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Estimating Probability of Informed Trading on the Bucharest Stock Exchange

Cosmin Octavian CEPOI—Bucharest Academy of Economic Studies (cosmin.cepoi@fin.ase.ro), *corresponding author*

Filip Mihai TOMA—Bucharest Academy of Economic Studies (toma.filip.mihai@gmail.com)

Abstract

Informed trading is a major concern within the domain of financial markets microstructure, as it represents a proxy for the efficient functioning of a market during a specific timeframe. The implications of whether information asymmetries occur on financial markets are important. From a trading perspective, excess information events can lead to efficiency biases and can also be associated with spikes in intraday volatility, as well as sharp modifications of intraday liquidity. The probability of informed trading (PIN) metric can provide a viable mean for noise traders in understanding rapid fluctuations in microstructure indicators, such as those indicated above. Even though PIN estimation has been covered in the academic literature from a microstructure vantage point, to our knowledge there are no studies assessing the relationship between macroeconomic variables and the PIN. We find that the exchange rate, the interest rate and the oil price are better suited than microstructure indicators to explain the PIN on the Bucharest Stock Exchange. The current study brings insight into the dynamics of certain macroeconomic indicators and informational asymmetries on the Bucharest Stock Exchange. Furthermore, estimating the PIN on this stock market has not yet been tackled in the current literature.

1. Introduction

In recent decades, the development of financial microstructure theory has led to important insights on the functioning of the market, its organizational structure, trading costs and asset prices. We can confidently state that one of the most important goals of financial microstructure modeling is to understand and describe the quality of markets. Price and volume dynamics from order flows of various financial instruments can be used to infer investor behavior on markets, as well as the amount of information investors can use when trading.

From a historical perspective, traditional financial market theory envisioned the formation of prices as the confrontation between supply and demand, bringing about their equality at some point. However, reality has shown that there are factors which can put the price off of its equilibrium level, such as information asymmetry and different arrival times for trades, among other things. These factors therefore led to the development of inventory-based and information-based models.

Within the first generation of microstructure models, it is the market maker that provides liquidity to the market. This provision of liquidity in turn compensates the market maker with the bid-ask spread for price risk on inventory. The second generation of models concerns market asymmetry among market participants, establishing the formation of the spread as compensation for adverse selection costs.

In considering the second generation of models, we distinguish between two types of informed traders: those who know the fundamental value of a given asset based on their private information which is not available to other traders or by exploiting in skillful and profitable ways public information that any trader has access to but does not necessarily know how to act upon and those who do not have any private information on the issuing company and trade based only on public information. Public information investors are usually regarded as noise traders and are purely liquidity motivated.

Private information might refer either to information revealed by order flow or to information made available to the public. Moreover, such information can also be acquired through more complex analyses provided through specialized and costly research, making it legal. The costlier such information is, the more credible a financial market becomes. On the other hand, not all private information is precise.

Information asymmetry in financial market microstructure studies can be considered important from many perspectives. Firstly, national authorities which regulate the functioning of markets are interested in eliminating insider trading, as it can ultimately lead to financial downturns. In this sense, José Manuel González-Páramo, a member of the executive board of the ECB, made the following comment in a speech he gave in December 2007 as a result of the financial crisis at that time: "When talking about information in the context of the financial turmoil, a key dimension of interest regards the role of informational asymmetries." Secondly, uninformed traders will want to learn the true value of an asset and therefore are interested in assessing the level of information transparency at the aggregate market level, as this would eventually increase market efficiency. Thirdly, academic research deals with incorporating the behavior of market actors and the information they use in estimating the equilibrium price of an asset.

The main purpose of this paper is to estimate the probability of informed trading on the Bucharest Stock Exchange in order to see if the non-informative market feature is a characteristic of an immature market. Subsequently, we want to determine what the main drivers for the PIN on said market are.

In the present study, we emphasize the importance of information asymmetry studies for emerging financial markets, as well as that of other market microstructure aspects. For instance, Chauhan *et al.* (2014) assess a comprehensive review of insider trading on the U.S. market and in the rest of the world and state that the issue should be evaluated more thoroughly on emerging markets from a regulatory standpoint. Damianova (2014) studies market inefficiency on the Bucharest Stock Exchange employing a GARCH methodology and confirms the inefficiency of the Romanian stock market. In addition to the two perspectives mentioned above, we continue the research on emerging financial markets through this current study.

However, a key question arises: how can publicly available data be used in measuring informed trading? While not being the first of its kind, the cornerstone study on detecting informed trading is that conducted by Easley *et al.* (1996), in which they develop a model based on imbalances between buy and sell order flows in order to estimate the probability of informed trading (hereinafter referred to as after as the "PIN"). We depart from their described methodology in estimating the PIN on the Bucharest Stock Exchange for three equities and we further test whether microstructure indicators or macroeconomic variables play a role in the presence of information asymmetry.

The remainder of the paper is structured as follows: Section 2 reviews the main literature on market microstructures and information asymmetry. Section 3 presents the theoretical and applied approaches to estimating (i) the probability of informed trading, (ii) liquidity microstructure indicators and (iii) volatility from the microstructure vantage point and using a GARCH model. Section 4 presents an econometric analysis on verifying whether the aforementioned indicators or certain macroeconomic variables can explain the presence of informed traders. The analysis is conducted for three of the main stocks traded on the Bucharest Stock Exchange. Section 5 presents the main results and conclusions regarding the importance of PIN estimation in an emerging market economy. References are given in Section 6.

2. Literature Review

A common feature of many market microstructure theoretical models is the existence of a competitive, risk-neutral specialist who faces two types of traders: informed and liquidity (uninformed) traders—Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hara (1987), Easley, Kiefer and O'Hara (1997) to name a few studies. While several predictions of these models have been extensively tested, relatively less attention has been paid to estimating the probability of informed trading. The main metric that captures the probability of informed trading and is widely used in the existing literature is the one developed by Easley, Kiefer, O'Hara and Paperman (1996).

