will be executed in the order in which they arrive on the central book. There is no designated market maker who has the obligation to provide liquidity. Therefore, limit orders provide liquidity to those who demand immediacy (market order traders).

The trading day is ten hours, beginning at 7:15 a.m. and ending at 5:30 p.m. Paris local time. From 7:15 a.m. to 9:00 a.m., the market is in pre-opening phase and orders are fed into the centralized order book without being executed. The market opens at 9:00 a.m. The central computer automatically calculates the opening price or call auction price at which the largest quantities can be traded. From 9:00 a.m. to 5:25 p.m., trading takes place on a continuous basis. The arrival of a new order immediately triggers one or several trades if matching orders exist on the other side of the book. From 5:25 p.m. to 5:30 p.m., the market is in its pre-closing period. As in the pre-opening session, orders are fed into the order book. The market closes at 5:30 p.m. with a call auction that determines the closing price. Trading is anonymous. Cancellation of orders may be done at any time.

Starting on January 4, 1999, the new pricing grid sets a sliding scale of tick size (Table 1).

Subsection 3.1 deals with the definition of the sample period. Following, subsection 3.2 explains our data selection/construction procedures. To conclude, subsection 3.3 gives the notation and statistical tests runs on the data.

3.1 Sample definition

Our sample period runs from January 2000 to January 2004. We only consider highly liquid stocks (we focus on the CAC 40 shares). Numerous studies show that price clustering increases with uncertainty about firm value. We first consider two proxies for it : market return (trend) and market-wide volatility. We

Table 1: Pricing Grid

Price €		Tick €	Relative tick (%)	
Min	Max		Min	Max
	50.00	0.01	0.02	
50.05	100.00	0.05	0.05	0.10
100.10	500.00	0.10	0.02	0.10
500.50		0.50		0.10

This table presents details related to the pricing grid available. Maximum relative tick size is the ratio of the price increment to the minimum share price for each category. Minimum relative tick size is the ratio of the price increment to the maximum share price for each category.

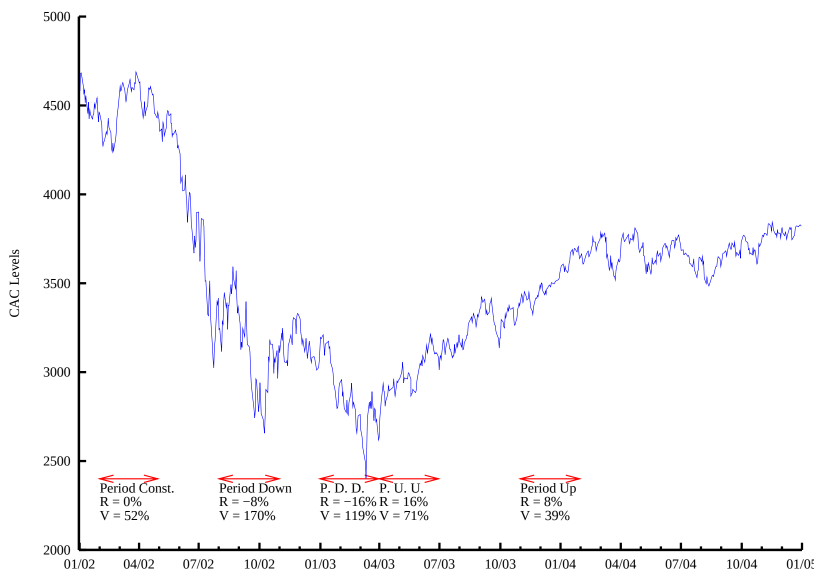
use the CAC 40 index as our proxy for the market return and volatility.

Figure 1 shows the CAC 40 levels from January 2002 to December 2004 with the selected quarters. Indeed, we select 5 non overlapping periods with contrasted returns and volatility levels

- A Up Up trend period (hereafter *UUP*)

  04/01/2003 - 30/06/2003 Return: 16% Volatility: 71%

Figure 1: Selected periods & CAC 40 Levels



This figure provides the evolution of the CAC 40 from the beginning of year 2002 until the end of year 2004. Selected quarters are indicated by an arrow with CAC's Return and Volatility below.

- A Up Trend Period (hereafter *UTP*)

  01/11/2003 - 01/31/2004 Return: 8% Volatility: 39%

- A Constant period (hereafter *C.P*)

  02/01/2002 - 04/30/2002 Return: 0% Volatility: 52%

- A Down Trend Period (hereafter *DTP*)

  08/01/2002 - 10/31/2002 Return: -8% Volatility: 170%

- A Down Down trend period (hereafter *DDP*)

  01/01/2003 - 03/31/2003 Return: -16% Volatility: 119%

Table 2 provides descriptive statistics on returns and activity measures for the different tick groups and the different sub-periods.

As one can notice, shares trading within the 0.1 and 0.05€ tick groups are few (the number of stocks varies from 0 to 7 with a mean of 3.3 stocks). Testing the clustering effect when there are numerous stocks within one tick group is of course more robust[15].

3.2 Data Selection

This study uses public data broadcasted each month by Euronext Paris: the database BDM. We mainly use three files:

a. The trades file gives the date, time, price and volume of each trade recorded by the market.

b. The orders files gives the definition of almost all orders introduced into the system.

c. The best quotes file provides the best bid and ask quotes with price, date, time, depth and number of orders.

Several analysis (detailed hereafter) rely on appropriate merging of these files to reflect the succession of events on the market[16].

Trades: we exclude "applications". These trades are concluded in upstairs market and only registered in the order book.

[15] Hence, even if we first study the whole sample, we mainly focus our analysis on the 0.01€ tick group.

[16] Although the time precision is high (the second), the timing of events within a same second is determined by a sequence number on a file basis. Hence, when there are several events of different types (e.g. several trades and an order or a trade and several orders or several trades and several best quotes...) there is no way to compute exactly the true sequence of events. Consequently, even if we merge the file using the "ecology" of an order driven market (that is to say order $\rightarrow$ quotes $\rightarrow$ trades), the sequence within the second is not necessarily exact when there are several events of different types.

Table 2: Descriptive Statistics

				Trades		Orders			Quotes			
Tick	#	R (%)	σ (%)	Vol. €	#	Vol. €	#	Buy (%)	Spread (%)	#	Buy (%)	Sell (%)
						d						
0.01 €	20	-0.14	4.92	290200	3246	848821	7231	49.6	0.26	4818	55.83	56.16
		0.29	1.52	162516	2432	590892	4854	1.15	0.06	2475	1.83	1.59
0.05 €	3	-0.03	2.26	672868	1958	1.83E6	4528	49.8	0.23	3405	56.00	55.59
		0.21	0.44	552291	1324	1.22E6	2457	0.78	0.04	1652	0.87	0.41
0.1 €	3	0.04	2.68	2.5E6	3793	5.9E6	7765	49.9	0.18	5780	57.34	56.16
		0.12	0.86	1.88E6	2199	3.55E6	3552	0.17	0.05	2470	1.07	1.58
						dd						
0.01 €	26	-0.33	3.48	366181	3214	990853	7013	49.6	0.21	4757	56.90	53.98
		0.30	0.83	281526	2194	790243	4191	1.34	0.06	2539	1.61	1.77
0.1 €	1	-0.30	2.26	4.15E6	6418	8.69E6	12E3	49.2	0.11	8481	57.76	54.94
		.	.	.	.	.	.	.	.	.	.	.
						u						
0.01 €	20	0.11	1.52	417532	3388	1E6	6572	50.1	0.10	4672	57.56	55.46
		0.17	0.43	193415	1905	448100	2794	1.12	0.02	1862	2.81	2.60
0.05 €	7	-0.00	1.22	833984	2550	1.98E6	5064	50.2	0.11	3811	56.43	55.15
		0.11	0.21	333671	988	613612	1577	0.92	0.02	1161	1.91	1.37
0.1 €	3	0.07	0.90	2.22E6	3547	4.68E6	6271	50.8	0.10	4894	56.94	54.46
		0.01	0.19	1.47E6	1801	2.45E6	2530	0.63	0.02	1847	0.99	1.20
						uu						
0.01 €	24	0.37	2.64	355548	3188	932743	6898	50.0	0.17	4792	55.11	53.75
		0.15	0.37	226791	1913	659113	3923	0.84	0.04	2389	1.91	1.70
0.05 €	2	0.22	1.83	739223	2340	2.06E6	5525	47.9	0.18	3994	53.78	54.10
		0.08	0.05	556485	1681	1.08E6	2664	2.92	0.06	2125	1.20	0.83
0.1 €	3	0.09	1.56	2.21E6	3661	5.18E6	7331	50.2	0.13	5655	55.13	53.23
		0.07	0.08	1.39E6	1895	2.5E6	2943	0.55	0.04	2218	0.66	0.05
						z						
0.01 €	13	-0.04	2.20	438117	3158	978226	5514	51.4	0.14	3559	57.36	56.05
		0.27	0.63	293311	2039	833683	3471	1.93	0.04	1855	2.73	2.96
0.05 €	6	0.01	1.74	1.01E6	2620	1.99E6	4408	51.7	0.12	3200	56.94	55.92
		0.20	0.51	391642	883	724100	1423	1.92	0.02	988	1.81	1.59
0.1 €	4	0.13	1.12	2E6	2665	3.75E6	4244	49.8	0.10	3314	59.25	52.90
		0.07	0.10	1.22E6	1202	1.93E6	1611	0.70	0.02	1272	2.26	1.74

