Do Big Investors' Trades Have Predictive Power? A Note on Istanbul Stock Market

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Abstract

The net buying (selling) volume of the most net buyer (seller) brokers over a unit period is a widely followed piece of information in Istanbul Stock Market, which most market commentaries inaccurately refer to as "the net money in- or outflow". It is, in fact, a proxy for big investors' trading. In this note, we test whether this information has predictive value, whether market participants' emphasis on this information is justified, or just an illusion. By doing so, we add to the literature on the relationship between big investors' trading and stock returns, using a unique information set. Results suggest a significant contemporaneous association between the "net inflow" and current returns, but little predictive value.

Keywords: *The Relationship Between Big Investors' Trading and Returns, Predictive Value of Large Trades, Market Microstructure, Istanbul Stock Market*

JEL Classification: *G14*

Özet - Büyük Yatırımcıların İşlemleri Öngörü Gücü Taşır mı? İstanbul Borsası Üzerinde Bir İnceleme

İMKB hisse senetleri piyasasında, en fazla net alım/satım yapan aracı kurumların net işlem hacimleri, piyasa katılımcıları tarafından yakından izlenen ve piyasa analiz ve yorumlarında hatalı şekilde "net para girişi veya çıkışı" şeklinde adlandırılan bir veri setidir. Esasen, bu veri seti, büyük yatırımcıların işlemlerini yansıtmaktadır. Bu çalışmada, bu veri setinin gerçekten öngörü gücü taşıyıp taşımadığı, piyasa katılımcılarının bu bilgiye verdikleri önemin haklı olup olmadığı araştırılmaktadır. Böylece, özgün bir veri türü kullanılarak, büyük yatırımcıların işlemleri ile hisse senedi getirileri arasındaki ilişkiyi inceleyen literatüre katkı sağlanmaktadır. Sonuçlar, "net para girişleri" ile hisse senedi getirileri arasında kuvvetli bir eşzamanlı ilişkiye işaret etmekte, fakat "net para girişleri"nin önemli bir öngörü gücü taşımadığını göstermektedir.

Anahtar Kelimeler: *Büyük Yatırımcı İşlemleri ile Getiriler Arasındaki İlişki, Büyük Hacimli İşlemlerin Öngörü Gücü, Piyasa Mikro-Yapısı, İMKB Hisse Senetleri Piyasası*

JEL Sınıflaması: *G14*

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1. Introduction

The predictive value of big investors' trades has long been noticed by financial market participants, and tested by empirical researchers.

As the literature reviewed in the next section suggests, the predictive value of big investors' trades may result from two sources: i) Big investors are more likely to be informed, so their trades may contain private information. ii) Big investors' trades are generally of larger size, executed over a longer time span. They tend to be autocorrelated when measured at high frequency. Thus, current trades of big investors may signal further trades in the same direction in the near future. To the extent that price pressure exists (i.e.; trades have a short-term impact, beyond their information content, on market price), current trades of big investors may imply further price pressure in the same direction in the next periods.

Large-volume trades are naturally likely to be trades of big investors. Hence, large-volume trades can be used as a proxy for big investors' trades.

In Istanbul Stock Market (ISM)[1], where market depth is believed to be relatively thin, and the trades of foreign institutional investors and groups of local big speculators are believed to have strong impact on prices, the summary information of net buying and selling volume by the most net buyers and net sellers over a unit period has been popular recently. This information has been routinely sought by a large portion of market participants, and regularly discussed in many stock market commentaries. Our observations suggest that this information, along with share ownership data from the clearing house (Takasbank), is regularly studied, even used as the primary forecasting tool, by some big individual traders, and even by some fund managers. In TV commentaries, this information has often been inaccurately referred to as "the net money inflow into (outflow out of) the market".

