MARKET ABUSE DETECTION: A METHODOLOGY BASED ON FINANCIAL TIME SERIES

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Abstract

We propose a statistical methodology to detect insider trading and market manipulation phenomena. The methodology is based on financial time series analysis, and in particular we consider asset return (serial correlation and the market model as a benchmark) and trading volume (large values, serial correlation) anomalies. The methodology works quite well: there is little noise (false signals are limited) and we have been able to "replicate'' the authority behavior at a satisfactory level (more than 70% of cases).

The theoretical and regulatory debate on insider trading and market manipulation is rather intense. The two phenomena have been recently regulated in the European Union through the Market Abuse Directive that aims to ensure integrity of financial markets and to enhance investor confidence.

The two phenomena have common and distinct features. The main difference is that insider trading is related to the exploitation of private information, instead market manipulation is not necessarily related to a piece of private information. An insider usually hides his behavior (limiting price movements and trading volume effects) to preserve the value of his information and always trades in the same direction (e.g. buy in case of a positive news), instead a market manipulator wants explicitly to affect asset prices either releasing false/misleading information or buying/selling the asset intertemporally in order to gain from price movements; in case the manipulator is endowed with private information he may trade in a direction which is the opposite to the information. Simplifying, the insider trader is likely to act as a price taker and the manipulator instead affects asset prices.

The regulator associates insider trading and manipulation to a fraud against market integrity. However, while there is a widespread opinion that market manipulation negatively affects welfare, the debate on insider trading is more complex: on one hand insider trading is a fraud against retail (uninformed) investors who are on the wrong side of the market and trade at unfair prices, on the other hand insider trading helps to disseminate private information (insiders signal their information by trading) and therefore helps the market to correctly evaluate assets, as an example if insider trading is forbidden then research activity on companies is likely to be limited. These results suggest that a limited amount of insider trading may be beneficial.

The predominant regulatory orientation is in favor of insider trading regulation by mandatory rules/self regulation. As a matter of fact, Bhattacharya and Daouk (2002) have shown that among 103 countries that have a stock market 87 have an insider trading law, but insider trading has been persecuted only in 38 countries. We can conclude that it is difficult to detect and to persecute insider trading, however persecution (and not insider trading regulation) plays a crucial role: after the first insider trading persecution case (and not after regulation approval), the cost of capital goes down.

To cope with market abuse detection problems, the new regulation requires financial intermediaries to develop a methodology to signal to the stock market financial authority (CONSOB in Italy) all the trades suspect of insider trading or manipulation[1].

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[1] *Regulation on insider trading and market manipulation is contained in Testo Unico della Finanza (art. 180, 181, 184, 187) and Regolamento mercati by Consob (art. 61-67). According to art.187 bis insider trading occurs by trading on the basis of private information, or suggesting to other people to trade on the basis of private information. Market manipulation occurs through: diffusion of false/misleading news; trades that provide false/misleading information about the market of the asset, trades aiming to alter the asset price, wash trades (trades of different sign with no net change of ownership signaling the existence of a market), trades of different sign correlated with upward-downward movements, non executed market orders intended to alter the asset book, trades directed to marking the close.*

In this paper we propose a methodology to detect market manipulation and insider trading based on the analysis of daily financial time series. To this end, we exploit the literature on financial markets theory. In Section 1 we provide a review of theoretical insights on the topic. In Section 2 we discuss empirical evidence on insider trading days. In Section 3 we describe the market abuse detection methodology. In Section 4 we provide a backtesting of the method by evaluating its capability to detect those days that CONSOB has identified as suspect of insider trading.

1. THEORETICAL INSIGHTS

To detect market abuse phenomena we can build on financial markets theory and on its financial time series implications. We refer to two strands of literature: models with homogeneous information, models with heterogeneous-asymmetric information, see Barucci (2003) for a comprehensive reference.