This table gives descriptives statistics for the different sub-periods. R, σ are the mean daily returns and volatility in percent. # is the number of events (shares, trades, orders and quotes) and Vol. € is € trading volume. Buy gives the proportion of buy orders. Fore quotes, buy and sell gives the proportion of buy and sell best quotes. Since a best quote change can modify both (buy and sell) sides these two proportions sum up to more than 100%. The line below the statistic provide the standard deviation of the variable over the various shares in the tick group.

Orders: since we study order price clustering, we only keep limit orders for analysis.

As the tick size changes automatically with the price level specified in the order submission, we only examine the clustering pattern for cases where a stock does not cross tick breakpoints. We consider that a stock is traded within a given tick size group with a 10% margin around the theoretical limit[17]. Table 15 in appendix provides a description of the selected shares according to the sub-period and the tick group.

Besides, as traders can label any price limit when submitting a limit order, for example when a stock is traded at 75€ an investor can submit an order at 75.05€ (within the 0.05€ tick category), at 100.10€ (within the 0.1€ tick category) or even an order at 49.99€ (within the 0.01€ tick category), we therefore exclude orders introduced with a limit price below the lower or above the upper breakpoint of each tick category[18].

3.3 Notation - Methodology

All events[19] are defined by a bunch of features:

- a sample period $p \in \{UUP, UTP, C.P, DTP, DDP\}$
- an equity $e \in \Omega(p)$ the set of equities is defined on a per period basis, it includes all stocks that do not cross tick breakpoints during one sample period (table 15 gives $\Omega(p)$).
- a tick level t_e. The tick size is associated with the equity. Since we delete equities that cross tick breakpoints during a period, an equity (in a period) trades within a one-tick group[20].
- a sign $s \in \{Buy, Sell\}$. Since T are unsigned, the sign is only defined for O and Q.
- a price and hence a decimal $d \in \Omega(t_e)$ where $\Omega(t_e)$ is the set of possible decimals that changes according to the tick category (t_e) of the stock e[21].

[17] For example, a share is traded within the 0.01€ tick category if its' trade price is always below $90\% \times 50€= 45€$, a share is traded within the 0.05€ tick category if its' trade price is always above $110\% \times 50€= 55€$ and below $90\% \times 100€= 90€$, and so on.

[18] Finally, to eliminate some few errors in the order file. For example, an investor can introduce an order at a level of 1.30€ whereas the trade price is 13€. So we exclude orders for which:

$$\frac{|\text{Order price} - \text{Prevailing trade price}|}{\text{Prevailing trade price}} \geqslant 50\%$$

.

[19] It can be a trade, a best quote or an order. The features of the events vary according to the type. For instance, an order is signed (buy or sell) whereas trades are unsigned. We refer these events respectively by T, Q and O.

[20] As we already mentioned, $t_e \in \{0.01, 0.05, 0.1\}$. t_e determine the set of decimals $\Omega(t_s)$and hence the theoretical probabilities.

[21] We also study the last digit of the price. We refer this as $l \in \Omega(t_e)$.

From the data we compute:

- $N(d = d_i)$ the number of observations of each digit d_i
- $F(d = d_i)$ the frequency of the digit d_i
- $R(d = d_i)$ the rank of the digit $d_i among \in \Omega(t_s)$

All computation are first made on a per share basis and then, eventually, aggregated by tick group. We also decompose these measures according to the features[22].

Under the hypothesis of a uniform distribution (no clustering), one should have $\forall d_i \in \Omega(t_e)$: $E(N(d_i)) = \frac{\sum_{d\in\Omega(t_e)}}{N(\Omega(t_e))}$[23]; $E(F(d_i)) = t_e$; $E(R(d_i)) = \frac{1+1/t_e}{2}$[24]

The price clustering defines a situation where the frequency of some decimals are significantly different from the theoretical level. Hence, we can test a price clustering effect using either a parametric test (Fisher test) or non parametric tests (χ^2, Kruskal-Wallis, Ansari-Bradley[25]).

4 Results

We first choose to only present a detailed analysis of the trade price and order clustering for the flat return sub-period (02/01/2002 - 04/30/2002)[26].

Results are organized as follows. We first analyze trade price clustering (subsection 4.1), then we go back in the exchange process through analyzing the limit order price clustering (subsection 4.2). Finally, we present some preliminary results related to the depth clustering and the resulting price barriers at round numbers in the order book (subsection 4.3).

4.1 Trade Price Clustering

It is useful to specifically analyze separately opening, intraday and closing periods to encompass the variability of price clustering on an intraday basis and to gauge for the role of the price formation process on the clustering phenomenon. Therefore, we examine separately the continuous trading period (4.1.1) and the fixing (opening and closing) periods (4.1.2).

[22] To say it differently, we can compute, for instance, $N(d = d_i|e = e_i)$.

[23] The number of each digit should be equal whatever the digit.

[24] The expectation of a discrete uniform variable $\in$ [1, $1/t_e$] (for the Wilcoxon score) is $\frac{1+1/t_e}{2}$. We compute other ranks as the Ansari-Bradley Scores (see SAS Documentation for further information.) the theoretical level under H_0 is easily deduced.

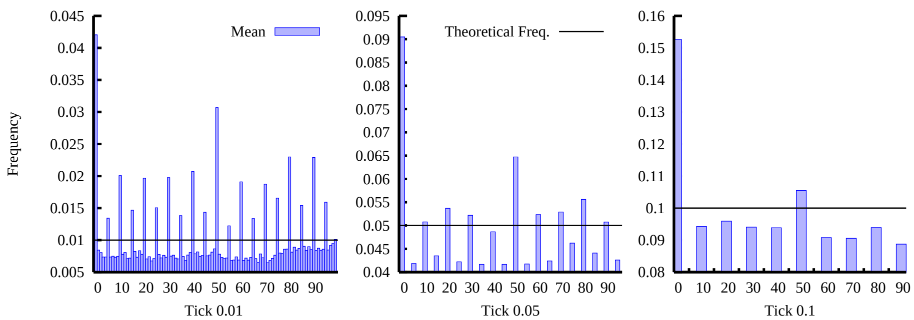
[25] χ^2, Kruskal-Wallis test equality of the mean (or the equality of the number of observations) the whereas Ansari-Bradley tests the equality of the scale among the variables.

[26] We are conducting additional research to find if the clustering effect is more pervasive during flat/bullish/bearish markets and/or low/high market volatility periods.

4.1.1 Continuous trading period

For the continuous trading session, we delete opening and closing trades from the analysis. In the absence of price clustering, the distribution of the last digits of price is expected to be uniform across all integers. Figure 2 show frequencies for the different price increments and for the last two digits.Table 3 gives the results of an Anova on the frequency distribution of the last two digits (grouping shares by tick group).

