Price discovery in the Greek preopening
by
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Abstract:
In this paper the role of the preopening period in the price discovery process is analyzed, using for the first time a set of continuous intra-daily transactions, orders and quotes data from the Athens Stock Exchange, for a sample of 20 actively traded stocks making up the FTSE/ASE-20 index. The informational content of the opening price and indicative clearing prices is explored by means of predictive regressions (Biais et al., 1999). Results show that: a) opening price is an unbiased predictor of fair value, b) indicative prices computed over all forms of orders follow a U-shaped process towards the latter, revealing an informational deterioration in the mid-preopening, c) limit clearing prices computed solely over limit orders predict fair value better than indicative prices, indicating a higher informational content of limit orders (Madhavan and Panchapagan, 2000).

EFM classification: 360, JEL classification: G14

Keywords: market microstructure; opening price; call auction; price discovery

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1. Introduction

What does a peripheral stock market like the Athens Stock Exchange (ASE) have to offer to the discussion of optimal trading mechanisms? Despite its small size and recent torments, ASE possesses a fully automated quoting and trading mechanism, and operates as an order-driven market under a regulation (MIFID) common to all EU stock markets. Therefore, reliable high-frequency stock data could provide additional bits of empirical evidence on the quality of various market mechanisms in price discovery. ASE opening call auction constitutes an interesting case of non-trading mechanism, operating much like the ones in larger markets, and seems to deliver efficient price discovery at the start of daily stock trading in Athens. Hence, extending Domowitz and Madhavan’s (2001, p.18) argument from assets to markets, the issue arises as to whether an opening call is more valuable for thin markets “where public information is poor and adverse selection is a serious problem”.

Call auction is directly related to the archetypical model of Walrasian or Böhm-Baverkian commodity auction that leads to a single Pareto efficient price (Blais et al., 1999; Domowitz, 1990; Mendelson, 1982). Nevertheless, multilateral market mechanisms were rightfully considered nonfunctional in the pre-computer age, with Tokyo Itayose and Tel Aviv C-Method being the exceptions (Amihud and Mendelson, 1991; Amihud et al., 1997). Therefore, prevailing forms of bilateral trading, requiring less computational resources, were at the heart of both theoretical and practical discussion.

The role of trading processes, rules and market mechanisms in price discovery, i.e. in delivering efficient prices which incorporate available information, has been at the core of the microstructure literature. Stock market prices are the outcome of a trading process under explicit rules in a specific market mechanism (Easley and O’Hara, 1995). In earlier single period models the focus was put on the existence of efficient prices in a market with zero-profit dealers, and informed and uninformed traders, submitting various forms of orders
in a centralized mechanism (Admati and Pfleiderer, 1988; Kyle, 1985; Ho et al. 1985). In subsequent models the scope was extended to sequential (continuous) trading and the existence of a bid-ask spread was imputed to dealers encountering informed traders in an asymmetric information setting (Easley and O’Hara, 1987, 1992; Glosten, 1991; Glosten and Millgrom, 1985). Information asymmetries raised concerns about market stability, since, as it is known from Akerlof’s “lemons” market, too many informed traders may cause a market failure. Uninformed traders, i.e. noise traders who have been so much blamed for causing market inefficiency in macro-finance, became precious liquidity traders who provide liquidity and stability in the market microstructure frame.

In their quest for efficient market structures, both regulators and researchers explored the call auction mechanism as a complement to prevailing quote or order-driven exchanges; for instance when stock trading starts or restarts after a period of no trading (opening calls) or a period of highly volatile trading (circuit breakers) (Abad and Pascual, 2010; Madhavan, 2000). Efficiency of the call auction, especially in determining an opening price after a long time of no trading, was established in a large and growing number of exchanges, e.g. Madhavan and Panchapagesan (2000) and Garbade and Sekaran (1981) for the NYSE, Ellul et al. (2005) for the London Exchange, Blais et al. (1999) for the Paris Bourse, Kehr et al. (2001) for the Frankfurt Exchange, Amihud and Mendelson (1991) for the Tokyo Exchange, Barclay and Hendershot (2003, 2008) for the NASDAQ, Comerton-Forde and Rydge (2006) and Moshirian et al. (2012) for the Australian Exchange, Amihud et al. (1997) and Kalay et al. (2004) for the Tel Aviv Exchange, Davies (2003) for the Toronto Exchange, Brusco et al. (2003) for the Madrid Exchange.

Although higher stock price volatility, recorded in the opening, somehow obscures the efficiency of multilateral mechanisms (Amihud and Mendelson, 1987, 1991; Stoll and Whaley, 1990), empirical findings from Milan and Tel Aviv
suggest that alternative opening mechanisms would perform even worse (Amihud et al., 1990).

Call auction openings determine a starting price by an algorithmic procedure, either directly in order driven markets (Biais et al., 1999) or indirectly in dealers markets, by allowing the latter to take into account the average trader’s “feeling” (Madhavan and Panchapagesan, 2000), or parallel to unregulated market segments, e.g. ECNs (Barcley and Hendershott, 2008; Ellul et. al, 2005). The auction is preceded by an official time period, called preopening, during which orders are submitted and batched, although in several cases the term encompasses unofficial quoting in ECNs outside the official exchange as well.