In this study, the predictive value of this information set is tested. The practical goal is to provide conclusive evidence on whether the emphasis put by market participants on this information is justified or just an illusion. From the point of contribution to the literature, on the other hand, the study adds to the literature on information content (predictive value) of big traders' transactions by using a unique

(1) *Throughout the paper, we refer to the main (national) stock market in Istanbul Stock Exchange as "ISM" for the sake of practical simplicity.*

type of data: In most of the tests in extant literature, a relationship between trades sorted either by trade size or trader type and stock returns are sought. The data at hand here is aggregated market-wide, but still a good proxy for big traders' transactions. The study is unique in that it seeks a relationship between the market-wide aggregated net buying or selling volume of the brokers (member institutions of the Istanbul Stock Exchange) with the highest volume of net trades and the market index returns.

In Section II, a review of literature on why big traders' trades may be expected to have predictive value and on findings of similar empirical tests in the previous literature is provided. In Section III, the data and methodology employed in this study are described. In Section IV, results are presented. Section V summarizes the main findings, together with relevant interpretations.

2. Literature Review

Microstructure literature generally finds a positive relation between trade size and information content (Easley and O'Hara, 1987), however this relationship is not uniform (Easley et al., 1997). Most researchers expect informed trades to be medium-size trades rather than large-size, because a motive to conceal would lead informed traders to refrain from large-size trades: Barclay and Warner (1992) find that "although majority of trades are small, most of the cumulative stock-price change is due to medium-size trades; consistent with the hypothesis that informed trades are concentrated in the medium-size category, and that price movements are due mainly to informed traders' private information". Thus, use of larger-size trades as a proxy for informed trading is justified in general, however caution is needed with overt large-size trades.

Institutional trades typically have larger size. Nofsinger and Sias (1999) find a strong monotonic relationship between changes in institutional ownership and current returns, which is not reversed in the first post-herding year. Moreover, changes in institutional ownership help forecast future returns even after controlling for return momentum, suggesting that institutional trading may be correlated with information. Wermers (1999) presents similar results for mutual funds. Dennis and Strickland (2002) find that high-volatility days are associated with significant changes in institutional ownership. These evidence suggest that institutional trades have information content. As institutional trades typically have large volume, the use of large-volume trades as a proxy for informed trading is thus warranted.

Symmetrically, small-size trades are generally regarded as uninformed (noise) trading. Basic models of trading assume a random arrival of uninformed traders (for instance, Kyle, 1985), while alternative noise trading models have been proposed that regard them as positive feedback traders attempting to mimic, with some lag, informed traders' actions reflected by price change trends, or as contrarians providing liquidity to informed traders (see Lee et al., 1999).

The other potential source of predictive power of large trades is that they may signal further large-size trades in the same direction, either because they are part of a bigger trade executed in increments over time or because they come from institutional investors, who are known to be more likely involved in herding and positive feedback trading. On the former, there is evidence that large-size trades are split into smaller parts, and execution of parts is spread over time to minimize transaction costs (see Keim and Madhavan, 1995). On the latter, there is direct evidence that institutional investors trade in large sizes and their trades are serially correlated (Sias and Starks, 1997); that institutional trades are associated with price pressure though the average effect is small (Chan and Lakonishok, 1993). See also Dennis and Strickland (2002). Contrary evidence, however, also need to be mentioned here: Lakonishok et al. (1992) find that pension managers do not strongly pursue positive feed-back trading strategies; adding caution that some of the overt large trades, especially those from non-tactical traders, may not necessarily signal further trades in the same direction.

The discussion above explains why one might expect larger trades to have value in predicting future returns. However, fully revealing rational expectations (i.e.; efficient markets hypothesis) requires such predictability to be economically insignificant. As a fully revealing rational expectations model is rejected over a noisy rational expectations equilibrium (see Lang et al., 1992, for a test on US data), finance literature does not rule out such predictive ability. In an emerging market, there might even be more potential for such predictability.

Indeed, empirical results by Lee et al. (1999) in a study on Taiwan Stock Exchange, which is similar to the study in this paper, indicate that large individual trades and institutional trades Granger-caused stock returns in the next 15 minute interval, with the former having a stronger effect; whereas small individual trades had almost no effect on future stock returns. Among the three groups of investors (small individual, large individual and institutional, as sorted by Lee et al.) trading by the big individual investors is reported to have the strongest contemporary correlation (around 0.40) with stock returns.