Figure 2: Clustering of Trade Prices (last two digits)



These figures plot for each tick category the frequency of trade prices based on the last two digits of the trade prices during the continuous trading period.

Table 3: Trade Price Last two Digits - Anova Analysis

Tick	Fischer	Kruskall-Wallis	Ansari-Bradley
0.01	64^{***}	756^{***}	452^{***}
0.05	31^{***}	96^{***}	46^{***}
0.10	40^{***}	30^{***}	23^{***}

This table gives the results of Fisher, Kruskal-Wallis and Ansari-Bradley tests of equality between the frequencies. *** indicates a test significant at a 1% level. Frequencies are computed on a per share basis and then a join test is run on all equities in each tick group.

A price clustering pattern centers on prices that represent prominent numbers in the decimal system (multiple of nickels and dimes).

The highest proportion of trades occurs at prices with last digit 00 (whole integer value). Figures show that whatever the price increment category, the second highest proportion of trades cluster at prices with last digit 50. For example, and as can be noticed in figure 2 for stocks trading with a tick size of 1 cent, the frequency of trades occurring at prices ending in round numbers of 00 is more than 4% while the expected proportion under the hypothesis of a uniform distribution is 1%.

All tests are significant at a 1% level. Hence, whatever the tick level, we are able to reject the hypothesis that the sample is drawn from a uniform distribution. Both Fisher and Kruskal-Wallis are significant (the clustering impact both the frequency levels and their rankings). Moreover, the Ansari-Bradley test shows that clustering also affects the scale of the frequency. Nevertheless, since equities are grouped by tick level, this phenomenon could be due to one specific share whereas other stocks would not show any evidence of clustering. Table 4 gives the min and max values χ^2 test of equality of frequencies by share. Since the min of the test is highly significant, we conclude that all the stocks in our sample show evidence of clustering[27].

Table 4: Trade Price Last two Digits - χ^2

Tick	#	min	max
0.01	14	17415***	632827***
0.05	7	4068***	42252***
0.10	5	2058***	17223***

This table gives the min and max values of a χ^2 test of equality of the frequencies. *** indicates a test significant at a 1% level. # gives the number of equities by the tick group. Frequencies are computed on a per share basis and then tested for equality.

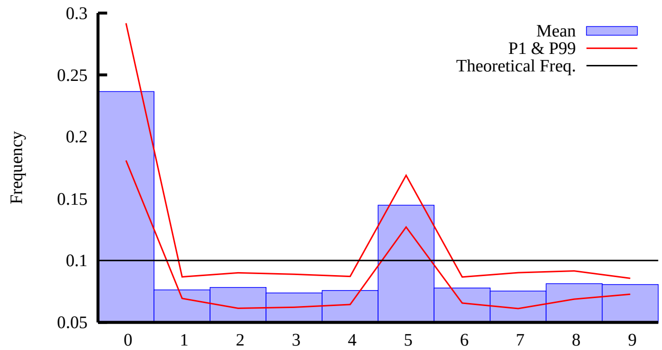
Figure 3 plots an histogram for decimal fractions at the one-cent level (prices where the last digit range from 0 to 9) for stocks trading with a tick size of 0,01 euros. We find evidence of price clustering at zero and five cents ticks. At the one-penny level, and in the absence of price clustering, we expect to see each of the ten bins to hold one-tenth of the trades. For the 0.01€ group, the Fisher, Kruskal-Wallis and Ansari-Bradley tests of equality in frequencies show respective values of 195***, 75*** and 54***. Hence, clustering effect is (not surprinsingly) equally highly significant for the last digit of price. Moreover, the χ^2 test on the individual equities[28] ranges from 6174*** to 522220***.

Table 5 shows the proportion of trades that clusters at prominent number for each category of price increment. For example, in the 1 cent tick size group, the observed frequency for dimes and nickels is double what is expected under a uniform distribution. It must be noticed that the clustering pattern is more pronounced for stocks trading with a 1 cent tick. Thus, the observed frequency for prices ending in 00 (whole integer value) is 4.4 times what is expected under

[27]We also report that the agreement measures between the equities are highly significant. Hence all stocks are subject to a similar clustering pattern.

[28]For equities belonging to the 0.01€ group, 14 shares.

Figure 3: Clustering of Trade Prices (last digit) - 0.01€ Group



This figure plots for the 0.01€ tick size group the frequency of trade prices based on the last digit of the trade prices during the continuous trading period.

a uniform distribution for the 1 cent tick size group, but only 1.82 times for the 5 cents tick size group and 1.53 for the 10 cents tick size group. It appears that the finer the price increment,the stronger is the clustering pattern. Note that, unlike US markets, stocks trade within a sliding scale of tick size on Euronext. Observing trade price clustering on a stock by stock basis, we noticed that inside a same tick size group, the clustering effect is more pronounced for high-priced stocks (low tick to price ratio) than for low-priced stocks (high tick to price ratio)[29]. This result seems consistent with the Negotiation/price resolution hypothesis (Ball *et al.*, 1985; Harris, 1991) according to which clustering should be more prevalent in high-price stocks (stocks with low tick to price ratio here) since the cost traders perceive from any rounding error decreases with price.

Table 6 confirms that investors have a striking preference for prices with a final digit of 0 and 5. Thus, we can observe that 38% of trades occurs at either a nickel or a dime. The next "prominent" numbers are "8" and "9" (with a frequency significantly lower than the expected one). This result is not consistent with the attraction hypothesis (Harris, 1991) which predicts the following relationship between the relative frequency : $0 > 5 > (2 = 8) > (3 = 7, 4 = 6) > (1 = 9)$.

On the contrary, all those results are consistent with the study of Ikenberry & Weston (2003) who analyze clustering in closing pries for US stock prices after decimalization[30]. Our results are also consistent with Hameed & Terry (1994)

[29]For example, a stock trading in the 0,01 cent tick size group at a price of 50 euros has a relative tick size of 0,02% while a stock trading in the same tick group at a price of 5 euros has a relative tick size of 0,2%!

[30]They even find that price clustering has increased with the onset of decimalization and indicate that investors voluntarily choose to trade using a coarser sub-grid of prices after the

Table 5: Trade Price Clustering and Price Increment

Tic (€)	Last digit	Exp (%)	Freq (%)	Ratio	Min (%)	Max (%)
0.01	00	1	4.4 ***	4.4	2.1	6.6
0.01	00 & 50	2	7.56 ***	3.8	3.9	10.5
0.01	X0	10	24.25 ***	2.42	18.1	29.2
0.01	X0 & X5	20	38.90 ***	1.945	31.0	46.1
0.05	00	5	9.07 **	1.82	7.6	11.2
0.05	00 & 50	10	15.55 **	1.55	13.7	18.6
0.05	X0	50	57.24 **	1.144	55	60.3
0.10	00	10	15.28 *	1.53	13.4	17.0
0.10	00 & 50	20	25.83*	1.29	24.1	27.9

In the second column, X is used as a wildcard. The column "Exp" shows the expected frequency under a uniform distribution. "Freq" shows the frequency observed and "Ratio" shows the ratio of the percentage observed to the expected one. "Min" and "Max" show the Min and Max percentages observed for each category. ***, **, * indicate a difference between the observed and the theoretical frequency significant at a 1%, 5% and 10% level. Significance is computed using Wilcoxon sign ranked test. T-test and median test give quite similar results.

Table 6: Trade Price Clustering (Last Digit) - 0.01€ Group

Last	Freq. (%)
0	23.66***
5	14.47***
8	8.12***
9	8.06***
2	7.82***
6	7.77***
1	7.62***
4	7.57***
7	7.53***
3	7.38***

This tables gives, for the 0.01€ group, the percentage of cases clustered at a final digit of 0-9. *** indicates a difference between the observed and the theoretical frequency significant at a 1% level. The significance is computed using Dunnett adjustment for multiple comparison.