The foundation of market microstructure models lies in the order-driven model developed by Kyle (1985), which implies that order flow moves prices. The model was later developed by Glosten and Milgrom (1985), who consider a dealership market, under which differences in information among traders can lead to information costs for dealers. Even though there are studies concerned with foreign exchange markets (Lyons, 1992, 1996) and government bond markets (Fleming and Remolona, 1999; Proudman, 1995), most financial microstructure studies have been focused specifically on stock markets, due to their simpler structure.

Starting in the 1990s, most microstructure models for inferring the level of information from a market have been divided into three major segments. The first segment covers models studying the price impact of information (Hasbrouck, 1991a, 1991b; Madhavan and Smidt, 1991).

The second group of models uses certain proxies, such as the bid-ask spread (Bagehot, 1971; Jaffe and Winkler, 1976; McInish and Wood, 1992), trade volume and size (Keim and Madhavan, 1995, 1997), firm size (Hasbrouck, 1991b), number of trades (Jones *et al.*, 1994) and the proportion of insiders (Chiang and Venkatsh, 1988).

The third generation presents sequential trade models that describe the process of trading and focus on estimating the probability of informed trading. The first formal quantitative approaches to PIN estimation were developed by Easley and O'Hara (1992, 1996) via the means of maximum likelihood estimation. A series of subsequent models have been developed. Easley, Kiefer, O'Hara and Paperman

(1996) and Easley, Kiefer and O'Hara (1997a, 1997b) assume one information-generating event per trading day, which, alongside the number of buys and sells and trade size, is used to estimate the probability of informed trading. An important hypothesis of the models is that they assume that the noise traders' decision during the current period depends on their decision to buy or sell from the previous period. An important implication of the above-mentioned studies is that they pinpoint a relationship between the volume of traded stocks and the PIN—the higher the volume, the lower the PIN. However, the PIN should not be viewed exclusively as a private insider measure, as it can also incorporate large orders given and executed by institutional investors.

An interesting and more recent study was conducted by Hanousek and Kopřiva (2011), who focused on the Prague Stock Exchange, analyzing the behavior of market makers and their ability to maintain private information on large orders on an electronic dealers' market. Their approach consists in a modified Easley *et al.* (1996) methodology. By applying a jackknife approach, they leave out trades of a particular market maker from the sum of all buys and sells. Upon estimation, they find significant differences in behavior among the market makers and they conclude that they indeed can play an important role in affecting the price on the market, as private investors cannot reveal the full information.

Departing from the above-mentioned classification of the development in financial microstructures and information asymmetry, it is natural to capture relationships between the dynamics of certain microstructure indicators and the PIN. From this point of view, the most important microstructure proxies addressed in previous studies are market liquidity and volatility (Nyholm, 2002; Jayaraman, 2008). Interestingly enough, though the above proxies have been addressed in the development of studies on PIN estimation, in the academic literature there has not been much interest in identifying the correlations between macroeconomic fluctuations and the PIN.

An innovation of the current study consists in performing an extensive econometric analysis between certain macroeconomic indicators which we consider relevant for our study and the probability of informed trading for three of the most traded stocks on the Bucharest Stock Exchange. The results we obtain are robust to say the least and present important economic interpretations. However, we note that there may be other indicators which can present analytical relations for the PIN. It would be interesting to find out how major sectors of the economy are driven by the evolution of the PIN for the main traded stocks from the respective sector in the financial market. We leave this topic open for further research.

In addition, Kizys and Pierdzioch (2011) perform an extensive analysis of stock markets in CEE countries in order to study whether the collapse of financial markets in 2007–2008 was due to international linkages of fundamentals or spillovers of speculative bubbles. They find that intraregional linkages in three CEE countries (the Czech Republic, Hungary and Poland) have changed over time. They suggest that future research on the contagion of financial crises among emerging market countries should be performed using also macroeconomic variables. It might be interesting to also include in a similar study an information asymmetry indicator—such as the PIN—in assessing whether contagion is also determined by the presence of informed traders on one market or another.

3. Theoretical Background

In this section we present the sequential trade model of market making developed by Easley *et al.* (1996), as well as some measures of trading costs and intraday variance which, from our point of view, are very important in order to explain the dynamics of the PIN.

3.1 Probability of Informed Trading

In their model, Easley *et al.* (1996) assume that individuals trade a risky asset and money over $i = 1,...,N$ days, where time is indexed by t for each trading day and is considered continuous. The market maker quotes the bid and ask prices at which investors buy and sell securities and is considered to be risk-neutral, so the prices are the expected value of the stock, conditional on the information the dealer has when making the transaction.

In the current methodology, there are two types of traders—informed traders who benefit from signals that give the true value of a stock and uninformed traders who receive no signals on the future movement of a stock's price. Both groups of traders enter the market following independent Poisson processes at any minute during the trading day; however, in the case of informed traders, they receive good-news signals that encourage them to enter the market. When such signals reveal themselves, the traders buy the stock.

Easley *et al.* (1996) define information events α which can occur both with probability δ for good-news events and $1-\delta$ for bad-news events whenever the nature of the news determines from the sample at the beginning of each day whether an event with informational impact on the fundamental value of the asset will appear. In this scenario, $(V_i)_{i=1}^{N}$ represents a random variable which gives us the fundamental value of the asset at the end of every day in the sample. The value of the asset on a day with good news is given by the random variable denoted by $\overline{V}_i$, while $\underline{V}_i$ denotes the value of the asset on a bad-news day. If the value of the asset on a day with no information is denoted V_i^*, we will have the inequality $\underline{V}_i < V_i^* < \overline{V}_i$

The model is developed using simple binomial logic. The event generating news at the beginning of each day can be of either a good-news or bad-news type, and the appearance of informed traders that are competitive and risk-neutral does not depend on the nature of the news. The arrival of the news to one trader at a certain moment in time and that trader's actions in the market follow a Poisson process with the arrival rate denoted by μ. We note that all arrival processes are assumed to be independent in the Easley *et al.* (1996) framework.

On days when good-news events are generated (through an independent Poisson process), the arrival rates are given by $\varepsilon+\mu$ for buy orders and ε for sell orders. On days when bad-news events are generated, the arrival rates are given by ε for buy orders and $\varepsilon+\mu$ for sell orders. If, at the beginning of the tree, there is no news-generating event, then only uninformed traders take part in the process, with an arrival rate equal to ε.