Nevertheless, call auction opening is not “a one size fit all” mechanism. Various features, such as duration, transparency, order bindingness and dealers or designated market makers (DMM) interference, interweave to produce different degrees of efficiency in price discovery. For instance, Mendelson (1982) points out that intervals should be adjusted to size, thinness and volatility of the market. Hauser et al. (2012) find empirical support for the beneficial role of a random time opening adopted in the Tel Aviv Stock Exchange, especially in days when volatility and liquidity were problematic due to derivative settlement activity. Barcley and Hendershott (2008) and Ellul et al. (2005) corroborate previous results on the role of company size, suggesting that call auctions perform better for large stocks. Comerton-Forde and Rydge (2006) provide evidence on the positive effect of a random opening time on price discovery quality (i.e. price efficiency, noise, orders frequency) especially for large stocks. In an experimental setting, Biais et al. (2009) find that transparency and non-binding orders leave room for price manipulation (“cheap-talk”) in the preopen and thus reduce trade efficiency gains and distort price discovery, confirming Medrano and Vives’s (2001) analysis. Finally, Moshirian et al. (2012) indicate the improvement of opening price predictability in case of overnight announcement.
Eventually, the question of whether a call auction opening mechanism fits a particular stock exchange or a specific group of stocks is an empirical issue.

Two lines of empirical assessment for the quality of the opening price have been proposed in the existing literature. On one hand, unbiasedness and statistical efficiency in predicting fair value are examined. Unbiasdeness is inferred on the basis of the value and significance of the prediction equation coefficient in a Biais et al. (1999) or Hansen-Hodrick (1980) regression, assuming fair value is reached in a particular time of the day (Biais et al., 1999; Barclay and Henderson, 2003, 2008; Brusco et al. 2003; Ciccotello and Hatheway, 2000; Comerton-Forde and Rydge, 2006; Hauser et al., 2012; Madhavan and Panchapagesan, 2000; Moshirian et al., 2012). On the other hand, opening prices should be less volatile and autocorrelated compared to prices generated in the rest of the trading day. Inference is based on the time-series properties of open-to-open versus close-to-close returns (Amihud and Mendelson, 1987; Stoll and Whaley, 1990; Amihud and Mendelson, 1997).

The objective of this paper is to investigate whether the Athens Stock Exchange (ASE) conforms with findings in larger exchanges in terms of price discovery in the opening session and thus strengthens the case for call auctions in the beginning of stock trading globally. More specifically, we evaluate the information content of indicative prices, disclosed during the preopening, and the opening price itself. Additionally, we investigate the role of various order forms posted in the preopening by generating limit clearing prices and assessing their performance in price discovery. Finally, we statistically assess and infer upon the presence of mean reversion in price formation during the preopening.

Empirical evidence is based on a unique data set consisting of all orders posted during the preopening, i.e. limit, market and at-the-open orders, and all transactions and limit order data for the subsequent daily session. Data refer to 20 actively traded stocks making up the FTSE/ASE-20 index for March 2010, provided by ASE authorities and the Hellenic Capital Market Commission (HCMC).
The rest of the paper is structured as follows. Section 2 describes the institutional setting of the Athens Stock Exchange, Section 3 presents the algorithm of opening price determination, Section 4 presents descriptive statistics of the ASE preopening, Section 5 sets out the methodology, Section 6 presents and discusses the results and conclusions are presented in a final section.

Research hypotheses
a) Indicative prices and opening prices contain valuable information
b) Indicative prices depict gradual learning
c) Limit clearing prices are more informative

2. Institutional setting
Athens Stock Exchange (ASE) is the unique organized stock market in Greece operating under the provisions of the European Union Markets in Financial Instruments Directive (MiFID). After a long history of pit and outcry trading, and physical exchange of titles, in 1999 ASE was converted into a full-fledged electronic platform supported by an automated trading and quotation system (OASIS) of dematerialized stocks. Certified brokers are members of the ASE and are mostly large brokerage firms. At the end of 2010, there were 277 companies listed in ASE, while trading was operated by 60 ASE members and 18 remote members. Total market capitalization in the same year was approximately 53.6 billion euros whereas total transactions totaled 35.1 billion euros (Athens Stock Exchange Fact Book, 2011).

Trade takes place from 10:15 am to 17:20 pm, starting with an opening session which lasts fifteen minutes and leads to the determination of a single opening price through a call auction randomly performed around 10:30. Opening price determination algorithms are described in ASE Articles 2332 and 216 (ASE Stock Exchange Regulation 2010). Traders are allowed to anonymously submit, modify or cancel their orders, which may be limit, market or at-the-open orders,
so that bids are effectively non-binding, allowing for market price manipulation. However, given that a random opening time is picked for each stock between 10:29 am and 10:30 am, price manipulation becomes riskier. Also, ASE regulation provides for the possibility of disclosing “projected auction price–volume pairs” (indicative price – volume), enhancing transparency to the process. Non executed or partially executed limit orders as well as partially executed market and at-the-open orders are forwarded to the continuous session at the opening price (ASE Stock Exchange Regulation 2010).

Brokers satisfying specific financial, logistic and technological conditions may be designated to act as market makers (DMM). Despite their important role in providing liquidity and/or containing price volatility for specific stocks, ASE DMMs are not dealers and consequently intervene in the stock market by submitting orders anonymously through the limit order book like the rest of traders.

Opening trading, i.e. trading executed at the opening price, accounts for 2% of the average daily transactions. This is relatively small compared to 9.7% in the NYSE preopen (Madhavan and Panchapagesan, 2000), to 10% in the Paris Bourse preopen (Biais et al., 1999), to 3.4% for active and 14.5% for less active stocks in the Australian Exchange (Comerton-Forde and Rydge, 2006) and almost half the daily trade in Tel Aviv Exchange (Amihud et al. 1997).