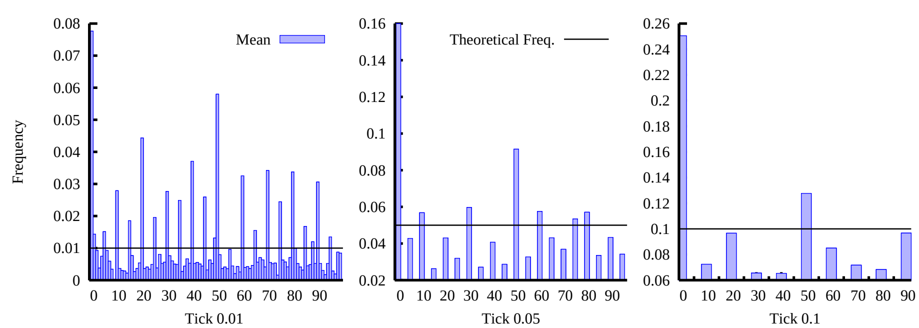
who investigate the distribution of daily closing prices of stocks trading on the Singapore Stock Exchange, an order driven market with no designated market makers.

4.1.2 Fixing Period

Euronext Paris manages opening and closing periods using fixings. Opening and closing prices are determined by a call market system designed to maximize the number of shares traded. All trades are recorded at the same fixing price. Unexecuted orders are left on the opening order book for the subsequent continuous trade period or on the closing order book for the subsequent call[31].

Figure 4 provides the frequency of the last two digits for fixing trades. The clustering effect is clearly apparent. Moreover, it is even more pronounced for the opening and closing transaction prices than for the trade price observed during the continuous trading session. For example, for stocks trading with a tick size of 1 cent, the frequency of fixing trades occurring at prices ending in round numbers of 00 is not far from 8% (while the expected proportion under the hypothesis of a uniform distribution is 1%). It is clearly higher than the frequency observed during the continuous trading session. The results for stock trading with a tick size of 5 cents or 10 cents are similar[32].

Figure 4: Clustering of Fixing Prices : Last Two digits



This figure gives the frequencies of the last two digits for the trades at the opening and closing fixings. We compute these frequencies first on a share by share basis and we then obtain means and quantiles among the shares in the same tick group.

decimalization reform. They also suggest that a policy change to price increments of five cents may not have a major effect on observed transaction prices!!.

[31] During the period preceding the opening and the closing call auction, limit orders can be submitted, canceled or modified. No trades can occur.

[32] For the 5 cents tick category (resp the 10 cents tick category), the frequency of trades occurring at prices ending in round numbers of 00 is 16% (resp 25%) in the fixing period and 9% (resp 15%) in the continuous trading session.

To analyze the significance of the clustering effect for fixing trades, we run similar tests as we did for continuous trading periods and obtain almost identical results: the clustering phenomenon is highly significant for both continuous trading and fixing periods.

During the pre-opening period, limit and market orders present in the book are aggregated into a supply curve and a demand curve. During the period preceding the call auction, indicative prices are quoted so that investors can adjust their orders to market conditions. Biais *et al.* (1999) document the significant information content of these indicative prices and their convergence process toward the end of the pre-opening period (which precedes the opening call auction on Euronext)[33].

As the fixing price is set to maximize trading volume, all limit buy (sell) orders with a price above (below) the fixing price are first executed at this uniform price. Limit orders with a price equal to the market clearing price are then executed. Knowing the prevalence of round prices, possibly reflecting nothing but investor tendency to trade in round numbers, buyers (sellers) could be prompted to introduce limit orders at and just above (below) round numbers thus leading to an increase in cumulated depth on round numbers[34]. This result is consistent with Kandel *et al.* (2001) who found round number clustering in orders submitted by investors in Israeli IPO auctions[35].

4.2 Order Price Clustering

As suggested before, in a computerized limit order market, trade price clustering is directly related to limit order price clustering because transaction prices are the result of market orders hitting best quotes and other limit orders standing in the order book. Analyzing price clustering for both best quotes (4.2.1) and all limit buy and sell orders available in the order book (**??**) could largely improve our understanding of this pervasive fact[36].

As trade price clustering is negatively related to the absolute tick size (it is

[33] They found that, 30 minutes before the opening, learning takes place, both convergence and order placement accelerate dramatically in the last ten minutes of the pre-opening. Moreover traders behave strategically by delaying their order placement until the latter part of the pre-opening period to minimize the revealing private information.

[34] Note that before December 2003, only Euronext members had access to the whole limit order book except hidden quantities and members' identification codes (ID codes) while others traders could only observe the aggregate five best limits of the order book during the continuous trading session. Today, the access to all quotes have been extended to the market place. Nevertheless, during the pre-opening and the pre-closing periods, only buy (sell) limit orders with a price above (below) the indicative market clearing price together with the indicative trading volume at that price are disclosed.

[35] On the IPO day, investors submit multiple limit buy orders and the auctioned IPO price is the highest price at which demand at least equals the predetermined supply.

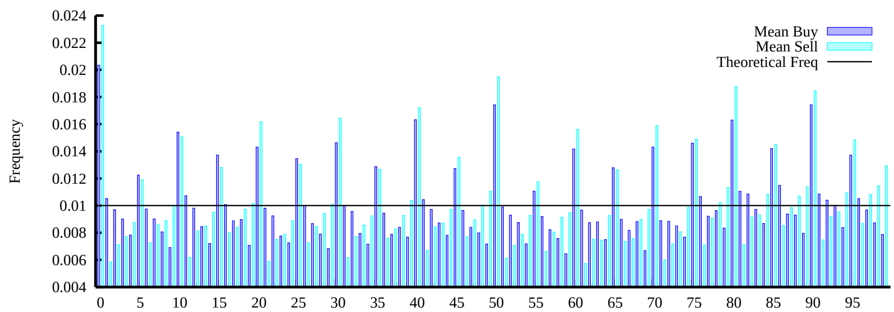
[36] Except the study ofAhn *et al.* (2005) there is non evidence on the clustering of limit order prices on equity markets.

more pronounced for the 0.01€ tick group) and as this sub-sample contains the most numerous stocks, hereafter we present the following results only for this category.

4.2.1 Best Quotes

Figure 5 shows the proportion of quotes (best limits) clustering for the 0.01€ tick group. The last digit or the best quotes is most often either 0 or 5 (nearly 30% of time). The differences between buy and sell quotes are not statistically significant. This result is similar to those in Chung *et al.* (2006) who analyze closing bid and ask quotes clustering using data from the Kuala Lumpur Stock Exchange[37]. Table 7 gives the results of an Anova on the best quotes frequency distribution for the 0.01€ group according to the sign of the quote.

Figure 5: Clustering of Best Quotes (last two digits) - 0.01€ Group



This figure plots for the 0.01€ tick size group the frequency of buy and sell best quotes based on the last two digits of the quotes during the continuous trading period.

Table 7: Best Quotes Last two Digits - Anova

Sign	Fischer	Kruskall-Wallis	Ansari-Bradley
Buy	20***	724***	362***
Sell	25***	826***	478***

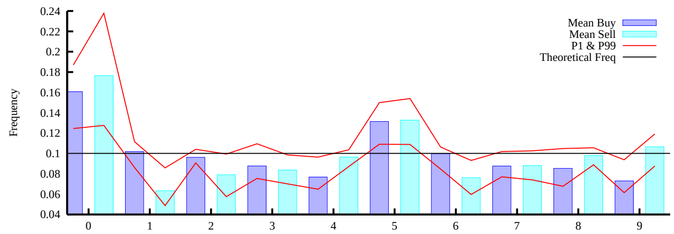
This table gives the results of Fisher, Kruskal-Wallis and Ansari-Bradley tests of equality between the frequencies. *** indicates a test significant at a 1% level. Frequencies are computed on a per share basis and then a joined test is run on all equities in the tick group.

As for transaction prices, we observe a highly significant clustering effect on best quotes. Moreover, the phenomenon seems more pronounced on the sell

[37] This Exchange is a computerized and purely order driven market and uses seven different tick size.

side. Among the 14 equities in the 0.01€ group, the χ^2 test of the equality in frequencies ranges from 7523^{***} to 101765^{***} on the buy side and from 8097^{***} to 146646^{***} on the sell side. Hence, clustering is overwhelmingly significant for all equities on both the buy and sell sides.

Figure 6: Clustering of Best Quotes (last digit) - 0.01€ Group



This figure plots for the 0.01€ tick size group the frequency of buy and sell best quotes based on the last digit of the quotes during the continuous trading period.