At the end of the day, the market maker has complete information on each actor in the market and quotes the true value of the stock. The market maker has information on the probabilities for the above events and on the information arriving in the market. The occurrence of such events is unknown. Easley *et al.* (1996) assume that the dealer is Bayesian in the sense that his information is being updated with the arrival of new trade orders. The information is treated independently across days—therefore, each day is treated as a different observation in computing the probability of informed trading. Based on this fact, if we denote $P(t) = (P_n(t), P_b(t), P_g(t))$ as the market maker's prior beliefs regarding information events at the beginning of each day, when $t = 0$, we will have: $P(0) = (1-\alpha, \alpha\delta, \alpha(1-\delta))$.

If we denote $P(t \mid S_t)$ as the market maker's updated belief vector that takes into account the history of trades and quotes prior to time *t,* by using the Bayes rule the posterior probability of no news at time *t,* if an order to sell arrives at *t*, is:

$$P_n(t \mid S_t) = \frac{P_n(t)\varepsilon}{\varepsilon + P_b(t)\mu} \tag{1}$$

In a similar way, the probability of bad news will be given by:

$$P_b(t \mid S_t) = \frac{P_b(t)(\varepsilon + \mu)}{\varepsilon + P_b(t)\mu} \tag{2}$$

and the probability of good news is:

$$P_g(t \mid S_t) = \frac{P_g(t)\varepsilon}{\varepsilon + P_b(t)\mu} \tag{3}$$

If we take into account (1), (2) and (3) and the zero-profit hypothesis, the expected bid-price denoted $b(t)$ at any time *t* on day *I,* is:

$$b(t) = \frac{P_n(t)\varepsilon V_i^* + P_b(t)(\varepsilon + \mu)\underline{V}_i + P_g(t)\varepsilon\tilde{V}_i}{\varepsilon + P_b(t)\mu} \tag{4}$$

Based on a similar calculation, the ask price at time *t* is:

$$a(t) = \frac{P_n(t)\varepsilon V_i^* + P_b(t)\varepsilon\underline{V}_i + P_g(\varepsilon + \mu)\varepsilon\tilde{V}_i}{\varepsilon + P_b(t)\mu} \tag{5}$$

The expected value of the asset, $E[V_i \mid t]$, based on the values that we set at the beginning of this section is a function that depends on each probability that we computed in the first three equations. So, $E[V_i \mid t]$ is:

$$E[V_i \mid t] = P_n(t)V_i^* + P_b(t)\underline{V}_i + P_g(t)\tilde{V}_i \tag{6}$$

Based on relation (6), the values of the bid and ask prices that market makers calculated based on prior information until time *t* on day *i* are given by:

$$b(t) = E[V_i \mid t] - \frac{\mu P_b(t)}{\varepsilon + \mu P_b(t)}\left(E[V_i \mid t] - \underline{V}_i\right) \tag{7}$$

and

$$a(t) = E[V_i \mid t] - \frac{\mu P_g(t)}{\varepsilon + \mu P_g(t)}\left(\overline{V}_i - E[V_i \mid t]\right) \tag{8}$$

Let $\Sigma(t) = a(t) - b(t)$ be the spread at time *t*. Then, in order to identify the factors that are influencing the spread, we can write $\Sigma(t)$ as:

$$\Sigma(t) = \frac{\mu P_g(t)}{\varepsilon + \mu P_g(t)}\left(\overline{V}_i - E[V_i \mid t]\right) + \frac{\mu P_b(t)}{\varepsilon + \mu P_b(t)}\left(E[V_i \mid t] - \underline{V}_i\right) \tag{9}$$

According to Easley *et al.* (1996), the spread at time *t* represents information-based probability multiplied by the expected loss to informed buyers plus a symmetric term for sells. So the probability of informed trading represents the sum of the aforementioned probabilities, explicitly:

$$PI(t) = \frac{\mu\left(1 - P_n(t)\right)}{\mu\left(1 - P_n(t)\right) + 2\varepsilon} \tag{10}$$

When the market opens, at $t = 0$, if we assume that good and bad news occurs with the same probability, then the spread can be computed as:

$$\Sigma(0) = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}\left[\overline{V}_i - \underline{V}_i\right] \tag{11}$$

In what follows, we will give an overview of the analytical and empirical implementation of the above model.

On a day with a bad-news event, the observed sequence of buy and sell trades has the following probability:

$$P(B,S) = e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\varepsilon+\mu)}\frac{\left[(\mu+\varepsilon)T\right]^S}{S!} \tag{12}$$

On a day with no information-revealing events, the probability becomes:

$$P(B,S) = e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} \tag{13}$$

On a day with a good-news event, the probability is:

$$P(B,S) = e^{-(\mu+\varepsilon)T}\frac{\left[(\mu+\varepsilon)T\right]^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} \tag{14}$$

We write the likelihood of trading activity, which is independent across days:

$$\begin{aligned} L\left[\{B,S\} \mid \theta\right] = {} & (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\varepsilon+\mu)}\frac{\left[(\varepsilon+\mu)T\right]^S}{S!} + \\ & + \alpha(1-\delta)e^{-(\varepsilon+\mu)}\frac{\left[(\varepsilon+\mu)T\right]^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} \end{aligned} \tag{15}$$

The parameter space is given by $\theta = \{\alpha, \delta, \varepsilon, \mu\}$.

The likelihood of observing the data $M = (B_i, S_i)_{i=1}^{h}$ is given by the product of daily likelihoods:

$$L[M \mid H] = \prod_{i=1}^{h} L(\theta \mid B_i, S_i) \tag{16}$$

The above function is rearranged as per Aktasa *et al.* (2007) and Easley *et al.* (2008). Subsequently, the probability of uninformed trading is the unconditional probability that traders buy or sell assets at any point in time *t*. The higher this probability is, the higher the risk uninformed traders face in their actions of buying or selling stocks.