The literature on financial markets with homogeneous information has shown that under the risk neutral probability measure or under the historical probability measure with risk neutral agents, the discounted asset price is a martingale and therefore the market is a fair game: the conditional expected excess return (asset return minus the risk free return) is equal to zero and excess returns are serially uncorrelated. This framework rationalizes the so called *market efficiency hypothesis* due to Fama (1970): according to the weak market efficient hypothesis, future excess returns cannot be predicted on the basis of past returns, i.e., they follow a random walk.

However, serial correlation cannot be interpreted univocally as a signal of market abuse. There is a large literature showing that asset returns with a holding period smaller than one year are positively serially correlated and that returns with a holding period greater than one year are negatively serially correlated. The phenomenon is observed on equity and market indexes and therefore cannot be attributed entirely to insider trading/market manipulation. Considering daily returns of stocks the evidence in favor of the random walk is more positive, i.e., the noise component is so relevant that it is difficult to ascertain a return pattern.

In the presence of insider trading and market abuse, return serial correlation is expected. While the insider trader always trades a limited amount in the direction of his information, the manipulator either releases information and trades in the opposite direction or trades intertemporally in different directions to gain from sequential trades. If insider trading occurs, then we expect positive (negative) daily returns to follow positive (negative) returns because private information is incorporated gradually in asset prices, in case of manipulation we expect a price reverse (mean reversion) due to the release of false information or to large trades in different directions. A model that rationalizes this type of behavior by the insider trader is provided by Kyle (1985). According to these theoretical results we have the following hypothesis.

Insight 1. In the absence of market abuse phenomena we do not observe return serial correlation. In the presence of insider trading we observe positive serial correlation in daily returns (trend), instead in case of market manipulation we observe negative serial correlation.

The random walk hypothesis holds true in case of risk neutral agents. If agents are risk averse then asset demand depends on its riskiness. Financial markets theory has proposed a set of models that explain asset risk premia on the basis of no arbitrage/equilibrium arguments. The benchmark model is provided by the CAPM: if agents' preferences are represented by a quadratic utility function or the two mutual funds separation theorem holds true (e.g. asset returns are distributed as a normal random variable) and markets are in equilibrium, then the asset risk premium is positively and linearly related to the beta. According to the CAPM we can establish the equilibrium risk premium of the asset and then we can detect anomalies with respect to it: we can take the market model derived from the CAPM as a benchmark to evaluate abnormal comovements of the asset return with the market.

Insight 2. In the absence of market abuse phenomena, daily returns should be in line with what is predicted by the CAPM: excess returns (daily asset return minus the risk free return) should not be different from the value estimated by the market model.

Classical literature with homogeneous information is unable to provide an explanation to several financial market stylized facts. In particular, the literature is unable to explain the large trading volume that occurs in the market. Trading volume is due to two main reasons: risk sharing and speculative trading. If information is homogeneous then the second motivation is absent and agents only trade to exploit Pareto improvements associated with differences in agents' risk exposition. In particular, if markets are complete, then trading is rather limited and occurs only in case of a preference/technology shock.

The literature on models with heterogeneous information is quite large. Under general assumptions, it can be shown that in a perfectly competitive market with heterogeneous private information (all agents observe a private signal on the asset value) and no noise (e.g. liquidity traders are absent) prices fully transmit information, i.e., equilibrium prices are fully revealing, they instantaneously reveal private information and coincide with those of an economy where all private signals are public (they are observed by all agents), see Grossman (1989). If noise is added, then prices are not fully revealing and the trade size is increasing in the precision of information, on this point see for example Kim and Verrecchia (1991). Therefore, precise private information (insider trading) is associated with large trades. Also in the presence of market manipulation we expect a large trading volume, i.e., large trades are needed to affect market prices. According to these results we have the following insight.

Insight 3. In the absence of market abuse phenomena daily trading volume is limited, private information/market manipulation are associated with large trades.

Speculative trading and therefore large trading volume can originate from public or private information. In the first case we have a news for example on company profitability, investment decision or mergers, agents trade because they revise company growth opportunities (time varying investment opportunities). If this is the case, then large trading volume is mainly concentrated around the announcement date and does not last for a long period. Instead, in case of private information we have that insiders trade until the asset price incorporates the new information, i.e., there is a public announcement or other agents detect private information. As a consequence, serial correlation of trading volume is an interesting way to discern pure risk sharing/public information based trading from private information trading. A model that disentangle the type of information arriving in the market according to trading volume serial correlation is provided by He and Wang (1995).