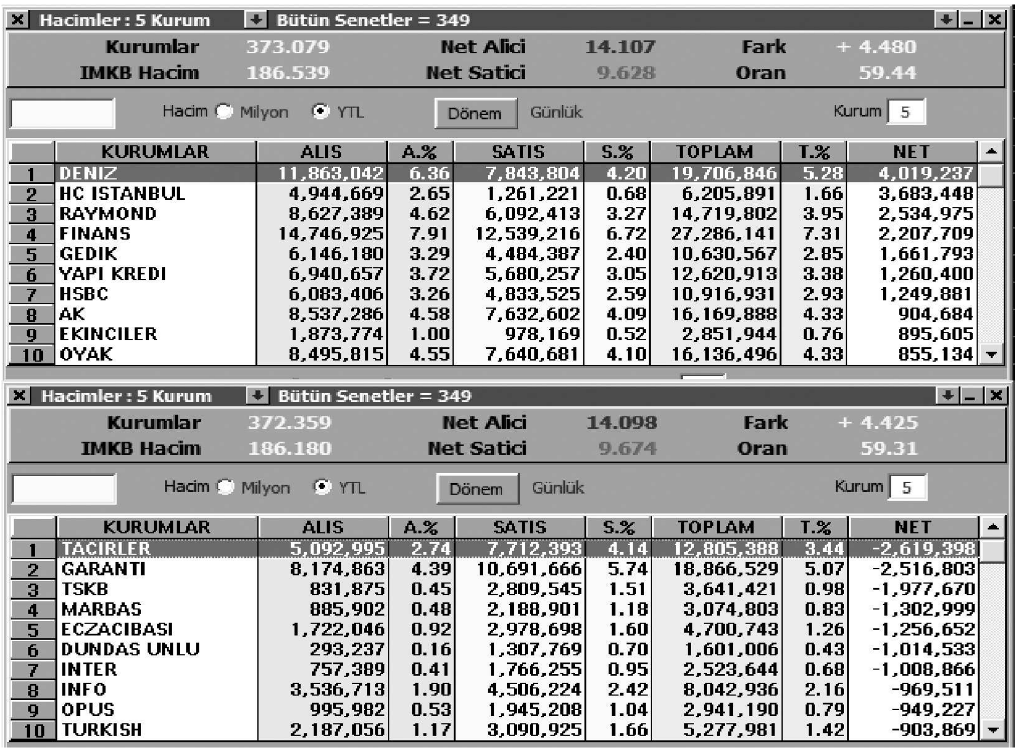
In the light of these findings, it remains interesting to see if the information on the net trading volume of the largest net volume brokers in ISM does really have predictive power. While the information set used in this study is not the same type as in extant literature, it is very similar in terms of what it reflects.

3. Data and Methodology

The information set, the inspiration of this study, consists of the net of buying (in excess of selling) volume by the most net buying and selling brokers over a unit period of time. A positive reading implies net buying while a negative reading implies net selling on the part of a particular brokerage institution. This data is derived from cumulative trades of each and every broker in ISM. Hence, an important difference from Lee et al.'s data set is that we cannot group trades directly by their size, nor by the identity of the parties. Our data set does only allow us to identify the brokers, and the cumulative summary nature of our data leads to the loss of information on particular trades; however, this is the way market participants and commentaries employ this information. As a result, this is not a direct study of the price impact or return predictive ability of trades sorted by sizes or investor type as in Lee et al. Rather, this is a simple straightforward test of whether this particular information set, widely used in ISM, is really useful or emphasis put on it was just an illusion. However, it is also, indirectly, a test of whether big investors' trades have information content, thus is particularly relevant to literature.