We write the probability of informed trading as:

$$PIN_t = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{17}$$

4. Data

In this section we will present some of the stylized facts of the main data used in our estimations in order to set the stage for the subsequent econometric analysis.

Before we embark on the actual estimation process, we will present some general characteristics of the Bucharest Stock Exchange (hereinafter referred to as the "BSE") and provide a general overview of the market within a historical context and some recent developments. The BSE started operating in 1882 as a "commercial effects, stocks and exchange market". Its activity was interrupted by the First World War and ceased in 1948, when the Communist regime took control of the country. The BSE was formally reopened in 1995 through the efforts of the ruling party at that time. Its main index, the BET, was first listed in 1997 and represents a weighted average of the top ten most liquid equities.

The market's activity was fragmented between its official reopening and 2004 and it experienced severe decline in the first few years following its reopening, mainly because of unregulated activities and the general fear of investors and companies alike of getting involved in capital market financing. The market presents some stylized facts, namely its dearth of efficiency during its transition years (1997–2002), according to Harrison and Patton (2005), while others such as Damianova (2014) reject market efficiency even in more recent years, from 1997 to 2008. The main index has experienced some extreme variations in comparison with other indexes in more developed markets.

Next, we will provide an overview of some characteristics of the real tick-by-tick intraday data from the BSE that we used in our analysis. We chose the top three equities from the BET index based on total traded value, namely the Romanian Development Bank-Groupe Société Générale (in Romanian: *Banca Română de Dezvoltare*—BRD), Property Fund (in Romanian: *Fondul Proprietatea*—FP) and OMV Petrom (SNP)—spanning the period from 19 October 2012 to 5 May 2013 with a total number of observations of 130 trading days and 24,687 intraday observations (4,844 for BRD, 12,199 for FP and 7,644 for SNP). All data are extracted from the Thomson Reuters Eikon platform, while trade direction is calculated using

Table 1 Trade Statistics

Stocks	Average Trade Duration (minutes)	Average Trades Per day	Max Price	Min Price	Average Mid Price	Spread Mid Price
BRD	10.6	36	9.6500	7.1300	8.3350	0.60%
FP	4.38	92	0.5221	0.6729	0.5887	0.14%
SNP	6.93	57	0.4748	0.3872	0.4353	0.15%

Source: Authors' own calculations.

the Lee and Ready (1991) algorithm. The issuing companies of the latter are from three different fields: BRD is from the banking industry, FP is a company that manages Romanian state-owned real-estate properties and SNP is from the oil industry. A summary of trading statistics is presented in *Table 1.*

The selected equities were the top three in the Bucharest Stock Exchange ranking by market capitalization from the First Tier Section. The first is FP with nearly 40% market capitalization, followed by SNP with 15% market capitalization and BRD with nearly 10% market capitalization. The total capitalization for the chosen stocks amounts to 65%, which can be considered enough to pursue a statistical analysis with conclusions that can be used to infer information on the general development of the Bucharest Stock Exchange.

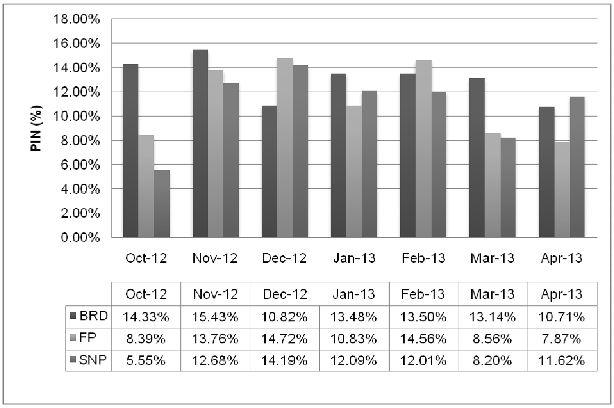
As can be seen, the most liquid equity is FP, with 92 transactions per day on average, followed by SNP with 57 transactions per day and BRD with 36 daily transactions. From this perspective, if we are to compare the results with more developed markets where trading takes place at millisecond intervals, the Romanian market is poorly developed, with a reduced liquidity level. For example, from 19 October 2012 to 5 May 2013 the average trade size was EUR 12.861 for SNP, EUR 11.800 for FP and EUR 12.172 for BRD. Those values are extremely low if we compare them with the top most traded equities on exchanges in countries such as the Czech Republic, Hungary and Poland, where daily trade values easily pass the threshold of EUR 1 million/day.[1]

5. Results

The main purpose of this paper is to estimate the probability of informed trading on the Bucharest Stock Exchange in order to see if the non-informative market feature is a characteristic of an immature market. In order to estimate the PIN, we employed a maximum likelihood estimation method. For each day in our sample we estimate the values of $\theta = \{\alpha, \delta, \varepsilon, \mu\}$ based on equation (15), upon which we compute the daily values of the PIN based on relation (17). We chose this time window, rather than the whole sample of seven months, in order to see if the value of the daily PIN is influenced by variables such as the daily average trade duration, daily realized volatility and the daily quoted spread. This is in line with other studies, such as those performed by Nyholm (2002) and Jayaraman (2008).

[1] According to information from the official websites of the Prague Stock Exchange, Budapest Stock Exchange and Warsaw Stock Exchange

Figure 1 Monthly Average PIN for BRD, FP and SNP (October 2012–April 2013)



Source: Authors' own calculations.

Table 2 Probability of Informed Trading (in %)

	BRD	FP	SNP
Average ε	97.51	96.31	98.10
Average μ	98.56	99.84	99.53
Average α	26.79	24.63	26.70
Average δ	51.32	60.95	50.03
Average *PIN*	**13.01**	**11.37**	**11.29**

Source: Authors' own calculations.

Table 2 contains information both on the daily average estimators of each of the PIN's components and the PIN itself for all three equities. We note similarities between each variable for each stock and we see that, on average, the daily PIN did not surpass 14% or fall below 11%. The parameters of α for all three equities suggest that more than 24% of days are informative, which means that in one out of four trading days there is a high probability of informational asymmetries occurring in the market. During the informative days, the probability of a low signal is given by the values of δ. We can see that δ registers around 50% for BRD and SNP, while that of FP is 10% higher. We note that orders are informative from a trader's perspective with a probability higher than 95%, which is the same as the probability of the existence of liquidity traders for all equities.