Insight 4. In the absence of market abuse phenomena and when public information arrives on the market, daily trading volume is not serially correlated. Trading volume serial correlation is associated with the presence of private information.

The presence of heterogeneous information also affects the relation between trading volume and asset returns. If large trading volume is due to uninformative motives (liquidity/preference shocks) then market pressure lasts for a short period and it is likely that we are going to observe price reversal or mean revesion, i.e., negative return-volume correlation, see Campbell et al. (1993) and Conrad et al. (1994); instead, if trading volume is due to private information then the relation can have a different sign, i.e., positive return-volume correlation, see Wang (1994) and Llorente et al. (2001). Then we have the following:

Insight 5. In the presence of private information large trading volume is associated with a price trend (positive return-volume correlation), if trades are due to liquidity motives then negative correlation is more likely.

2. EMPIRICAL EVIDENCE

The above insights have been empirically tested through two different exercises: considering illegal insider transactions and transactions by agents defined de jure as insider traders, i.e., directors of the company.

There are few papers on illegal insider trades. Results provide an empirical evidence in favor of the above theoretical insights. Meulbroek (1992) has shown that days with trades by insiders are characterized by large trading volume and high excess returns (in absolute value) with respect to the market model (CAPM). Similar results have been obtained by Cornell and Sirri (1992). Bhattacharya et al. (2000) analyze the effect of news on companies listed at the Mexican stock exchange (a market with a very weak regulation against insider trading, i.e., no insider trading case has been detected in the period analyzed), they show that news about listed companies do not affect asset returns, trading volume and volatility. They interpret these results as evidence of an intense insider trading activity before announcements.

Bagliano et al. (2001) provides an interesting analysis of Italian illegal insider trading investigating a dataset partially overlapping with the one analyzed below. They consider the cases that the CONSOB has detected as suspect of insider trading and look for effects on returns, trading volume, serial correlation of trading volume and returns. The analysis only shows a positive effect on excess returns, the effect on serial correlation is non significant.

3. THE METHODOLOGY

The methodology aims to detect days that may be characterized by insider trading or market manipulation. Building on theoretical insights illustrated in Section 1 we consider five alerts. The analysis concentrates on daily market indicators. The five alerts concern:

a) Trading volume,

b) Returns,

c) Autocorrelation of returns,

d) Autocorrelation of trading volume,

e) Correlation between trading volume and one step ahead return.

We now consider the construction of the alerts in detail. Construction of the alerts passes through the definition of two parameters: the window of days considered to build the alert, the threshold that marks significativity of the anomaly.

a) Large trading volume.

The alert signals a day if the trading volume is high compared to trading volume occurred in previous days. We have to define a threshold to detect rare trading volume days. We have not been able to identify a theoretical probability distribution of trading volume and therefore we have opted to compare daily trading volume of day t (v(t)) to values observed in the 75 days before day t. The statistical threshold to identify an anomalous day refers to the empirical distribution. In detail, day t is identified as anomalous if its trading volume belongs to the 3% upper quantile: v(t) is higher than the third highest value observed in the previous 75 days[2].

b) Anomalous excess return.

In equilibrium asset returns (r(t)) are explained through risk factors. We consider a market model, i.e., returns are explained by a one factor model represented by the return of the market index ($r_m(t)$). At time day t we estimate the market model on the sample of 70 days before day t:

$$r(s) = \alpha_t + \beta_t r_m(s) + e(s) \qquad s = t - 71, \ldots\ldots t\text{-}1$$

Estimated α_t and β_t, the model is employed to forecast the first value out of sample: the return of the asset in day t ($\underline{r}(t)$). The return at day t (r(t)) is compared to the estimated value. Assuming that daily asset returns are distributed as a normal random variable we perform a Student-t test on the null hypothesis that the actual returns and the returns estimated through the market model coincide:

$$H_0 : r(t) - \underline{r}(t) = 0.$$

Statistical significance to detect an anomalous day is evaluated with a 5% quantile on both sides.