Figure 6 plots an histogram for decimal fractions at the one-cent level (prices where the last digit range from 0 to 9). We find strong evidence of price clustering at zero and five cents ticks. Interestingly, Ahn *et al.* (2005) find that on the Stock Exchange of Hong Kong[38], clustering is more frequent for dimes with a percentage frequency of 18.2% and less pronounced for nickels with a percentage frequency of 10.7%. We also observe a very significant clustering effect for best quotes at the one-penny level. Statistical tests are shown in table 8. Contrary to the result observed in table 7 and figure 5(last two digits), the sell side does not show any evidence of more clustering than the buy side. Hence, the higher clustering effect on the sell side seems only related to "the first digit" without significantly affecting the last digit[39].

Table 8: Best Quotes Last Digit - Anova

Sign	Fischer	Kruskall-Wallis	Ansari-Bradley
Buy	85^{***}	111^{***}	80^{***}
Sell	79^{***}	116^{***}	83^{***}

This table gives the results of Fisher, Kruskal-Wallis and Ansari-Bradley tests of equality between the last digit 's frequencies. *** indicates a test significant at a 1% level. Frequencies are computed on a per equity basis and then a joined test is run on all equities in the tick group.

[38] Also a computerized limit order market for which the tick size increases with the share price in a stepwise fashion.

[39] One can think for instance to a move from 10 to 00 that does modify the last digit frequency.

Table 9 confirms that the observed frequency for prices ending in 00 (whole integer value) is 2 times what is expected under a uniform distribution for the best buy quotes and 2.3 times for the best sell quotes.

Table 9: Buy and Sell Best Quotes Clustering and price increment - 0.01 Group

Last Digit	Exp (%)	Buy (%)	Sell (%)
00	1	2.04***	2.33***
00 & 50	2	3.78***	4.28***
X0	10	16.07***	17.64***
X0 & X5	20	29.21***	30.91***

In the first column, X is used as a wildcard. "Exp" shows the expected frequency under a uniform distribution. "Buy" and "sell" show the frequency observed for the best buy (sell) quotes. *** indicates a difference between the observed and the theoretical frequency significant at a 1% level. Significance is computed using Wilcoxon sign ranked test. T-test and median test give quite similar results.

Besides, table 10 shows that after dimes and nickels, the next "prominent" numbers are "1", "6" and "2" for the buy quotes and "9" and "8" and "4" for the sell quotes. Moreover, frequencies for "4" and "9" (quotes just under 5 and 0) are the two lowest ones for the buy quotes (significantly under the expected frequency). Inversely, frequencies for "6" and "1" (quotes just over 5 and 0)are the two lowest ones for the sell quotes.

Table 10: Buy and Sell Best Quotes Clustering (Last Digit) - 0.01€ Group

Buy		Sell	
Freq (%)	Last	Last	Freq (%)
16.07***	0	0	17.64***
13.14***	5	5	13.27***
10.18	1	9	10.66
9.97	6	8	9.78
9.62	2	4	9.63
8.77**	3	7	8.81
8.75**	7	3	8.37**
8.54***	8	2	7.90***
7.67***	4	6	7.61***
7.30***	9	1	6.33***

This tables gives, for the 0.01€ group, the percentage of cases clustered at a final digit of 0-9. ***, ** indicates a difference between the observed and the theoretical frequency significant at a 1% and 5% level. The significance is computed using Dunnett adjustment for multiple comparison.

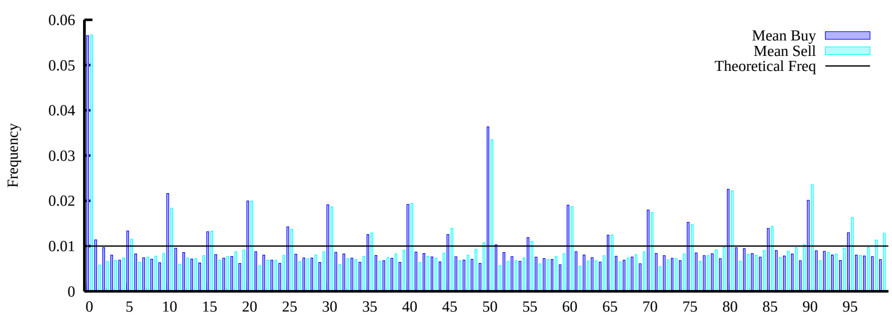
4.2.2 Limit Orders

Niederhoffer (1965) already suggested that clustering of individual stock trade prices is caused by relatively many limit orders at round numbers, and that it can cause barriers or resistance points at these numbers. Euronext is an order driven market. The price clustering effect observed above for transaction price and best quotes is indeed related to specific patterns in limit order placement strategies of multiple anonymous traders.

Frequency distributions of the last two digits and last digit of all limit buy and sell orders available in the book are plotted in figures 7 and 8.

These results indicate that the trade price and best quotes clustering patterns are in fact related to specific limit order placement behavior[40]. The trading mechanism of a centralized limit order book resulting in a continuous matching orders process reinforces the clustering effect by generating best quotes clustering and of course trade price clustering.

Figure 7: Clustering of Limit Order Prices (last two digits)- 0.01€ Group



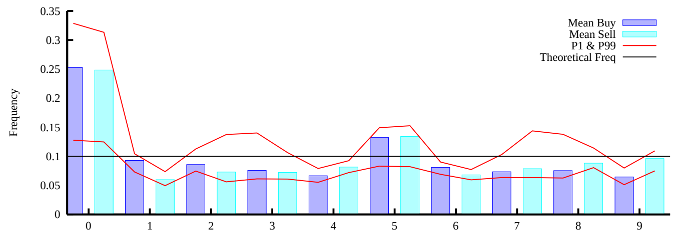
This figure plots for the 1 cent tick category the frequency of limit order prices based on the last two digits of the prices during the continuous trading period.

Indeed, Table 11 shows that, for stocks trading with a price increment of 1 cent, the buy limit order clustering on prices ending with X0 and X5 is not far from 40% and similar to the the sell limit order clustering. Limit order prices ending with 00 and 50 attain a frequency of quite 10%. Moreover, one limit order over 4 ends with X0.[41]. The limit order clustering on Euronext is clearly more pronounced beyond the best quotes than that observed by Ahn *et al.*

[40] We run the same statistical tests on limit orders frequencies as we did on the best quotes with almost identical significant results.

[41] Considering three different sample periods (down, constant and up), we observe that the clustering effect of buy and sell orders is largely higher for the flat period than for bearish or bullish periods. Besides, whereas the clustering is of same level on the bid and ask sides for the constant period, it is more pronounced on the buy (ask) side during the bearish (bullish) period. We are conducting statistical tests to assess the significance of these results.

Figure 8: Clustering of Limit Order Prices (Last Digit) - 0.01€ Group



This figure plots for the 1 cent tick category the frequency of limit order prices based on the last digit of the prices during the continuous trading period.

(2005) over the five first queues of the limit order book for the Stock Exchange of Honk Kong. However Ahn *et al.* (2005) show that prices in deeper queues cluster more than best quotes, and conclude that one possible implication is that the book's information content varies among different queues.

Table 11: Buy and Sell Limit Order Clustering (Last two Digits) - 0.01€ Group

		Buy			Sell		
Last digit	Exp (%)	Freq (%)	Min	Max	Freq (%)	Min	Max
00	1	5.65***	2.4	8.9	5.66***	2.5	7.9
00 & 50	2	9.29***	3.8	13.7	9.01***	3.8	12.6
X0	10	25.25***	12.8	32.9	24.85***	12.5	31.3
X0 & X5	20	38.48***	21.1	47.2	38.28***	20.7	46.0

In the first column, X is used as a wildcard. The column "Exp" shows the expected frequency under a uniform distribution. "Freq" shows the frequency observed. "Min" and "Max" show the Min and Max percentages observed for each category. *** indicates a difference between the observed and the theoretical frequency significant at a 1% level. Significance is computed using Wilcoxon sign ranked test. T-test and median test give quite similar results.