In order to have a more comprehensive view of the time dynamics of the PIN, we present the monthly average values for all equities in *Figure 1*.

We can see from *Figure 1* that the probability of informed trading (vertical axis) is low for all three stocks in our seven-month sample (horizontal axis), as compared with other results from similar markets like the Czech Republic (Hanousek and Kopřiva, 2011), which is expected if we take into account the fact that the Bucharest Stock Exchange was at that time a less developed market recovering after the financial crisis of 2008–2010. However, some conclusions regarding the values of the PIN can be drawn if we take a closer look at the political and economic events during the time period under consideration.

The financial sector in Romania has suffered a lot since 2009, when most underperforming loans started to be provisioned, causing some massive losses for BRD by the end of 2012. This event was combined with a massive fraud in which some members of BRD's executive staff were involved; this information was revealed to the public by Romanian authorities in the middle of December 2012. As such, BRD's PIN reached high values (31% on 10 December and 25% on 12 December). We can see that during a period of one month (October 2012–November 2012), the average values of BRD's PIN are higher in comparison with those of FP and SNP (15.10% versus 12.5% and 10.5% respectively). Furthermore, following some street protests in January and February 2013, the PIN values for FP were higher during that time period (10.9% for January, 14.5% for February), as opposed to March and April of 2013, when the PIN was roughly 8%. This could be expected, given that FP is a company managing state-owned property.

5.1 PIN, Spreads, Volatility and Trade Duration

The relationship between the PIN and spread was studied by Easley *et al.* (1996), who described the daily quoted spread as a function of informational asymmetry and daily traded volume. Easley *et al.* (2010a, 2010b) studied the relationship between the VPIN (volume synchronized probability of informed trading), which is an extension of the PIN model, and the absolute values of returns. The results revealed a positive relationship between the VPIN and volatility. However, in order to better capture the relationship between the PIN and volatility at the intraday level, we need to carefully choose a proper risk estimator. We use the daily average trade duration, considering that, in an insufficiently developed market such as the Bucharest Stock Exchange, periods with information asymmetry are related to a higher volume and a higher number of trades. Such stylized facts are also true on markets with a high level of liquidity, as Easley *et al.* (1996) have shown. In what follows, we present three microstructural characteristics of our three equities and finally estimate the linear model with the PIN as the dependent variable and the spread, and volatility and trade duration as explanatory variables.

We begin by defining the *quoted spread* of a stock quote as:

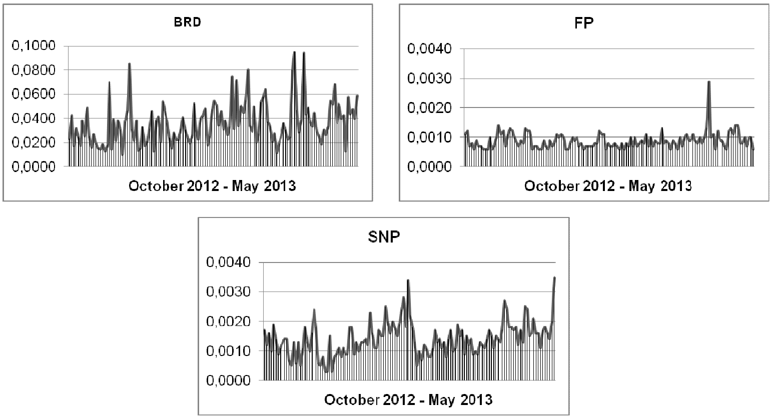
$$s_i = a_i - b_i \tag{18}$$

The quoted spread for BRD, FP and SNP are presented in *Figure 2*. As a measure for trading cost, the average quoted spread represents nearly 0.6% of the mid-price. For FP and SNP, the effective spread is smaller, measuring 0.15% of the mid-price on average.

We continue our empirical analysis by calculating the realized kernel on a ten-minute aggregation period and we annualize the percentage for each day. The presence of microstructure noises can be detected if the value of variance computed at higher intervals becomes stable after some aggregation point. In our case, the presence of microstructure noise is visible in all three cases, causing a bias in the realized volatility estimator.

Barndorff-Nielsen *et al.* (2011) proposed a class of consistent kernel-based estimators, namely realized kernels, in order to obtain an unbiased estimator for realized variance. The realized-kernel estimator is defined by:

Figure 2 Quoted Spread for BRD, FP and SNP



Source: Authors' own calculations.

$$KRV_{t,M} = \gamma_{t,0}\left(h\right) + \sum_{i=1}^{H} k\left(\frac{i-1}{H}\right)\left\{\gamma_{t,i}\left(h\right) - \gamma_{t-i}\left(h\right)\right\} \tag{19}$$

$$\gamma_{t,i}\left(h\right) = \sum_{j=1}^{M}\left(s_{t-1+jh} - s_{t-1+(j-1)h}\right)\cdot\left(s_{t-1+(j-i)h} - s_{t-1+(j-i-1)h}\right) \tag{20}$$

where $\gamma_{t,i}\left(h\right)$ denotes the *i*-th realized auto-covariance function, H is a parameter which controls the *bandwidth*, and $i \in \left\{-H, \ldots, -1, 0, 1, \ldots, H\right\}$. $k(x)$ is the kernel function with $x \in \left[0,1\right]$. If $k\left(0\right) = 1$, $k(1) = 0$, and $H = cM^{2/3}$, the resulting estimator is asymptotically Gaussian mixed and converges at a rate of $M^{1/6}$. Here, the constant c can be optimally chosen as a function of the kernel and the integrated quarticity in order for the asymptotic variance of the estimator to be minimized.