3. Opening price determination
According to Article 2332 of the ASE Regulation, determination of an opening price by call auction takes the following steps. First, a price grid is defined: the price grid of the call is the set of prices of all orders submitted in the preopening period. To this follows an aggregation of ordered shares: aggregate buy (sell) volume at each price is computed by summing buy (sell) volume offered up to (down to) that price.
A price-volume pair is an opening equilibrium, if the maximum voluntary exchange is attained at this price. Denoting $B(p)$ and $S(p)$ the aggregate buy and sell functions, an equilibrium price $p^*$ verifies $\max\{\min\{B(p^*)-S(p^*)\}\}$, where the $\min\{\}$ operator expresses the assumption that no one must be compelled to trade at an undesirable price-volume pair. In case of multiple equilibrium prices – a possibility arising when the price grid is not dense up to the minimum tick – the nearest to previous close is selected or in case of a tie the previous close itself.

ASE Regulation makes clear that market and at-the-open orders are counted in the determination of opening price. Absent a detailed official description of how these orders are taken into account, a treatment similar to Garbade and Sekaran (1981), Comerton-Forde and Rydge (2006) and Madhavan and Panchapagesan (2000) is performed: buy (sell) market and at-the-open orders are added to the highest bid (lowest ask). Calculation of a system clearing price based on our data corroborated the algorithm description.

Although market and at-the-open orders do not indicate a price preference, they intervene in the opening price determination by shifting total limit buy and total limit sell curves to the right. As a consequence, a different opening equilibrium is obtained from the one that would prevail if only total limit orders were counted in, with larger volume and probably different price. This is obviously true, when total buy and sell curves cross, but it also holds when they don’t.

It is worth noting that two possible configurations of demand and supply curves exist. The first and more frequent configuration has two characteristics: best ask is lower than best bid (negative spread) and demand and supply curves cross producing an equilibrium price-volume pair. In the second configuration, in contrast, best ask is greater than best bid (positive spread) and demand and supply curves do not cross; Mendelson (1982, p.1513) describes this case as an “empty market”. Although crosses are typical in order driven markets, similarly to dealers markets (Cao et al.,2000), locks (best ask equal to best bid) are
extremely rare. Moshirian et al. (2012) report a minimal percentage of locks in the Australian exchange preopening, yet we did not manage to cross a single lock in our sample.

Figure 1a depicts the working of the algorithm at the opening of Coca-Cola Hellas stock on 3-3-2010 which was a cross (negative spread). A large volume of shares, emanating from buy market and at-the-open orders, were added to the

![Figure 1: Opening cross, Coca Cola Hellas, 3-3-2012](a)

![Figure 1: Opening cross, Coca Cola Hellas, 3-3-2012](b)
highest bid price. In contrast, an infinitesimal volume, coming from sell market and at-the-open orders, is barely visible at the lowest ask price. Figure 1b zooms into the equilibrium range; there were four prices satisfying the equilibrium condition and the one nearest to the previous close was picked by the system.

FIGURE 2: Opening lock-in, Viohalko, 8-3-2012

(a)

(b)
Empty markets (positive spreads) are quite infrequent in our sample; only 39 out of 420, i.e. approximately 9%, resulted in a positive spread. In this case, ASE Regulation Article 216 provides that the opening price is set equal to the price of the first trade in the continuous session. Figure 2a shows the opening of Viohalko stock on 8-3-2010 which was an empty market, i.e. the best ask was higher than the best bid, thus Article 2232 algorithm was superseded. In this particular setting, zoomed in Figure 2b, the first order of the day was a sell which matched the best bid of the unsettled opening book at 4.64 euros.

A continuous flow of stock value information is delivered to the market during the preopening through indicative prices. Indicative prices are computed so as to clear the order book up to the particular time of disclosure, according to the opening algorithm, and are continuously adjusted to the order flow of the preopening. Indicative prices are entirely notional in that no trading takes place since orders are not binding. Since there is no record of indicative prices, we reproduced them by applying the opening algorithm in regular time intervals. Similarly to the opening, indicative prices may be the result of either a cross or an empty market; in the latter case we set the indicative price equal to the mid-price. As the preopening time runs out, crosses become dominant, and the opening price is the limit towards which indicative prices tend to.

Interestingly, our data enable us to compute clearing prices over different forms of orders. Indicative prices computed over the entire set of orders (i.e. limit and market-at-the-open), may be contrasted to prices computed exclusively over the limit order book, i.e. limit clearing prices according to Madhavan and Panchapagesan (2000). As a consequence, the contribution of different forms of orders to price discovery can be assessed.
4. Data and preliminary statistics

The data set contains the entire intraday trading history for March 2010 for stocks included in the FTSE/ASE-20 Index. The set of 20 companies making up the index