Most market participants and commentaries in ISM refer to the difference of the net buys of 5 or 10 most net buyers from the net sells of the 5 or 10 most net sellers, as the "net money inflow", with a negative number implying "money outflow". In reality, the sum of net buys of all brokers in ISM is always zero; in other words, there can be no in- or outflows. What they refer to as inflow (outflow) is, in fact, that largest net buyers (sellers) have bought from (sold to) relatively smaller net sellers (buyers). Thus, the "net buys" figures are indirectly a proxy for big investors' trades.

In Figure 1, our raw data can be seen, in the form it is broadcast on a real-time basis by data vendor *Euroline*.



Hacimler : 5 Kurum | Bütün Senetler = 349

Kurumlar 373.079 | Net Alici 14.107 | Fark + 4.480

IMKB Hacim 186.539 | Net Satici 9.628 | Oran 59.44

Hacim Milyon YTL | Dönem | Günlük | Kurum 5

	KURUMLAR	ALIS	A.%	SATIS	S.%	TOPLAM	T.%	NET
1	DENIZ	11,863,042	6.36	7,843,804	4.20	19,706,846	5.28	4,019,237
2	HC ISTANBUL	4,944,669	2.65	1,261,221	0.68	6,205,891	1.66	3,683,448
3	RAYMOND	8,627,389	4.62	6,092,413	3.27	14,719,802	3.95	2,534,975
4	FINANS	14,746,925	7.91	12,539,216	6.72	27,286,141	7.31	2,207,709
5	GEDIK	6,146,180	3.29	4,484,387	2.40	10,630,567	2.85	1,661,793
6	YAPI KREDI	6,940,657	3.72	5,680,257	3.05	12,620,913	3.38	1,260,400
7	HSBC	6,083,406	3.26	4,833,525	2.59	10,916,931	2.93	1,249,881
8	AK	8,537,286	4.58	7,632,602	4.09	16,169,888	4.33	904,684
9	EKINCILER	1,873,774	1.00	978,169	0.52	2,851,944	0.76	895,605
10	OYAK	8,495,815	4.55	7,640,681	4.10	16,136,496	4.33	855,134

Hacimler : 5 Kurum | Bütün Senetler = 349

Kurumlar 372.359 | Net Alici 14.098 | Fark + 4.425

IMKB Hacim 186.180 | Net Satici 9.674 | Oran 59.31

Hacim Milyon YTL | Dönem | Günlük | Kurum 5

	KURUMLAR	ALIS	A.%	SATIS	S.%	TOPLAM	T.%	NET
1	TACIRLER	5,092,995	2.74	7,712,393	4.14	12,805,388	3.44	-2,619,398
2	GARANTI	8,174,863	4.39	10,691,666	5.74	18,866,529	5.07	-2,516,803
3	TSKB	831,875	0.45	2,809,545	1.51	3,641,421	0.98	-1,977,670
4	MARBAS	885,902	0.48	2,188,901	1.18	3,074,803	0.83	-1,302,999
5	ECZACIBASI	1,722,046	0.92	2,978,698	1.60	4,700,743	1.26	-1,256,652
6	DUNDAS UNLU	293,237	0.16	1,307,769	0.70	1,601,006	0.43	-1,014,533
7	INTER	757,389	0.41	1,766,255	0.95	2,523,644	0.68	-1,008,866
8	INFO	3,536,713	1.90	4,506,224	2.42	8,042,936	2.16	-969,511
9	OPUS	995,982	0.53	1,945,208	1.04	2,941,190	0.79	-949,227
10	TURKISH	2,187,056	1.17	3,090,925	1.66	5,277,981	1.42	-903,869

Figure 1: The raw data of largest net buying and selling brokers, as it is broadcast by the data vendor. The picture represents the situation at 10.15 a.m. on 22.April.2005. The tables in the picture are obtained by ranking of all brokers in terms of their cumulative net buys (seen under the column with the heading "net"). Net buys are obtained by deducting total selling volume (under the column with the heading "satış") of a broker from its total buying volume (under the column with the heading "alış"). In the top part, the 10 brokers with the largest net buys are seen, while 10 brokers with the largest net sells are in the bottom part.
(printed under permission).