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2 *We have evaluated the performance of the alerts changing the sample defining the distribution. We have a tradeoff: a short window invalidates the statistical significance of the procedure, a long window introduces inertia in the detection of rare observations (it is weakly sensitive to structural breaks and does not account for non stationarity of the time series). As an example, consider a stock that has been the object of rumors about a takeover one month ago, in those days large trading volume occurred and this renders the trading volume alert mute for a while. The 75 days window represents an equilibrium along this tradeoff.*

c) Serial correlation of returns.

To capture days characterized by anomalous return serial correlation we consider a one lag autoregressive model without a constant, we estimate it on a sample of 21 daily observations and we test the hypothesis that the autoregressive coefficient is null. At time t the model is the following:

$$r(s) = \beta_t r(s-1) + e(s) \qquad s = t - 20, \ldots\ldots t$$
$$H_0 : \ \beta_t = 0.$$

We reject the null hypothesis if the autoregressive coefficient is positive and statistically significant (insider trading) and if it is negative and statistically significant (manipulation). The level of significance is 5% on both sides.

d) Serial correlation of trading volume.

To capture days characterized by anomalous trading volume serial correlation we consider a one lag autoregressive model with a constant, we estimate it on a sample of 21 daily observations and we test the hypothesis that the autoregressive coefficient is null. At time t the model is the following:

$$v(s) = \alpha_t + \beta_t v(s-1) + e(s) \qquad s = t - 20, \ldots\ldots t$$

$$H_0 : \ \beta_t = 0.$$

We reject the null hypothesis if the autoregressive coefficient is positive and statistically significant (insider trading and manipulation). The level of significance is 2.5% on the right side (positive autocorrelation).

e) Trading volume and return correlation.

The correlation between trading volume and returns signals the presence of a preference shock or of private information. To disentangle the two phenomena we consider a model where daily return at time t (r(t)) is regressed on previous day trading volume (v(t-1)), the sample is made up of 21 observations and therefore the model is:

$$r(s) = \alpha_t + \beta_t v(s-1) + e(s) \qquad s = t - 20, \ldots\ldots t$$

$$H_0 : \beta_t = 0.$$

The level of significance is 2.5% on the right side.

Day t is suspect of market abuse if at least three alerts become active.

4. BACKTESTING

We have tested the methodology analyzing its capability to detect cases that the CONSOB has identified as being suspect of insider trading or manipulation. The ideal experiment would be to test the methodology on its capability to detect days that the judicial authority has judged as being object of insider trading/market manipulation. Unfortunately insider trading and market manipulation cases sentenced by the judicial authority are so few (less than ten in the last seven years) that the experiment would be non significant. All the details (assets and days) on cases under suspicion of market manipulation are gathered from CONSOB official releases. Note that the cases listed below are only suspect of market manipulation: no effective market abuse activity has been detected by the judicial authority. As a whole, we have eighty two market manipulation cases: fifty six cases of insider trading (art.180) and twenty six cases of market manipulation (art.181).

The main goal of the experiment is to verify the capability of the methodology to effectively detect days suspect of market manipulation with little noise, i.e., the number of "false'' days signaled by the method is limited. It would be easy to detect market abuse cases with a large number of false signals. Our goal is to have a methodology that detects the right days and a limited number of false days. To this end, we have used this sample to set the parameters (sample, quantiles) properly. The parameters defined in the last Section have been chosen accordingly.

Results reported in Table 1 are quite interesting. The methodology is selective: on average for each time series, with three over five alerts, the procedure signals 2.3% days. The methodology is also able to detect the right days: on the whole it detects 59 over 82 cases of insider trading and manipulation (72%), limiting our attention to insider trading cases the fraction goes up: 45 over 56 cases (80%).