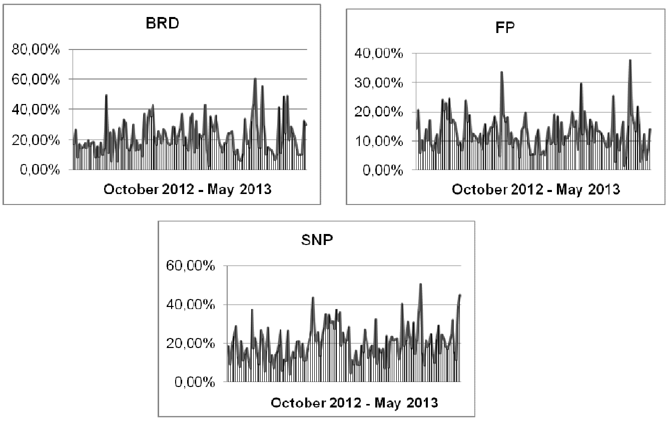
We see that the realized kernels for all three equities range on a yearly basis from 10% to a maximum of 60%, as can be seen in *Figure 3*.

We subsequently calculate the realized volatility for each day in the sample. Proposed by Andersen *et al.* (2001), the realized volatility estimator is governed by the hypothesis that the logarithms of the price time-series follow a continuous semi-martingale modeled by the following stochastic differential equation:

$$dy_t = \mu_t dt + \sigma_t dW_t \tag{21}$$

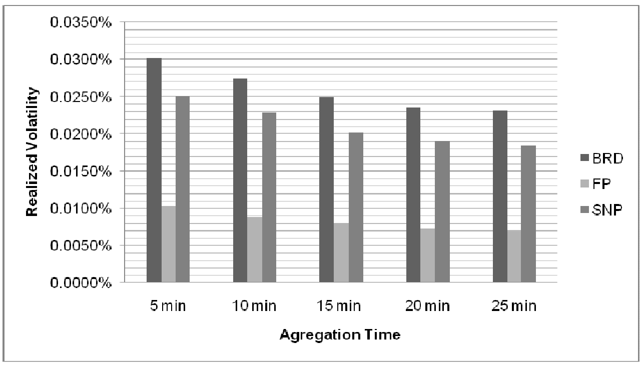
where μ_t represents the drift at time *t*, σ_t is the volatility of the return process of y_t at time t and W_t is a standard Brownian process. The realized volatility estimator represents an approximation of the integrated variance $\int_0^T \sigma_t^2 dt$. When $T = 1$, the daily realized volatility using intraday returns can be computed as:

Figure 3 Realized Kernel—Ten minutes (Annualized Percentage) for BRD, FP and SNP



Source: Authors' own calculations.

Figure 4 Signature Plot for Realized Variance (Percentage) for BRD, FP and SNP



Source: Authors' own calculations.

$$RV^2 = \sum_{j=2}^{M-1} \left(y_{j+1} - y_j \right)^2, j = 2, \ldots, M-1 \tag{22}$$

where y_j is the log price at time j on a certain trading day and M is the total number of subintervals of a trading day.

In *Figure 4* we can see the graph of average realized volatility computed at different aggregation intervals. On the vertical axis we have plotted the aggregation period in minutes.

We can also see in *Figure 4* that the presence of microstructure noises is visible especially for BRD and SNP, so the choice of a realized-kernel estimator instead of a realized-volatility estimator is well founded.

In order to have more than one measure for volatility estimation, we also estimate daily estimated volatility using a GARCH-GJR framework.

Generalized autoregressive conditional heteroskedasticity (GARCH) models were proposed by Bollerslev (1986) as a natural extension of ARCH models (Engle, 1982). The standard model assumes that financial time series are generated by a time-varying stochastic process, so variance is considered to be an autoregressive process.

The model is comprised of two equations: the conditional mean equation, which explains an *ARMA(p,q)* type of model for the expected return of the financial asset, and the conditional variance equation, which encompasses the conditional variance of the unknown process of returns.

The *ARMA(p,q)* model can be analytically expressed as:

$$y_t = c + \sum_{i=1}^{m} \phi_i y_{t-i} + \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{23}$$

where c is an intercept, y_{t-i} is the return of the series at the i-th lag(s), ε_{t-j} is the moving average term at the j-th lag(s), ϕ and θ are the corresponding coefficients for the above terms and ε_t is independently and identically distributed—$\varepsilon_t \sim i.i.d(0,1)$.

The conditional variance equation is written as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{24}$$

where ω is an intercept, σ_{t-i}^2 is the GARCH term at the i-th lag(s), ε_{t-j}^2 is the ARCH term at the j-th lag(s), ε_{t-j}^2 is the ARCH term at the j-th lag(s) and β and α are the corresponding coefficients for the above terms.

An alternative to the GARCH model is the GJR model described by Glosten, Jagannathan and Runkle (1993). The equation contains an extra term, which is used to depict the leverage effect of stock prices specifically and to better capture the volatility clustering phenomenon:

$$\sigma_t^2 = \omega + \sum_{i=1}^{P} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{Q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{Q} \gamma_j I_{t-j} \varepsilon_{t-j}^2 \tag{25}$$

where $I_{t-j} = \begin{cases} 1, \varepsilon_{t-j} < 0 \\ 0, \varepsilon_{t-j} \geq 0 \end{cases}$ and ε_{t-j}^2 is the leverage term at the j-th lag and γ is the corresponding coefficient.

Going through the Box Jenkins methodology, we arrive at estimating an *ARMA(1,1)-GJR(1,1,1)* model. We chose the GJR framework because it better incorporates the leverage effect specific for stocks than the basic GARCH or exponential GARCH models. (Glosten, Jagannathan and Runkle, 1993). The estimates are presented in *Appendix*. The residuals are no longer auto-correlated and the heteroskedasticity phenomenon is no longer present, as it was in the ARMA(1,1) model. We consider the analysis to be in line with financial econometric theory and

Table 3 ADF Unit Root Tests

Variable Equity	PIN	Quoted Spread	Realized Kernel	Average Trade
BRD	0% (-11.007)	0% (-8.724)	0% (-11.895)	0% (-9.883)
FP	0% (-9.545)	0% (-8.411)	0% (-9.086)	0% (-8.020)
SNP	0% (-10.871)	0% (-5.872)	0% (-10.699)	0% (-6.968)

Notes: * Equities are displayed in the rows, while the microstructure indicators for each stock are displayed in the columns. *t*-stats are in parentheses below the *p*-value results.