Table 1: FTSE/ASE-20 companies, tickers and industry

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Company</th>
<th>Industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALPHA</td>
<td>ALPHA BANK A.E.</td>
<td>Banks</td>
</tr>
<tr>
<td>ETE</td>
<td>NATIONAL BANK OF GREECE S.A.</td>
<td>Banks</td>
</tr>
<tr>
<td>TPEIR</td>
<td>PIRAEUS BANK S.A.</td>
<td>Banks</td>
</tr>
<tr>
<td>EUROB</td>
<td>EFG EUROBANK ERGASIAS S.A.</td>
<td>Banks</td>
</tr>
<tr>
<td>BIOX</td>
<td>VIOHALKO HELLenic COPPER AND ALUMINIUM INDUSTRY S.A.</td>
<td>Industrial Goods &amp; Services - Diversified Industrials</td>
</tr>
<tr>
<td>HTO</td>
<td>HELLENIC TELECOM. ORG.</td>
<td>Telecommunications - Fixed Line Telecommunications</td>
</tr>
<tr>
<td>TITK</td>
<td>TITAN CEMENT COMPANY S.A.</td>
<td>Construction &amp; Materials - Building Materials &amp; Fixtures</td>
</tr>
<tr>
<td>ELLAKTOR</td>
<td>ELLAKTOR</td>
<td>Construction &amp; Materials - Heavy Construction</td>
</tr>
<tr>
<td>EEEK</td>
<td>COCA-COLA E.E.E. S.A.</td>
<td>Food &amp; Beverage - Soft Drinks</td>
</tr>
<tr>
<td>MIG</td>
<td>MARFIN INVESTMENT GROUPS HOLDINGS S.A.</td>
<td>Financial Services - Specialty Finance</td>
</tr>
<tr>
<td>MYTIL</td>
<td>MYTILINEOS HOLDINGS S.A.</td>
<td>Basic Resources - Nonferrous Metals</td>
</tr>
<tr>
<td>BELA</td>
<td>JUMBO S.A.</td>
<td>Personal &amp; Household Goods - Toys</td>
</tr>
<tr>
<td>ELPE</td>
<td>HELLENIC PETROLEUM S.A.</td>
<td>Oil &amp; Gas - Integrated Oil &amp; Gas</td>
</tr>
<tr>
<td>BOC</td>
<td>BANK OF CYPRUS PUBLIC COMPANY LTD</td>
<td>Banks</td>
</tr>
<tr>
<td>ATE</td>
<td>AGRICULTURAL BANK OF GREECE S.A.</td>
<td>Banks</td>
</tr>
<tr>
<td>OPAP</td>
<td>GREEK ORGANIZATION OF FOOTBALL PROGNOSTICS S.A.</td>
<td>Travel &amp; Leisure - Gambling</td>
</tr>
<tr>
<td>MOH</td>
<td>MOTOR OIL (HELLAS) CORINTH REFINERIES SA</td>
<td>Oil &amp; Gas - Exploration &amp; Production</td>
</tr>
<tr>
<td>PPC</td>
<td>PUBLIC POWER CORPORATION SA</td>
<td>Utilities - Conventional Electricity</td>
</tr>
<tr>
<td>TT</td>
<td>TT HELLENIC POSTBANK S.A.</td>
<td>Banks</td>
</tr>
<tr>
<td>MARFB</td>
<td>MARFIN POPULAR BANK PUBLIC CO LTD</td>
<td>Banks</td>
</tr>
</tbody>
</table>
along with the corresponding tickers and trading sectors (FTSE Dow Jones Industry Classification Benchmark) are reported in Table 1. There were 22 trading days in March 2010, so that the entire sample consists of 420 stock-day returns (first day lost).

Trading history consists of three separate files: a) transactions, b) limit orders, c) opening session market and at-the-market orders. Transactions include price and volume pairs time-stamped to the centisecond. The second file records the state of the Limit Order Book up to the five best bid and ask quotes (price and depth) accurate to the centisecond; a new record is added upon submission, modification, cancelation or matching of a limit order. The third file contains information on the preopening activity only, consisting of market and at-the-open orders (volume and side) submitted, modified or cancelled, time-stamped to the centisecond. Preopening limit order activity was extracted from the second file and combined to market and at-the-open order activity of the third file, while opening price and volume were extracted from the first file.

All stocks traded with a minimum tick size of 1 euro cent. In March 2010 companies represented a capitalization of 65.8 billion euros, i.e. approximately 83% of total ASE capitalization, while average daily transactions on sample stocks were 172.3 million euros, covering almost 92% of total ASE trading activity. In the same period, sample stocks had 3.73 million euros of average daily opening transactions which represented 2.2% of total trading activity.

Table 2a presents the overall order flow during the preopen, for all available stocks and days in our data set. It is worth noticing that the rate of order posting for both market/at-the-open and limit orders follows a U-shaped pattern. That is, the majority of order submissions are concentrated in the first and last three minute intervals of the preopen. This characteristic is in
<table>
<thead>
<tr>
<th>Time Period</th>
<th>Total Orders</th>
<th>Total Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td>10:15-10:18</td>
<td>13,581</td>
<td>15,364,721</td>
</tr>
<tr>
<td>10:18-10:21</td>
<td>1,610</td>
<td>3,321,108</td>
</tr>
<tr>
<td>10:21-10:24</td>
<td>1,732</td>
<td>3,164,548</td>
</tr>
<tr>
<td>10:24-10:27</td>
<td>1,863</td>
<td>3,603,756</td>
</tr>
<tr>
<td>10:27 - open</td>
<td>2,970</td>
<td>5,739,866</td>
</tr>
<tr>
<td>Total Preopen</td>
<td>21,756</td>
<td>31,193,999</td>
</tr>
</tbody>
</table>

**Limit Orders**

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Canceled/Revised</th>
<th>Total Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td>10:15-10:18</td>
<td>654</td>
<td>2,343,703</td>
</tr>
<tr>
<td>10:18-10:21</td>
<td>93</td>
<td>1,092,497</td>
</tr>
<tr>
<td>10:21-10:24</td>
<td>233</td>
<td>1,424,916</td>
</tr>
<tr>
<td>10:24-10:27</td>
<td>308</td>
<td>1,710,577</td>
</tr>
<tr>
<td>10:27 - open</td>
<td>612</td>
<td>3,040,136</td>
</tr>
<tr>
<td>Total Preopen</td>
<td>1,900</td>
<td>9,611,829</td>
</tr>
</tbody>
</table>