Tab. 1

Stock	**Days identified**	**Fraction**	**Days suspect of market manipulation**	**Cause**	**Detection**	**Right signal**
Alleanza risp	8	0.019	8-12/11/2001	art.180	YES	1
Allianz subalpina	2	0.011	29-08/5-09-2000	art.180	YES	1
Amga	24	0.014	19/12/2000	art.181	NO	0
Autostrada to-mi	11	0.0065	19/12/1999	art.181	NO	0
Autostrade	16	0.010	29-7/31-10-2003	art.180	YES	1
Banca anotnvenet	16	0.021	January-october 2003	art.180	YES	5
Banca Intesa	16	0.093	13/07/2004	art.180	NO	0
Banca legnano	8	0.046	18-19/12/2000	art.180	YES	3
Banca profilo	30	0.0182	27-12/11-01-2000	art.180	YES	7
Benetton	17	0.0087	january-october 2003	art.180	YES	3
Buffetti	3	0.016	24- 23/12/1999	art.180	YES	3
Burgo	3	0.032	1.2/19.4.2000	art.180	YES	4
Cairo	9	0.021	01/01/02 - 15/12/02	art.181	NO	0
Capitalia	35	0.021	31/01/2000	art.181	NO	0
Capitalia			13/03/2001	art.181	NO	0
Chl	34	0.024	23-9/30-10-02	art.180	YES	2
Ciga	4	0.029	5/14.10.1999	art.180	YES	2
Ciga			21/28.10.1999	art.180	YES	2
Cir risparmio	3	0.02	28/07-12/09/2000	art.180	YES	1
Cofide	24	0.014	31-5/1-6-2000	art.180	NO	0
Cofide			1-1-02/15-12	art.181	YES	1
Cremonini	34	0.02	12/01/2001	art.180	YES	4
Dmail	16	0.013	29-10/7-11-01	art.180	YES	5
Engineering	4	0.011	13/02/02-22/02/02	art.181	NO	0
Ericsson	13	0.0714	25.11/7.12.1999	art.180	YES	11
Euphon	20	0.014	3-2-03/8-4-03	art.181	NO	0
Fiat	24	0.014	02/05-28/06/2002	art.181	YES	2
Fiat			06/04/2001	art.181	NO	0
Finmeccanica	6	0.0031	<14.10.1998	art.180	NO	0
Finpart	25	0.16	10-21/1.2000	art.180	YES	12
Generali	24	0.014	04-09-2000	art.181	NO	0
Generali			23-01/20-02-2003	art.180	YES	4
Hdp	10	0.068	1-11/2/2000	art.180	YES	1
Hera	5	0.008	20/10-28/10/2004	art.180	YES	2
Imm lombarda	37	0.022	7-20/03/2002	art.180	YES	2
Impregilo	32	0.019	1/1/2002-15/12/2002	art.181	YES	4
Ipi	15	0.014	8-11/13-11-2004	art.181	NO	0
Italiana assicuraz	7	0.021	11-19/04/2001	art.180	YES	1
It holding	37	0.0217	13-02/21-03-02	art.181	YES	5
Italmobiliare	5	0.0029	23-4/16-5-2002	art.180	NO	0