Source: Authors' own calculations.

cornerstone studies from this field with respect to volatility estimation (Bollerslev, 1986; Nelson, 1991).

Upon calculating the daily probability of informed trading for each stock from our sample, we continue by performing a multivariate regression analysis in order see if we can identify a causal relationship between the above-mentioned microstructure indicators computed from daily equity prices and the PIN. For each stock, we have considered the quoted spread, the realized-kernel estimator and the average trade duration as exogenous variables in a regression where the PIN acted as the endogenous variable. The average trade duration was calculated by summing up the total number of minutes between trades and dividing them by the number of periods, thus obtaining the arithmetic average.

We first run a univariate analysis for each of our variables. First, we quickly review the line graphs, the autocorrelation and partial autocorrelation functions of our time series and we see that all series appear to be stationary in level. Nonetheless, we still need to perform a unit root test for statistical confirmation. We choose the Augmented Dickey-Fuller test (Dickey and Fuller, 1979). The results are presented in *Table 3*.

From the above results, we see that all variables are stationary at the 1% confidence level, which allows us to continue with the multivariate regression analysis. The results are presented in *Table 4*.

As we can see in *Table 4*, given the high *p*-values and extremely low *R*-squared results, neither the volatility, spread nor trade duration can properly explain the probability of informed trading for any of the stocks in our sample. If we compute the Spearman correlation test among the PINs, we find that statistical dependence between BRD's PIN and that of FP is around 10%, with the same statistical dependence between BRD's PIN and that of SNP, while the dependence between FP's and SNP's PINs is 23%. We note that there is a certain degree of correlation between the calculated PINs, but it is not high enough to be considered significant.

With respect to the second regression and the GJR estimates as a substitute for volatility, we still cannot attain satisfactory results of statistical significance even if we see improvements in the estimates' values, as well as in the *p*-values. We confirm that introducing the daily GJR estimated volatilities into the equation along with the aforementioned variables does not bring any insight into the PIN estimation.

Table 4 Regressions Results*—Microstructure Indicators as Exogenous

	Intercept	Quoted Spread	Realized Kernel Estimator	Average Trade Duration	*R*-squared
PIN BRD	0.152* (8.865)	-0.373 (-0.865)	-7.022 (-0.339)	-0.0004 (-1.104)	1.9%
PIN FP	0.083* (3.286)	18.157 (-0.624)	-44.660 (-0.389)	0.010* (2.339)	6.1%
PIN SNP	0.130* (7.511)	1.868 (0.159)	12.574 (0.273)	-0.002 (-1.495)	2.45%
	Intercept	**Quoted Spread**	**GJR Estimator**	**Average Trade Duration**	
PIN BRD	0.203*** (4.454)	-0.399 (-0.959)	-4.036 (-1.228)	-0.0004 (-1.236)	2.9%
PIN FP	0.073** (2.366)	-27.934 (-1.232)	0.740 (0.608)	0.012*** (2.829)	6.4%
PIN SNP	0.154*** (3.281)	5.216 (0.409)	-1.953 (-0.526)	-0.03* (-1.752)	2.6%

Notes: * The values for *t*-stat are given in parantheses; ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The second part of the table switches the volatility estimate from the realized-kernel estimator to the GJR estimator.

Source: Authors' own calculations.

We note, however, an interesting finding. Judging from an intuitive economic perspective, the GARCH model encompasses the "rational" statistical volatility estimates, while the daily PIN estimate may be regarded as a proxy for "irrational" behavior of market participants. We argue that the higher this indicator is, the higher the number of market participants who do not rely on the same information as others is. As such, the unexplained factor of the GARCH model (i.e. the innovations series of the model) can have a similar statistical behavior as the PIN series, as the innovations may be considered as a proxy for the non-explained volatility phenomena. In this sense, we fitted the empirical data of the residuals and the empirical data of the PIN for each of the three stocks under analysis. We find that both of the series for all equities are well approximated by a lognormal distribution. However, the current study is not focused on these aspects, which we therefore leave open for further research. It might be interesting to find out from a microstructure point of view if other correlations can be found between other micro-financial indicators and the PIN.

As it can be seen at this point in our analysis, the PIN cannot be thoroughly explained on the Bucharest Stock Exchange from the perspective of the chosen micro-financial indicators.

5.2 PIN and Macroeconomic Variables

While there are studies, such as those previously mentioned, that have tried to capture causality effects towards the daily PIN from microstructure indicators, little is still known about macroeconomic variables as drivers of informed trading.

We therefore consider such variables to be the source of information asymmetry and we continue the empirical analysis including such factors. The motivation behind this approach is driven by the current and recent level of Romanian market development. Macroeconomic variables are a reasonably viable alternative to micro-financial indicators as PIN determinants based on aggregate market activity, which may be driven more by such macroeconomic developments, as might very well be the case for an emerging market. There are studies focusing on the local stock market which have put into context the market's general activity and macroeconomic variables.

Some authors such as Albu, Lupu and Călin (2015) have measured the asymmetric volatility effect on the stock markets of Central and Eastern European countries and found a high degree of dependence between the quarterly GDP differences and estimated volatilities, thus further suggesting that research should be expanded with respect to the stock market and macroeconomic developments. Furthermore, Geambașu *et al.* (2011) apply an APT model in order to isolate which macroeconomic variables are suited to explain the stock market in Romania, as compared to markets in other countries, and find that the interest rate and the exchange rate are among the most influential factors.

An intuitive way of thinking about the interdependence between the probability of informed trading and macreconomic variables is that the former can increase around the time when macroeconomic news is released. This would be even more apparent for news from more developed economies, such as the United States or EU countries, which affect stock markets worldwide through indirect channels. Such news can generate potential spillovers in stock markets' activity and lead to asymmetric risk-taking behavior, thus suggesting the presence of some sort of informed trading. For example, Hanousek and Kočenda (2011) examine spillovers and the effect of macroeconomic news on three emerging EU stock markets by analyzing high-frequency returns. Among the four classes of macroeconomic anouncements, they find that prices, the real economy class of announcements and the business climate and confidence announcements affect all of the analyzed stock markets, though there exist varied effects for each of the stock markets, while the monetary class of news has little influence. The results of their study indicate that the intra-day dynamics of European emerging markets are indeed strongly determined by macroeconomic news from more developed economies.