**Market/at-the-open orders**

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Total Orders</th>
<th>Total Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td>10:15-10:18</td>
<td>1,410</td>
<td>1,410</td>
</tr>
<tr>
<td>10:18-10:21</td>
<td>457</td>
<td>457</td>
</tr>
<tr>
<td>10:21-10:24</td>
<td>506</td>
<td>506</td>
</tr>
<tr>
<td>10:24-10:27</td>
<td>636</td>
<td>636</td>
</tr>
<tr>
<td>10:27 - open</td>
<td>1,517</td>
<td>1,517</td>
</tr>
<tr>
<td>Total Preopen</td>
<td>4,526</td>
<td>4,526</td>
</tr>
</tbody>
</table>

**All types**

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Total Orders</th>
<th>Total Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td>10:15-10:18</td>
<td>14,991</td>
<td>17,708,424</td>
</tr>
<tr>
<td>10:18-10:21</td>
<td>2,067</td>
<td>4,413,605</td>
</tr>
<tr>
<td>10:21-10:24</td>
<td>2,238</td>
<td>4,589,464</td>
</tr>
<tr>
<td>10:24-10:27</td>
<td>2,499</td>
<td>5,314,333</td>
</tr>
<tr>
<td>10:27 - open</td>
<td>4,487</td>
<td>8,780,002</td>
</tr>
<tr>
<td>Total Preopen</td>
<td>26,282</td>
<td>40,805,828</td>
</tr>
</tbody>
</table>

Average limit size (1)  | 1,189         | 2,189        |
Average market size (2) | 1,736         | 3,095        |
(1)/(2)                  | 0.68          | 0.71         |

TABLE 2a: Preliminary statistics of order submission in the preopening with three minute intervals
TABLE 2b: Summary statistics of close to indicative price, close to limit clearing price and close to close returns in the preopening

<table>
<thead>
<tr>
<th>Return</th>
<th>Close to 10:18</th>
<th>Close to 10:21</th>
<th>Close to 10:24</th>
<th>Close to 10:27</th>
<th>Close to open</th>
<th>Close to close</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IP</td>
<td>LCP</td>
<td>IP</td>
<td>LCP</td>
<td>IP</td>
<td>LCP</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.0005</td>
<td>-0.0010</td>
<td>0.0006</td>
<td>0.0002</td>
<td>0.0008</td>
<td>0.0003</td>
</tr>
<tr>
<td>Median</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Variance</td>
<td>0.0003</td>
<td>0.0003</td>
<td>0.0004</td>
<td>0.0003</td>
<td>0.0005</td>
<td>0.0003</td>
</tr>
<tr>
<td>StDev</td>
<td>0.0187</td>
<td>0.0171</td>
<td>0.0195</td>
<td>0.0179</td>
<td>0.0213</td>
<td>0.0162</td>
</tr>
<tr>
<td>Skewness</td>
<td>-3.5018</td>
<td>-4.3533</td>
<td>-3.0524</td>
<td>-3.9610</td>
<td>-2.3279</td>
<td>-3.2826</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>54.9912</td>
<td>75.3926</td>
<td>41.9389</td>
<td>57.6171</td>
<td>28.1023</td>
<td>41.4698</td>
</tr>
</tbody>
</table>

Returns are computed as log price differences. Indicative prices are computed, first, on the entire set of orders (first column, IP) and, second, on the set of limit orders only (second column, limit clearing prices LCP); opening price (OP) is itself a clearing price. Price and return computation is performed in three minute intervals.
contrast to other major exchanges of the world, where order submission grows monotonically towards the opening. Blais et al. (1999) and Ciccotello and Hathaway (2000) report that order submission frequency is significantly increased in the last minutes prior to opening in Paris Bourse and NASDAQ respectively. Comerton-Forde and Rydge (2006) and Moshirian et al. (2012) find similar results in the Australian exchange and Davies (2003) for the Toronto Stock Exchange.

Table 2b reports summary statistics of previous close to indicative, previous close to limit clearing price and previous close to current close returns over all stocks and days. Although mean and median returns do not differ significantly from zero, skewness and kurtosis imply deviation from normality.

5. Methodology

Many researchers have proposed theoretical underpinnings and provided empirical evidence on the interaction among strategic, informed and uninformed traders in the preopening. The common strand is that trends or movements of indicative prices follow trends or patterns which are directly related to preopening order flow. For instance, the existence of a strategic trader who submits manipulative orders at the start, in order to create a trend towards a desired opening price and then cancel it towards the end, or uninformative traders who submit their orders after having considered informed traders’ orders. To those, one should also add the activity of designated market makers whose quotes revamp the order book prior to the opening.

On one hand, interaction in the preopening can be expressed by the hypothesis that indicative prices and, finally, the opening price mirror the expected value of a stock conditional on a time varying information set:

\[ P_t = E(V|I_t) \] (1)
where $I_t$ contains information from previous and current bidding. In the special case where interaction signifies learning, the information set should be improving, i.e. $I_t \supseteq I_{t-1} \supseteq I_{t-2} \ldots$, so that indicative prices converge to the expected value of the stock.

On the other hand, if there is no interaction and thus traders independently submit orders that express their own perception of how stock values incorporate relevant overnight information, denoted $I_0$, then no particular pattern is expected to emerge and the corresponding hypothesis is that indicative and opening prices are noise around the expected value of the stock:

$$P_t = E(V|I_0) \quad (2)$$

The information set contains all overnight information and it is implicitly assumed that the flow of information does not extend into the preopening. The shorter the preopening is, the more realistic the assumption gets.