While it is a functionally good proxy for big investors' trades, one should note that it is not a perfect one: It can be that a broker with a large number of small investors, all of them being simultaneously net buyers in a particular period, appears as the biggest net buyer, despite the fact that in reality it reflects small trades; or vice versa. However, this happens rarely, if any, in real life. Most typically, a few big traders' transactions far outweigh, in volume, the sum of many small traders' transactions. Therefore, these figures generally reflect big individual, domestic institutional or foreign institutional traders' trades, and typically provide an accurate vision of big versus small players' direction of trading (i.e. whether big investors are selling to or buying from a crowd of relatively smaller investors).

A danger of misinterpreting this information set may, however, result from big investors' strategic behavior. A client in the stock market may trade through numerous brokers, even simultaneously buying through one and selling through another. The continuous auction, limit- and market order electronic trading system of ISM with irreversible limit orders, no market-making specialists, and a high level of pre-trade transparency encourages such fictive trades. There is some belief among experienced traders that big investors sometimes try to manipulate this data by appearing as large net buyer through a broker known to have foreign client base and being small net sellers through a number of other brokers, to mislead those who try to infer information from this data. Such a behavior would be consistent at least with a rational motive to conceal, if not to mislead. A remedy for this problem could be to include a higher number of largest net buyers and sellers in the analysis, since the number of different brokers a trader may use in the same period has some practical limits. We therefore use two versions in this study: one with top 5, and another with top 10 net buyers and sellers. That the results with the two versions are very similar suggests that the data set was not severely affected by such strategic behavior. In a separate test (not reported here), we also tried 15, and results were not different.

The data was obtained from *Euroline* who redistributes data from Istanbul Stock Exchange. Basically, cumulative data is summarized over periods of 1 day, so the study is at daily frequency. Additional tests using intraday data are also implemented. Daily data covers the period from 3.March.2004 to 20.October.2004 (164 trading days). To verify results out-of-sample, another test on data from 11.March.2005 to 29.April.2005 is conducted[2].

For intraday tests, historical intraday net trades data is not kept at the database of data vendor. However, it is broadcast on its screens on a real-time basis during the trading sessions. The author collected and accumulated intraday data manually for the period 4.April – 11.May.2005. The interval used in intraday tests is 1 hour. As a check for any possible impact of unequal observation periods, tests with equal periods of 1 session (i.e.; 150 minutes) are conducted[3].

Further, a high-frequency version of the test is conducted with observations at 15 minutes intervals.

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(2) *This period is characterized by increased market share of foreign institutional investors.*

(3) *A trading day in ISM consists of two sessions of 150 minutes: Morning session starts at 09.30 and ends at 12.00. The afternoon session starts at 14.00 and ends at 16.30.*

Finally, the test at the daily frequency is repeated for a sample of 15 selected individual stocks, on panel data from 4.April.2005 to 26.May.2005.

Henceforth, we will refer to the sum of net buys (sells) of the largest n net buyers (sellers) at period t as LNB_t^n (LNS_t^n). The explanatory variable in this study is the net of these two, or "the net money inflow" as inaccurately named by practitioners, (LNB_t^n - LNS_t^n), and its share in total trading volume in the other version of the tests. LNBtn and LNStn figures can be seen at the top of tables in Figure 1, respectively under the heading of "net alıcı" and "net satıcı".

Our primary interest is to see if this variable set has the ability to predict future returns of the ISE-100 index, the most widely followed market index in ISM. As a necessary first step, however, we test whether it has any association with the contemporaneous returns of the ISE-100 index.

$$Rt = a + b_1(LNB_t^n - LNS_t^n) + et \qquad (1)$$

where $R_t = \ln(P_t/P_{t-1})$ and Pt is the value of the ISE-100 index at the end of period t. A significantly positive value for b_1 would suggest an association between the information set tested in this study and current market returns, and might lend support to the price pressure hypothesis[4] or big investors' trades correlated with information arrivals in the current period, or both[5].