Analysing the clustering effect of limit orders at the one-cent level, we can notice interesting patterns related to the clustering of limit buy (sell) orders on prices just above (just under) round numbers ending in 0 (dimes). For example, as we can see in Table 12, the frequency of limit buy orders clustering on prices with "1" or "2" as the last digit is respectively 9,30% and 8,57% while it is only 5,99% (last rank) and 7,29% for limit sell orders. As well, the frequency of limit sell orders clustering on prices with "9" or "8" as the last digit is respectively 9,6% and 8,81% (not statistically different from the expected frequency), while it is only 6,44% (last rank) and 7,54% for limit buy orders (statistically different from the expected frequency). Those results indicate that after limit order prices ending with 00 and 50, the next "prominent" prices are "1", "2" and "6" for the limit buy orders and "9", "8" and "4" for the limit sell orders. It is possible that this result is related to strategic behavior of some limit order traders who anticipate clustering tendencies and can easily step-ahead of limit orders "congestion" to obtain priority[42]. The cost of such undercutting strategies is low for stock trading with a decimal tick size because, with a fine pricing grid, the cost of acquiring order precedence through price priority is marginal. Nevertheless, before adopting this "pennying"' behavior, investors must decide if the benefit from gaining time priority is worth the sacrifice of one cent of a **€**.

Table 12: Limit order price clustering (Last Digit) - 0.01**€** Group

Buy		Sell	
Freq (%)	Last	Last	Freq (%)
25.25***	0	0	24.85***
13.23***	5	5	13.43***
9.30	1	9	9.60
8.57	2	8	8.81
8.10	6	4	8.15
7.58**	3	7	7.87**
7.54**	8	2	7.29***
7.34***	7	3	7.23***
6.65***	4	6	6.79***
6.44***	9	1	5.99***

This table gives, for the 0.01**€** group, the percentage of cases clustered at a final digit of 0-9.***, ** indicates a difference between the observed and the theoretical frequency significant at a 1% and 5% level. The significance is computed using Dunnett adjustment for multiple comparison.

Thus, as the clustering effect is more pronounced for limit order with prices ending in 00 and 50 (see figure 7), we expect these undercutting strategies to be more frequent for limit orders to buy (sell) at prices just above (below) these price levels than for any other prices ending in X0[43]. Table 13 confirm this hypothesis. It shows that, for stocks trading with a price increment of 1 cent, the buy limit orders clustering on prices ending with 01 is over the expected frequency (a mean of 1,14%) while the sell limit orders clustering is largely under the expected frequency (a mean of 0,58%). On the contrary, and as expected,

[42]Nevertheless, the frequencies for limit buy (sell) orders with prices ending with last digit "1", "2" and "6" ("9", "8" and "4" respectively) are not statistically different from the expected one. This result is potentially due to the fact that congestion is mainly observed for prices with last digit ending in 00 and 50, leading us to look for more clustering for limit orders buy (sell) just over (under) prices ending in 00 and 50.

[43]Gaining time priority and ensuring quick order execution is of course a more profitable strategy when the depth available at integers or halves is high.

the buy limit orders clustering on prices ending with 99 is under the expected frequency (a mean of 0,70% and even 0,62% for prices ending in 49) while the sell limit orders clustering is over the expected frequency (a mean of 1,28% for prices ending in 99). Interestingly, note that the sell limit orders clustering on prices ending with X1 (other than 01 and 51) is significantly under the expected frequency (a mean of 4,84%)[44]. Besides, the buy limit orders clustering on prices ending with X9 (other than 99 and 49)is also significantly under the expected frequency (a mean of 5,12%).

These evidence are consistent with the observations of Niederhoffer (1965) and Niederhoffer & Osborne (1966),who suggested that congestion of limit orders on certain prices could "open up lucrative trading techniques" for well-advised investors[45]. If, as shown before, many limit sell (buy) orders are placed at some prominent figures, the associated depth could in fact result in "price barriers" and act as a resistance (support) level. The next section explores this hypothesis.

4.3 Limit Order Clustering and Price Barriers

There is some evidence that round numbers act as resistance or support on US stock markets. In a recent paper, Kavajecz & Odders-White (2004) show that, in the order book of NYSE listed stocks, there are often a few prices (frequently whole dollar and half-dollar prices) that contain a disproportionate number of shares available. These "peaks" of liquidity create a "congestion" effect, or a price barrier, wich is more difficult to penetrate[46].

4.3.1 Time Duration between Quotes

Since more volume will be necessary to push a stock through integers and halves than any of other prices, stocks probably spend more time at this level. We first propose to explore this hypothesis by providing a measure of time duration between two quotes conditionally on the last two digits of the quote (conditional duration). We first calculate the distribution of durations to next best quote (duration between two best quotes with or without any change in the deci-

[44] For case, the expected frequency under a uniform distribution is 8%

[45] For example, a trader anticipating a clustering of limit sell orders at a price of 50€ could short sells at 49,99 a share that recently rose from 49,91 to 49,99 so as to make a profit if, as expected, selling forces drive the price back to 49,91€.

[46] The analysis of limit order placement in Kavajecz & Odders-White (2004) indicates that limit orders tend to be placed near a new technical analysis level (resistance/support) prior to the level's creation more frequently than orders are placed near the new level after its creation. It is thus suggested that the connection between technical analysis and limit order book depth is driven by "technicians being able to identify locations with high cumulative depth already in place on the limit order book, and not by liquidity providers submitting limit orders at the place where technicians forecast support and resistance levels" (p. 1066).

Table 13: Buy and Sell Limit Orders Clustered at 01, 51, X1 and 99, 49 and X9 - 0.01€ Group

Period	Expected (%)	Last Digit	Buy (%)	Sell (%)	Last Digit	Buy (%)	Sell (%)
DDP	1	01	0.16***	-0.33***	99	-0.19***	0.17***
	1	51	0.06**	-0.28***	49	-0.30***	0.11***
	8	X1	-0.08	-2.12***	X9	-2.08***	-0.01’
DTP	1	01	0.18***	-0.32***	99	-0.26***	0.30*** ’
	1	51	0.10***	-0.32***	49	-0.28***	0.12***
	8	X1	-0.31***	-2.35***	X9	-2.16***	-0.04
C.P	1	01	0.14**	-0.42***	99	-0.30***	0.28***
	1	51	0.03	-0.43***	49	-0.38***	0.08
	8	X1	-0.89***	-3.16***	X9	-2.88***	-0.78***
UTP	1	01	0.09	-0.17***	99	0.08	0.26***
	1	51	-0.06	-0.25***	49	-0.19***	0.09**
	8	X1	-0.18*	-1.76***	X9	-1.37***	-0.17
UUP	1	01	0.10**	-0.29***	99	-0.18***	0.25***
	1	51	0.05	-0.29***	49	-0.24***	0.15***
	8	X1	-0.20*	-2.10***	X9	-1.67***	0.13*

This table examines the abnormal proportion of limit orders at price ending in last digits of 01, 51 and X1 (other than 01 and 51) and 99, 49 and X9 (other than 99 and 49). "Exp" gives the expected frequency under a uniform distribution. "Buy" and "sell" show the abnormal frequency observed for the limit buy (sell) orders. ***, **, * indicate a difference between the observed and the theoretical frequency significant at a 1%, 5% and 10% level. Significance is computed using Wilcoxon sign ranked test. T-test and median test give quite similar results.

mal price) and the distribution of durations to next decimal change (duration between two best quotes with a change in decimal price).We compute these durations conditionaly on the last two digits of the quotes (bar charts in Figures 9 and 10). Obviously, the (suitably weighted) mean of theses durations gives the unconditional duration (solid line). Indeed, when the conditional duration is under the unconditional one, it means that the quote frequency at this price is higher than the mean and that quote activity is intense. Inversely, when the conditional duration is over the unconditional one, it means that the quote frequency at this price is lower than the mean and that quote activity is low.