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Jolly hotels	16	0.009	23-4/16-5-2002	art.180	NO	0
Magneti marelli	2	0.018	28/04- 05/05/2000	art.180	YES	1
Marcolin	2	0.011	09/07/04 – 07/10/04	art.180	YES	1
Mariella burani	8	0.0055	23-04/16-05-2002	art.180	NO	0
Mediobanca	18	0.01	04/09/2000	art.181	NO	0
Mondatori	6	0.0035	23-11-1999/17-03-2000	art.180	YES	2
Olidata	22	0.0129	25/05/2000	art.180	NO	0
olivetti priv	2	0.0129	20.1/24.2.2000	art.180	YES	2
Olivvetti risp	1	0.0065	20.1/24.2.2000	art.180	YES	1
pirelli spa	14	0.008	25-26/9/2000	art.180	NO	0
pirelli spa			16-30/11/1999	art.180	YES	2
pirelli spa			13-17/12/1999	art.180	YES	2
Poligrafici	4	0.0134	03/03/03 - 17/07/03	art.181	YES	4
Ras risp	37	0.019	15-24/3/1999	art.180	NO	0
Rcs	27	0.016	13-11/29-11-2003	art.180	YES	1
Ricordati	28	0.016	2-12/5-12-2002	art.180	YES	1
Ricordati			1-9/19-9-2000	art.180	YES	1
Roncadin	33	0.020	21-11/26-04-2002	art.180	YES	3
Rotondi	6	0.033	1-7/6-7/1999	art.181	YES	3
Seat	6	0.029	24-01/10-02-2000	art.180	YES	1
Seat risp	13	0.07	24-1/10-2-2000	art.180	YES	2
Sirti	26	0.015	18/19-10-1999	art.180	NO	0
Sirti			21/28-02-2002	art.180	YES	3
Sirti			10/21-03-2002	art.180	YES	3
Smi	24	0.014	10-8/24-9-2002	art.181	YES	2
Snai	50	0.029	04/01/2001	art.181	YES	3
Snia	12	0.028	17-29/01/2002	art.180	YES	1
SS lazio	43	0.025	21/06/2004	art.181	YES	1
SS lazio			15/12/2003-16/1/2004	art.181	YES	3
SS lazio			2/2/04-9/5-04	art.181	NO	0
SS Lazio			30/6-21/7/03	art.181	YES	1
Telecom	25	0.0128	6-7/03/03	art.180	NO	0
Telecom			2-11-1998/19-2-1999	art.180	YES	1
Telecom			17/09/2001	art.180	YES	1
Toro	3	0.017	28-04/5-5-2000	art.180	YES	3
Unim	7	0.0419	17/9-24/9/1999	art.180	YES	4
Unicredito	27	0.014	15-12-98/4/1/1999	art.180	YES	2
Unipol priv	18	0.011	18-3/1-4-2003	art.181	YES	2
Rcs			January-july 05	art.180	YES	6
SS.Lazio			April 2005	art.181	YES	1
Banca antonveneta			november04-march05	art.180	YES	10
Fiat			24-agust-05	art.181	YES	1

Note: the first column reports the stock, the second and the third column report the number of days and the fraction of days signaled by the methodology, the third column reports the days that are suspect of market manipulation according to CONSOB, the fifth column reports the type of abuse (market manipulation art.181, insider trading art.180); the last two columns report cases that have been detected by the methodology (YES) and the number of "right'' days.

5. CONCLUSIONS

In this paper we have proposed a statistical methodology to detect insider trading and market manipulation phenomena. The methodology is based on five financial time series alerts of anomaly. The alerts have been constructed on the basis of models for financial markets in the presence of private information. The indicators concern asset return and trading volume. A day is identified as suspect of market abuse if three over five alerts become active.

As far as we know, the methodology represents a novelty. Market abuse detection is usually accomplished simply considering a threshold on the size of the trade and matching an "anomalous'' trade with special events concerning the life of the company (takeover, stock repurchases, mergers&acquisitions, etc.). Instead, our approach exploits financial market theory results to discern the presence of market abuse phenomena, given a suspect day then we can analyze each transaction in detail. This approach is appealing: the set of potential market abuse transactions is smaller than that obtained through a standard procedure.

The methodology works quite well: there is little noise (false signals are limited) and we have been able to "replicate'' the authority behavior at a satisfactory level. The method is based on daily data and is efficient to capture insider trading cases, performance in capturing manipulation cases, that often work at an intraday frequency is poorer.

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INDIVIDUAZIONE DEGLI ABUSI DI MERCATO: UNA METODOLOGIA BASATA SULLE SERIE STORICHE FINANZIARIE

Riassunto

In questo lavoro proponiamo una metodologia per individuare fenomeni di insider trading e market manipulation. La metodologia è fondata sull'analisi delle serie storiche dei rendimenti e dei volumi dei titoli. La presenza di autocorrelazione nei volumi e nei rendimenti è un indicatore di anomalia, volumi elevati e scostamenti dal modello di mercato per i rendimenti sono considerati segnali di anomalia. La metodologia funziona abbastanza bene: i falsi segnali sono limitati ed è in grado di "replicare'' le decisioni della Consob in materia (oltre il 70% dei casi istruiti dall'autorità).