The predictive power of indicative and opening prices is tested by means of Biais regressions which assess the quality of price discovery in the preopening (Biais et al., 1999; Brusco et al. 2003; Ciccotello and Hatheway, 2000; Comerton-Forde and Rydge, 2006; Hauser et al., 2012; Madhavan and Panchapagesan, 2000). Prices should be unbiased predictors of true values, and the slope coefficient should not be statistically different from unity. Stating prices and values in logarithms and assuming that true values are proxied at the closing session of the day, as in Biais et al. (1999), the prediction regression is expressed as follows:

$$p_{it}^{\text{close}} - p_{it-1}^{\text{close}} = a_k + b_k (p_{kt}^{k} - p_{it-1}^{close}) + z_t \quad (3)$$
where the dependent variable is the previous day close \((i, t-1)\) to current day \((i, t)\) close return and the independent variable is the previous close to current day indicative (opening) return for interval \((k)\) of the preopening and for stock \((i)\). Alternatively, mid-day prices may be used as proxies for true stock values; for instance, Comerton-Forde and Rydge (2006) and Ciccotello and Hatheway (2000) take 11am as the benchmark time, whereas Madhavan and Panchapagesan (2000) take 15pm.

In order to statistically assess the form of interaction in the preopening a test of mean reversion is performed from the start of the preopening and up to opening. Our test extends Ciccotello and Hatheway’s (2000) correlation approach which was originally applied in order to identify stock quote reversals beyond the opening and consists in regressing indicative to opening returns on previous close to given indicative return. Learning, i.e. a J-curve, is evidenced by a positive slope coefficient, whereas noise should not produce a significant coefficient. On the other hand, a mean reversal, i.e. a U-curve, should deliver a negative slope. The mean reversion regression can be expressed as follows:

\[
P_{it}^{open} - P_{it}^k = c_k + d_k \left( P_{it}^k - P_{it-1}^{close} \right) + e_t
\]

where the dependent variable is the indicative to opening return and the independent variable is the previous close to indicative return for stock \((i)\), and interval \((k)\). Ciccotello and Hatheway (2000, p.185,192) report strong evidence of price reversals following the opening on days with light opening trading volume and large price swings early in the preopening, while Cao et al.(2000) show that these changes contribute significantly to price discovery.

An additional measure of prediction quality of indicative and opening prices, besides unbiasedness, is statistical efficiency, i.e. the size of the statistical error of the prediction. Several residual variance measures have been proposed
such as the signal to noise ratio (Barcley and Hendershot, 2003), the variance ratio (Mandhavan and Panchapagesan, 2000) and the root mean square error (Biais et al., 1999). In this study we compute and plot root mean square errors (RMSE). As information is incorporated in prices, predictions become more accurate and thus RMSE should drop. Conversely, as prices get noisier, RMSE should increase and, in the extreme case where prices are totally uninformative, it should equal the standard deviation of the predictor.

6. Results
For each individual stock four indicative prices are generated, at 10:18, 10:21, 10:24 and 10:27 respectively, to which the opening price is added. It is worth noting that opening prices are not synchronous for two reasons: first, because of random opening time and, second, because of additional time given, in certain occasions, when a thin market occurs. Our choice is to accept the cost of some staleness in opening prices, as in Biais et al. (1999), in order to ensure synchronicity in indicative prices across stocks, in contrast to Comerton-Forde and Rydge’s (2006, p.206) choice to set equal time intervals backwards from the actual opening.

We first run prediction regressions for each individual stock and each time interval up to opening. Slope coefficients and their statistical significance are reported in Table 3. Indicative prices are computed, first, on the entire set of orders (first column) and, second, on the set of limit orders only (second column, limit clearing prices, LCP); opening price (OP) is itself a clearing price. Newey-West standard errors are computed and asterisks denote rejection of the null hypothesis $H_0(b_k = 1)$ at the 5% probability level. Although unbiasedness is statistically corroborated for the majority of stocks at the opening, large variations emerge across stocks and across days. Median prediction slope coefficients and confidence intervals at 5% probability are depicted in Figure 3.
Several interesting remarks emerge from Table 3 and Figure 3. Opening price is on the average a trustful predictor of stock true value. Indicative prices (solid line in Figure 3) predict equally well, whereas limit clearing prices (dashed line) perform better in the preopening. Figure 3 depicts a clear U-shaped pattern showing that price discovery deteriorates in the mid-preopening, to improve prior to opening. It is important to note that wide confidence intervals, due to large standard errors of individual estimates, may be the cause of such a generous acceptance of the null.

FIGURE 3: Individual stock median Biais regression coefficients for indicative, limit clearing and opening prices

Median prediction RMSE at different intervals and at the opening is depicted in Figure 4. The RMSE of indicative and opening price (solid line in Figure 4) follows an inverted U-shaped pattern, mirroring slope coefficients of indicative and opening prices in Figure 3. This finding implies that indicative prices in the mid-preopening become not only more biased but less efficient as well.
TABLE 3: Individual stock Biais regression coefficients for indicative, limit clearing and opening prices