If whole integers, halves or even dimes act as resistance/support, then, at price levels ending in 00, 50 or X0, the duration to next best quote should be below the mean and the duration to next decimal change should be higher than the mean. Figures 9 and 10 show our results for the buy (sell) side respectively. Considering wholes integers and halves, there is evidence that depth clustering probably generates price barriers that are more difficult to penetrate. Indeed, for best quotes ending in 00 an 50, the duration to next best quote is far below the mean, whereas the duration to next quote with a price change is clearly above the mean[47]. Thus, for best quotes ending in 00, the time duration to next decimal change is 55% and 75% higher than the mean for the buy and sell side respectively. For best quotes ending in 50, the time duration to next decimal change is 44% and 47% higher than the mean for the buy and sell side respectively. It results that the frequency with which market orders hit the best quotes, without generating any change in the decimal quote, is higher when the best quotes are whole integers or halves than any other quotes. As best quotes are spending more time at these price levels, our results on time duration are consistent with round numbers acting as price barriers[48].

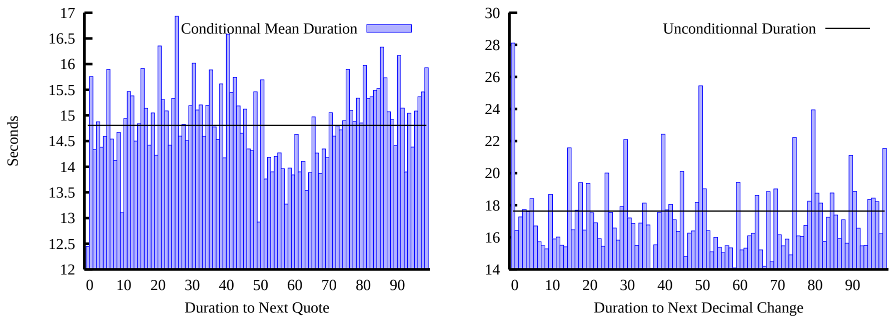
4.3.2 Clustering and Daily Highs and Lows

It has been shown that stocks spend an inordinate amount of time at some "prominent" price levels. Probably that more trading volume is necessary to push a stock price through integers and halves than any of other prices. Nevertheless, if the buying (selling) pressure is not sufficient, trends would be likely to be stopped or could even reverse when they hit limit order clusters at round numbers. Niederhoffer & Osborne (1966) showed that stock prices tend to reverse at

[47]When the best quote is a whole number, trading activity is high (small duration to next quote) but it does not generate any rapid change in best quotes (high duration to price change).

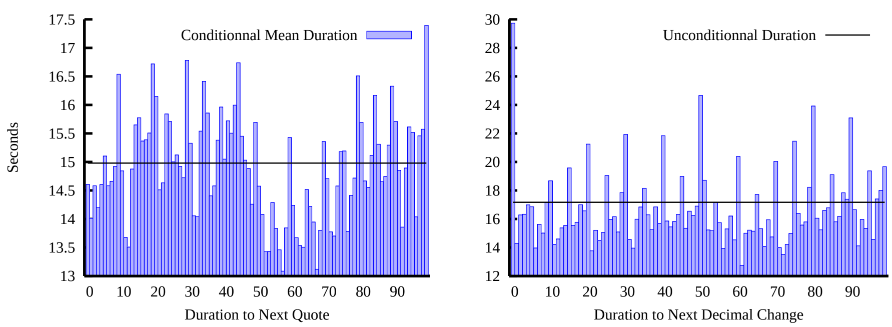
[48]We also calculated the frequency of "excess duration" to next decimal change between two quotes. The excess duration is defined as the difference between the conditional duration to next decimal change and the unconditional duration. As expected, we observe statistically significant frequencies of excess time durations to next decimal change for best bid (ask) quotes ending in 00, 50 and X0. For example, the frequencies of excess duration for best bid (ask) quotes ending in 00 are respectively 74% and 82% (p-value $<$ 0,001)

Figure 9: Time Duration: Best Buy Quote - Last Two Digits - 0.01€



This figure gives the time duration to next quote and time duration to next decimal change, conditionally to the last two digits of the best buy quote.

Figure 10: Time Duration: Best Sell Quote - Last Two Digits - 0.01€



This figure gives the time duration to next quote and time duration to next decimal change, conditionally to the last two digits of the best sell quote.

Table 14: Abnormal Proportion of Daily Highs and Lows Ending in X0, X1 and X9 - 0.01€ Group

Last(s) Digit(s)	Exp (%)	High (%)			Low (%)		
		Down P.	*C.P*	Up P.	Down P.	*C.P*	Up P.
00	1	3.42***	2.03	1.90***	2.94***	1.52*	0.69
50	1	2.51***	2.78***	2.26***	2.41***	2.91***	2.04***
X0	8	11.43***	8.39***	8.06***	9.99***	11.55***	7.91***
01	1	-0.36***	-0.24	-0.56***	0.02	0.01	-0.01
51	1	-0.63***	-0.37**	-0.71***	0.29	0.39	0.58
X1	8	-4.61***	-4.60***	-3.53***	0.43	0.83	0.61
99	1	0.15	1.27	0.50	-0.46***	-0.75***	-0.67***
49	1	0.60	0.13	0.17	-0.56***	-0.75***	-0.71***
X9	8	-0.89***	0.32	-0.63	-4.80***	-5.10***	-3.49***

This table examines the mean abnormal proportion of daily highs and lows with price ending in last digits of 00, 50 and X0 (other than 00 and 50), 01, 51 and X1 (other than 01 and 51) and 99, 49 and X9 (other than 99 and 59). We present results for separated periods (down, constant and up). "Exp" is The expected frequency under a uniform distribution. It is 1% for prices ending in 00 or 50, and 8% for prices ending in X0. Abnormal proportion is the difference between the realized and the expected frequency. "high" and "low" are the proportion of daily highs and lows registered at prices endind in X0, X1 and X9. *** and ** indicate a difference between the observed and the theoretical frequency significant at a 1% and 5% level. Significance is computed using Wilcoxon sign ranked test. T-test and median test give quite similar results.

limit order cluster points because limit orders act as barriers to continued price movement[49]. As highs and lows are the upper (lower) price levels observed for any stock during a trading day, it is possible that the proportion of daily highs and lows registered at prices ending in 00, 50 or X0 is largely above the expected frequency. Table 14 shows the results for our sampling period. We calculate the mean abnormal proportion of daily highs and lows with price ending in last digits of 00, 50 and X0 (other than 00 and 50). Abnormal proportion is the difference between the realized frequency and the expected one under a uniform distribution. The expected frequency is 1% for trade prices ending in 00 or 50, and 8% for trade prices ending in X0 (other than 00 and 50). Results are shown for 3 different periods (bearish, flat and bullish). We can notice several interesting facts. First, for the constant period, the mean abnormal proportion of daily highs with price ending in last digits of 00 and 50 is respectively 2,03% and 2,78%. The second is statistically significant. The corresponding abnormal proportions for lows are 1,52% and 2,91%. Second, the mean abnormal proportion of daily highs and lows with price ending in last digits of X0 (other than 00 and 50) is much larger and not far from 10% (it ranges between 8,39% and 11,55%). Analysing the abnormal proportion over different periods, this fact is even more pronounced during bearish and high volatile markets than during bullish and low volatile ones. Thus, according to the period, between 20% and 25% of highs and lows registered on the highly liquid stocks trading with a tick size of one cent on Euronext are at prices with a last digit of 0[50]. It results from this analysis that the clustering of limit orders at round numbers generates price barriers that are sometimes not easily overstepped. That's why daily highs and lows are more often observed at prices ending in 0. A concentration of price reversals just below and above these peaks of liquidity can of course encourage day traders or professionals to try to make a profit by placing limit buy (sell) orders just above (below) round numbers and "getting the trade". We have shown before that the frequency of buy (sell) limit orders clustering on prices ending with 01 and 51 (99 and 49) is above the expected one. If this undercutting behavior is shared by numerous traders, we should therefore expect the proportion of daily lows with prices ending in 01 and 51 to be higher than the proportion of highs at these prices. Inversely, the proportion of daily highs with prices ending in 99 and 49 should be higher than the proportion of lows. Table 14 also examines the abnormal proportion of daily highs and lows with price ending in last digits of 01, 51 and X1 (other than 01 and 51) and 99, 49 and X9 (other than 99 and 49). We find that the mean abnormal propor-

[49]More precisely, the tendency for prices to reverse course at a given price level rises monotonically with the frequency with which limit orders are placed at that level.