Taking into account that the presence of informed trading on markets that are not yet very well developed, such as the Romanian market, is likely to be determined more by macro-drivers, we identified three macro variables which are measured daily and introduced them into a third regression. We chose the EUR/RON exchange rate (units of RON per EUR), the average interbank interest rate spread and the price of oil. Considering the relatively short time period on which our sample is based, we could not include other variables such as economic growth, unemployment, inflation, etc. or those that are more specific to the stocks' respective industries, such as the rate/volume of non-performing loans or house price index, as these data are measured on a more distant time horizon.

We can see that the estimates for the explanatory variables have massively changed in comparison with the previous regression results. An explanation for the numbers we obtain lies in the fact that all of the above-mentioned variables might be considered as the main drivers by more (the majority) of the actors trading the stocks in question, including noise traders. As more investors perform transactions, the probability of informed trading decreases and the chance that noise traders will intervene in the market rises (*Table 5*).

Table 5 Regressions Results*—Macroeconomic Variables as Exogenous

	Intercept	Exchange Rate	Interest rate	Oil Price	*R*-squared
PIN BRD	1.0883* (1.895)	-0.319 (-1.591)	0.023*** (4.479)	-0.138* (-1.966)	18.2%
PIN FP	1.935*** (3.536)	-0.960*** (-5.022)	0.0723*** (14.418)	-0.182*** (-2.720)	63.53%
PIN SNP	5.148*** (7.871)	-1.824*** (-7.982)	0.0474*** (7.914)	-0.576*** (-7.202)	42.78%

Notes: * Values for t-stat are given in parantheses; ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Source: Authors' own calculations.

In interpreting the results, it should be noted that changes in each of the exogenous variables have indirect causality effects on the PIN. As such, all changes in the PIN are an indirect result of investors entering the market at signs of changes in such macro-drivers.

First of all, we note that both the exchange rate and the oil price have a negative impact on the PIN. As such, if the exchange rate rises, the investors' beliefs regarding the companies' performance change: banking profitability might change, as rates for loans in foreign currencies increase and there is a smaller chance for the population/non-financial companies to pay their debts. Also, the real-estate sector's profitability might change, as the demand for real estate might diminish, given that most real-estate prices in Romania are denominated in euros. Furthermore, using similar logic, the price of oil can be affected by an increase in the EUR/RON rate, depending on the investors' beliefs. Roughly stated, depending on the aggregate market interpretation of changes in the above-mentioned macroeconomic variables, there is a higher probability of noise traders entering the market and thus reducing the probability of informed trading.

Secondly, we see that a modification of the interbank interest rate average spread leads to an increase in the PIN. The interest rate is determined by banks activating on the interbank market. As such, it might be possible that some investors with access to private information may enter both the interbank market, modifying the interest rate through the supply and demand of loans and deposits, and the stock market based on their prior private beliefs with respect to upcoming events.

6. Conclusions

The main purpose of this study was to estimate the probability of informed trading on the Bucharest Stock Exchange and to assess whether or not we can identify a causal relationship between the PIN and (i) microstructure indicators and/or (ii) macroeconomic variables. The analysis was performed on the three most liquid equities listed on the Bucharest Stock Exchange which due to high market capitalization can serve as a benchmark in assessing the market's overall activity.

The initial analysis consisted in first estimating the PIN according to the Easley *et al.* (1996) methodology, which can be thought of as both an indicator of the market's efficiency through its capability of revealing informational asymmetry and as a variable which can be used by investors in establishing investment strategies. We subsequently calculated certain micro-financial indicators, such as the quoted spread, as a proxy for the market's liquidity and the realized-kernel estimator as a proxy for daily annualized volatility. We also estimated daily GARCH-GJR volatilities in order to have a comparison for the volatility proxy.

We continued the analysis by tracking causal determinants of the PIN from the microstructure point of view. We considered the realized-kernel estimator, the quoted spread and the average trade duration as exogenous variables in a multivariate regression setting. We note that none of the aforementioned factors has a statistically significant influence on the PIN. This was also performed using daily estimated GJR volatilities, without any improvements.

Considering that the Romanian market can be thought of as still being in its adolescence in terms of development, we performed a second regression in order to test the causality effects between certain macroeconomic variables and daily PINs. The approach we took was innovative, as to our knowledge no such analysis had yet been done. Furthermore, economic intuition dictated that an emerging market with a less-than-average propensity towards financial investment on an aggregate scale might be affected by changes in macro-drivers, such as the interest and exchange rates and the oil price. The results reflect an interesting and economically intuitive interpretation, as changes in such macroeconomic variables determine that more investors (and thus more noise traders) enter the market.

Therefore, we conclude that the current study brings insight into the PIN's determinants on an emerging market, both from a microstructure perspective and from a macroeconomic one. Our results are in line with other studies and we believe that the present paper may set the stage for further research which can be confirmed or infirmed on other emerging markets from the perspective of macroeconomic variables acting as the PIN's determinants. However, we stress the fact that further research in this area needs to encompass (i) a larger dataset and (ii) other macroeconomic indicators in the analysis, especially for similar emerging market economies or more developed economies, in order to analyze potential indirect spillovers.

APPENDIX

Table 1A ARMA-GJR Coefficient Estimates for BRD, FP and SNP

BRD							
c	*AR*	*MA*	*ω*	*ARCH*	*GARCH*	*Leverage*	*DoF*
-0.00013	0.87305	-0.71961	0.000126	0	0	0.48628	7.6119
FP							
c	*AR*	*MA*	*ω*	*ARCH*	*GARCH*	*Leverage*	*DoF*
0.00160	-0.47097	0.28889	-5	0.48444	0.67509	0.59171	3.9317
SNP							
c	*AR*	*MA*	*ω*	*ARCH*	*GARCH*	*Leverage*	*DoF*
0.00062	0.058021	-	0	0.12859	0.65309	0.04202	200

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