<table>
<thead>
<tr>
<th>Stock</th>
<th>up to 10:18 IP</th>
<th>up to 10:21 IP</th>
<th>up to 10:24 IP</th>
<th>up to 10:27 IP</th>
<th>opening time OP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LCP</td>
<td>LCP</td>
<td>LCP</td>
<td>LCP</td>
<td>LCP</td>
</tr>
<tr>
<td>ALPHA</td>
<td>0.60</td>
<td>1.72</td>
<td>1.21</td>
<td>1.57</td>
<td>1.26</td>
</tr>
<tr>
<td>ETE</td>
<td>1.02</td>
<td>1.59</td>
<td>0.91</td>
<td>0.99</td>
<td>0.36*</td>
</tr>
<tr>
<td>TPEIR</td>
<td>1.14</td>
<td>1.40</td>
<td>1.01</td>
<td>1.29</td>
<td>0.54</td>
</tr>
<tr>
<td>EUROB</td>
<td>0.58</td>
<td>1.19</td>
<td>0.94</td>
<td>0.97</td>
<td>0.09*</td>
</tr>
<tr>
<td>BIOX</td>
<td>-0.36*</td>
<td>-0.37*</td>
<td>-0.40*</td>
<td>-0.41*</td>
<td>0.08*</td>
</tr>
<tr>
<td>HTO</td>
<td>0.37</td>
<td>0.88</td>
<td>0.29*</td>
<td>0.15*</td>
<td>-0.04*</td>
</tr>
<tr>
<td>TITK</td>
<td>0.92</td>
<td>0.89</td>
<td>0.29</td>
<td>0.86</td>
<td>0.50</td>
</tr>
<tr>
<td>ELLAKTOR</td>
<td>0.12</td>
<td>0.29</td>
<td>-0.56*</td>
<td>-0.56*</td>
<td>0.26</td>
</tr>
<tr>
<td>EEEK</td>
<td>0.71</td>
<td>0.91</td>
<td>0.21*</td>
<td>0.15*</td>
<td>0.39*</td>
</tr>
<tr>
<td>MIG</td>
<td>1.32</td>
<td>0.86</td>
<td>1.27</td>
<td>1.29</td>
<td>1.09</td>
</tr>
<tr>
<td>MYTIL</td>
<td>0.95</td>
<td>0.95</td>
<td>0.53</td>
<td>0.53</td>
<td>0.37</td>
</tr>
<tr>
<td>BELA</td>
<td>0.47</td>
<td>0.47</td>
<td>0.56</td>
<td>0.56</td>
<td>0.80</td>
</tr>
<tr>
<td>ELPE</td>
<td>1.05</td>
<td>0.96</td>
<td>0.57</td>
<td>0.49</td>
<td>0.56</td>
</tr>
<tr>
<td>BOC</td>
<td>1.40*</td>
<td>1.56*</td>
<td>1.72*</td>
<td>1.89*</td>
<td>1.01</td>
</tr>
<tr>
<td>ATE</td>
<td>0.76</td>
<td>0.79</td>
<td>0.17</td>
<td>0.34</td>
<td>0.51</td>
</tr>
<tr>
<td>OPAP</td>
<td>0.56*</td>
<td>0.60*</td>
<td>0.46*</td>
<td>0.50*</td>
<td>0.48*</td>
</tr>
<tr>
<td>MOH</td>
<td>0.70</td>
<td>0.58</td>
<td>0.17</td>
<td>0.20*</td>
<td>-0.33*</td>
</tr>
<tr>
<td>PPC</td>
<td>1.46</td>
<td>1.25</td>
<td>0.90</td>
<td>1.23</td>
<td>0.76</td>
</tr>
<tr>
<td>TT</td>
<td>1.75*</td>
<td>2.33*</td>
<td>1.60</td>
<td>1.90*</td>
<td>1.29</td>
</tr>
<tr>
<td>MARFB</td>
<td>1.67</td>
<td>1.83</td>
<td>1.39</td>
<td>1.40</td>
<td>1.55</td>
</tr>
</tbody>
</table>

Prediction regressions \( p_{it}^{close} - p_{it-1}^{close} = \alpha_k + b_k (p_{it}^{close} - p_{it-1}^{close}) + \epsilon_t \) are estimated for each individual stock and each time interval. Indicative prices are computed, first, on the entire set of orders (first column, IP) and, second, on the set of limit orders only (second column, limit clearing prices, LCP); opening price (OP) is itself a clearing price. Newey-West standard errors are computed and asterisks denote rejection of the null hypothesis \( H_0(b_k = 1) \) at the 5% probability level.
In contrast, limit clearing prices (dashed line) exhibit no particular pattern during the preopening and resist to efficiency deterioration in the mid-preopening. However, limit clearing prices are less efficient predictors at the opening.

FIGURE 4: Individual stock median Biais regressions RMSE of indicative, limit clearing and opening prices

In order to account for the panel information of the sample and enhance the quality of our estimation, i.e. reduce standard errors, we estimate a mixed effects model of prediction equation (3) with fixed effect, $b_k$, and a random effect, $\tilde{b}_k$, with zero mean and variance $\sigma_b^2$. Results of the mixed effects estimation of the prediction equation are reported in Table 4 and depicted in Figure 4. Again, indicative prices are computed, first, on the entire set of orders (first column) and, second, on the set of limit orders only (second column, limit clearing prices, LCP); opening price (OP) is itself a clearing price. The null
hypothesis is $H_0(b_k = 1)$ and asterisks denote rejection of the null at the 5% probability level.

Table 4 provides clear evidence on the quality of the opening price as a predictor of true value of stocks. The prediction coefficient is 0.903, which is very close to unity, and the null is not rejected at the 5% probability level. It also reveals that both indicative prices and limit clearing prices are significantly different from unity at almost all intervals, thus the unbiased predictability assumption in the preopening is rejected. In addition, neat evidence is inferred on the superior quality of limit clearing prices in the preopening, since their prediction coefficients are systematically nearer to unity than those of indicative prices. Yet, limit clearing prices do not attain significant unbiasedness at the opening.