[50]i.e nearly 15% above the expected frequency

tion of daily lows with prices ending in 01 and 51 is positive for all periods but not statistically significant. On the contrary, the mean abnormal proportion of highs at these prices is negative and statistically significant. Besides, the mean abnormal proportion of daily highs with prices ending in 49 and 99 is often positive but not statistically significant, while the mean abnormal proportion of lows at these prices is negative and statistically significant.

Our results are clearly consistent with Niederhoffer (1965) who found that for eleven haphazardly chosen stocks quoted on the NYSE in 1961, there were more highs than lows at 7|8 and more lows than highs at 1|8. In our analysis, we further calculate the mean ratio of highs to lows for prices ending in 01, 51, X1, 99, 49 and X9. For the three first price levels, the mean ratio is under unity and it is above unity for the next ones.

Our results are also consistent with Osler (2000) who show that, on the Forex, 70% of published support and resistance levels are round numbers ending in 0. Thus, Osler suggests the possibility of a "*rational self-fulfilling dynamic between order placement and stock price dynamics*". Indeed, limit orders are closely related to what Forex traders call "take-profit orders". Take-profit orders also strongly cluster at round numbers and lead down trends (up trends) to reverse course when they hit support (resistance) levels[51].

Further research have to be conducted to make evidence that, on a pure order driven stock market, trends is likely to reverse when they hit limit order clusters at round numbers[52]. Recently, Kavajecz & Odders-White (2004) demonstrate that, on the NYSE, price reversals are likely near points of high cumulative depth on the limit order book. More specifically, they indicate that "future returns are likely to be large and positive when the bid price approaches a limit buy price with high depth and smaller when the ask price is close to a limit sell price with high depth". This is consistent with the analysis of Bagnoli *et al.* (2006) who find that excessive overnight selling tends to follow stocks that close on 9-ending prices[53]. Moreover, for companies whose stock prices close at or just below (above) round dollar amount, the average overnight return is significantly negative (positive). Further analysis indicates that this may be due to resistance level created by round dollar stock price clustering.

[51]See Osler (2003) for an extensive analysis on the Forex.

[52]Some preliminary results indicate that, for our sample stocks, trends actually reverse course when they hit prices ending in 00 and 50. We are currently conducting further research.

[53]on the contrary, closing prices that just exceed round-dollar amounts tend to be followed by significant net buying.

5 Conclusion and Further Research

In this paper, we provide evidence of trade price and limit order price clustering on stocks traded on Euronext, a pure computerized limit order market with stock trading within a sliding scale of tick size. Consistent with results observed on US financial markets, trade prices are found to cluster at 0 and 5. Looking at highly liquid stocks (we focus on CAC40 shares) we find that 38% of trades occur at either a nickel or a dime. The highest proportion of trades occurs at prices with last digits 00 (whole integer value), the second highest proportion of trades clusters at prices with last digits 50. The results suggest that price clustering is higher for stocks trading with a 1 cent tick than for stocks trading with a coarser price grid. Interestingly, fixing price clustering is even more pronounced as the frequency of fixing trades occurring at prices ending in round numbers of 00 is not far from 2 times the frequency observed during the continuous trading session.

Besides, we provide evidence that the price clustering effect observed above is indeed related to specific patterns in limit order placement strategies. We observe an important order price clustering on prices ending with 00 and 50 (more generally limit order clustering on prices ending with X0 and X5 is not far from 40%). We show that limit order clustering at round numbers generates depth clustering and price barriers. This means that there are price levels (whole integers and halves) for which a given stock spends an inordinate amount of time (congestion). In fact, stock prices tend to linger at cluster points for limit orders. This generates a concentration a demand (support level) and supply (resistance levels) at integers and halves. Moreover, daily highs and lows are more often trade prices ending in X0 than any other price levels.

Separating limit order to buy from limit order to sell, we find that the next price levels showing the strongest clustering effect are just above (beyond) dimes and nickels for the limit buy (sell) orders. We suggest a strategic undercutting behavior of some limit order traders who possibly anticipate clustering tendencies on dimes and nickels and try to place limit buy (sell) orders just above (beyond) prices where other limit orders to buy (sell) cluster.

Our results are such that it seems difficult to gauge if the price clustering arises from strategic behavior and/or bias in decision making caused by psychological attraction to certain prominent numbers. Nevertheless, investors appear to be naturally drawn to certain salient numbers when faced with making decision under general uncertainty. We suggest that, in their order placement strategies, traders rationally select prices that they believe others recognize as saliences. Schelling (1960) spoke of a "focal principle", a principle which, when employed by a large number of players, allows the determination of a unique strategy and leads to a successful coordination. Order clustering on prominent prices like whole integers and halves could be here considered as an example of coordination by focal points. Understanding (and giving some rational explanations for) this behavior is an important task for future research.

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Table 15: Selected Shares

Tick	#	Stocks
0.01	20	ACCOR, AGF, ALCATEL, AXA, BOUYGUES, CAP GEMINI, DEXIA, EADS, FRANCE TELECOM, MICHELIN, ORANGE, SAINT-GOBAIN, SODEXHO ALLIANCE, STMICROELECTRONICS, SUEZ, TF1, THALES, THOMSON MULTIMEDIA, VIVENDI ENVIRON., VIVENDI UNIVERSAL
0.05	3	CASINO GUICHARD, OREAL, VINCI
0.1	3	AIR LIQUIDE, GROUPE DANONE, TOTAL FINA ELF
		dd
0.01	26	ACCOR, AGF, ALCATEL A, AXA, BNP PARIBAS, BOUYGUES, CAP GEMINI, CARREFOUR, CREDIT AGRICOLE, DEXIA, EADS, FRANCE TELECOM, LAGARDERE, LVMH MOET VUITTON, MICHELIN, ORANGE, PEUGEOT, SAINT-GOBAIN, SODEXHO ALLIANCE, STMICROELECTRONICS, SUEZ, TF1, THALES, THOMSON, VIVENDI ENVIRON., VIVENDI UNIVERSAL
0.1	1	TOTAL FINA ELF
		u
0.01	20	ACCOR, ALCATEL, AXA, BOUYGUES, CAP GEMINI, CREDIT AGRICOLE, DEXIA, EADS, FRANCE TELECOM, MICHELIN, PEUGEOT, SAINT-GOBAIN, SODEXHO ALLIANCE, STMICROELECTRONICS, SUEZ, TF1, THALES, THOMSON, VIVENDI ENVIRON., VIVENDI UNIVERSAL
0.05	7	CASINO GUICHARD, LAFARGE, LVMH MOET VUITTON, OREAL, PINAULT PRINTEMPS, SOCIETE GENERALE, VINCI
0.1	3	AIR LIQUIDE, GROUPE DANONE, TOTAL FINA ELF
		uu
0.01	24	ACCOR, AGF, ALCATEL, AXA, BOUYGUES, CAP GEMINI, CARREFOUR, CREDIT AGRICOLE, DEXIA, EADS, FRANCE TELECOM, LAGARDERE, MICHELIN, ORANGE, PEUGEOT, SAINT-GOBAIN, SODEXHO ALLIANCE, STMICROELECTRONICS, SUEZ, TF1, THALES, THOMSON, VIVENDI ENVIRON., VIVENDI UNIVERSAL
0.05	2	CASINO GUICHARD, OREAL
0.1	3	AIR LIQUIDE, GROUPE DANONE, TOTAL FINA ELF
		z
0.01	13	ALCATEL, AXA, BOUYGUES, DEXIA, EADS, FRANCE TELECOM, ORANGE, STMICROELECTRONICS, SUEZ, TF1, THALES, THOMSON MULTIMEDIA, VIVENDI ENVIRON.
0.05	6	AVENTIS, CAP GEMINI, CASINO GUICHARD, OREAL, SANOFI SYNTHELABO, SOCIETE GENERALE
0.1	4	AIR LIQUIDE, GROUPE DANONE, SAINT-GOBAIN, TOTAL FINA ELF

This table gives the selected shares according to the period and the the tic level.