Important evidence is also deduced on the existence of prediction coefficient variation. On one hand, opening price predictability may be less volatile across stocks than across days. On the other hand, opening price predictability may vary more across stocks but less across days. Standard errors of individual stocks, as implied in Table 3, capture variation across days for each stock. The extremely low, almost zero, standard deviation of the random effect, $\sigma_b$, reported in last row of Table 4, indicates that the source of variation is not stock heterogeneity but daily variation in predictability. As a result, one may expect that rather time specific factors, e.g. day-of-the-week effect, volatility episodes, than company specific factors, e.g. size, marketability, primarily affect the predictability of opening prices. In contrast, the predictability of indicative prices within the preopening is affected by company specific characteristics as well.
Table 4: Mixed effects Biash regression coefficients for indicative, limit clearing and opening prices

<table>
<thead>
<tr>
<th>Up to</th>
<th>10:18</th>
<th>10:21</th>
<th>10:24</th>
<th>10:27</th>
<th>opening</th>
</tr>
</thead>
<tbody>
<tr>
<td>IP</td>
<td>LCP</td>
<td>IP</td>
<td>LCP</td>
<td>IP</td>
<td>LCP</td>
</tr>
<tr>
<td>(\hat{b})</td>
<td>0.651*</td>
<td>0.826</td>
<td>0.555*</td>
<td>0.636*</td>
<td>0.389*</td>
</tr>
<tr>
<td>SE((\hat{b}))</td>
<td>0.122</td>
<td>0.147</td>
<td>0.125</td>
<td>0.145</td>
<td>0.102</td>
</tr>
<tr>
<td>p-value</td>
<td>0.004</td>
<td>0.237</td>
<td>0.000</td>
<td>0.012</td>
<td>0.000</td>
</tr>
<tr>
<td>(\sigma_b)</td>
<td>0.352</td>
<td>0.457</td>
<td>0.394</td>
<td>0.455</td>
<td>0.303</td>
</tr>
</tbody>
</table>

Prediction regressions \(p_{it}^{\text{close}} - p_{it-1}^{\text{close}} = a_k + b_k (p_{it}^k - p_{it-1}^{\text{close}}) + z_t\) are estimated for each individual stock and each time interval are estimated by a mixed effects model with fixed effect, \(b_k\), and random effect, \(\hat{b}_k\), with zero mean and variance \(\sigma_b^2\). Indicative prices are computed, first, on the entire set of orders (first column, IP) and, second, on the set of limit orders only (second column, LCP); opening price (OP) is itself a clearing price. Newey-West standard errors are computed and asterisks denote rejection of the null hypothesis \(H_0(b_k = 1)\) at the 5% probability level.

Table 5: Mean reversion coefficients for indicative, limit clearing and opening prices

<table>
<thead>
<tr>
<th></th>
<th>10:18</th>
<th>10:21</th>
<th>10:24</th>
<th>10:27</th>
</tr>
</thead>
<tbody>
<tr>
<td>IP</td>
<td>LCP</td>
<td>IP</td>
<td>LCP</td>
<td>IP</td>
</tr>
<tr>
<td>(\hat{d})</td>
<td>-0.37*</td>
<td>-0.27*</td>
<td>-0.26*</td>
<td>-0.39*</td>
</tr>
<tr>
<td>SE((\hat{d}))</td>
<td>0.08</td>
<td>0.10</td>
<td>0.08</td>
<td>0.10</td>
</tr>
<tr>
<td>t-statistic</td>
<td>-4.54</td>
<td>-2.67</td>
<td>-4.30</td>
<td>-2.73</td>
</tr>
<tr>
<td>p-value</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Reversion regressions \(p_{it}^{\text{open}} - p_{it}^k = c_k + d_k (P_{it}^k - p_{it}^{\text{close}}) + e_t\) are estimated by a mixed effects model with fixed effect, \(d_k\), and random effect, \(\hat{d}_k\), with zero mean and variance \(\sigma_d^2\). Indicative prices are computed, first, on the entire set of orders (first column IP) and, second, on the set of limit orders only (second column, LCP). The null hypothesis is \(H_0(d_k = 0)\) and asterisks denote rejection of the null at the 5% probability level.
We now turn to the statistical validation of indicative price patterns in the preopening. As proposed in Section 5, patterns can be statistically established by estimating a mean reversion regression of the form presented in equation (4). Mean reversion, i.e. significantly negative slope coefficients at all intervals, indicates that the U-shaped pattern presented in Figures 3 and 4 is not a random realization, i.e. it is not noise. In contrast, a price trend, i.e. significantly positive (possibly greater than unity) slope coefficients, would signify learning. Finally, insignificant coefficients would be evidence of pure noise in the preopening.

Figure 4: Mixed effects BiAs regression coefficients for indicative, limit clearing and opening prices

Estimation results of equation (4) are presented in Table 5. Indicative prices are computed, first, on the entire set of orders (first column) and, second, on the set of limit orders only (second column, limit clearing prices, LCP). The null hypothesis is $H_0(d_k = 0)$ and asterisks denote rejection of the null at the 5% probability level. Slope coefficients, presented in the first row, are significantly negative for all order forms and intervals, showing that mid-preopening prices
revert at the opening. It is important to note that reversion encompasses overshooting as well as undershooting of prices in the preopening. For example, a value of -0.37 for previous close to 10:18 return, implies that the 10:18 to opening return is corrected by -37% at the opening.

7. Conclusions
Strong evidence on the information content of opening prices was found in Athens Stock Exchange. Opening price is on average an unbiased predictor of true value, even though its performance varies across individual stocks. Estimation of a mixed effects model showed that neither indicative prices nor limit clearing prices contain statistically significant information, although the latter perform better.

Opening price predictability is found to vary rather across days than across stocks. As a result, time specific factors, e.g. day-of-the-week effect, volatility episodes, rather than company specific factors, e.g. size, marketability, primarily affect true value discovery.

A distinct U-shaped pattern of indicative prices implies that after an informative start, price discovery deteriorates in the mid-preopening, to improve in the last intervals. Estimation of a mean reversion regression that resulted in significantly negative slope coefficients at all intervals, statistically confirmed the existence of this pattern.
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