This version (version 1) seeks a link between the monetary value of net buys and market returns. One may claim that it is the ratio of net buys to total trading volume, rather than its numeric value, that moves prices. Further, the net buys variable, nominally, may not be stationary over time. Then, in the other alternative version (version 2), we test the relationship between the net buys relative to total trading volume and current returns:

$$Rt = a + b_1[(LNB_t^n - LNS_t^n) / TV_t] + et \qquad (2)$$

where TV_t is the total trading volume in ISM at period t.

Next, we move to our main question, assessing predictive value of this information set by estimating Equation 3:

$$R_t = a + b_2(LNB_t^n\text{-}1 - LNS_t^n\text{-}1) + e_t \qquad (3)$$

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(4) *Price pressure hypothesis implies that it is the trading itself, rather than its information content, that moves prices. Existence of a contemporaneous positive relationship between trades and returns, reversed over time, is consistent with price pressure hypothesis rather than trades having information content. Note that both effects may apply at the same time. A significantly positive relationship between current trades and future returns would be consistent with asymmetrically informed trading.*

(5) *A subsequent reversal in the next period would support the former, while absence of subsequent reversal would be consistent with the latter.*

A significantly positive estimate of b_2 would suggest that the "net inflow" information has indeed predictive value. It would also imply that big investors' trades contain asymmetric information. Further, it would reject market efficiency.

Again, we implement the test also in the alternative version with the ratio of net buys to trading volume as the independent variable:

$$R_t = a + b_2 [(LNB^n_{t-1} - LNS^n_{t-1}) / TV_{t-1}] + e_t \quad (4)$$

Equations 1-4 are estimated by OLS. Each test is repeated twice: one with n=5 and then with n=10.

Note that while a VAR specification would normally be more appropriate in modeling the relationship between trades and returns, in this paper we are primarily interested in the assessing the predictive value of the single variable (LNB^n_{t-1} - LNS^n_{t-1}) in the form it is used by market participants, thus univariate regressions are the preferred methodology here. Some consequent econometric issues are then handled separately.

Tests on intraday data are conducted in a similar fashion. For the sake of accuracy, we made the following correction before using intraday data: It has been commonly observed that the ISE-100 always jumps at the daily close. This results from some investors' attempt to uptick the daily closing price of the stocks, for which they hold a stake, by buying a symbolic 1 lot at the ask price. The large tick sizes in ISM ranging between 0.5 to 1 %, and portfolio valuation at the daily closing price seem to create an incentive for this kind manipulative behavior. We estimate the effect of such behavior on the closing level of the ISE-100 index at 16.30 to be around 0.2% on average[6]. The impact of this would be an overstatement (understatement) of returns for the last interval ending at 16.30 (first interval commencing at 09.30). To avoid such bias, which might lead to distortions in our intraday analysis, we correct ISE-100 levels at 16.30 close by 0.2% of index points.

To provide some insight, we look at the relationship between largest net buys and sells and the total trading volume over a unit period, a day. The correlation between (LNB^{10}_t+ LNS^{10}_t) and the total trading volume of ISM (TVt) in our main sample was +0.696 (significant at p=0.000), suggesting that the net trades of largest net buyers and seller were a major driver of total trading volume. Note that (LNB^{10}_t+ LNS^5_t) ranged between 9-15% of daily total trading volume, while (LNB^5_t + LNS^5_t) ranged between 6-14% of it. The correlation between (LNB^{10}_t- LNS^{10}_t) and the total tra-

(6) *The estimate is the average of observed jumps during our sample period. The magnitude of the jump in the ISE-100 index depends on the tick-size and the weighted proportion of stocks upticked at the close.*

ding volume was +0.349 (significant at p=0.000) suggesting that net buying, rather than net selling, by largest net traders contributed to volume.

4. Results

Results of estimating equations 1 and 2 over the main sample, reported in Table 1 below, suggest a strong positive association between the "net money inflow" (or more accurately LNB_t^n - LNS_t^n, the net buys of n biggest net traders) and the current period returns of the ISE-100 index, at the daily frequency. All b_1 coefficients are positive and significant at p<0.001. The association is stronger when the monetary value of the net buys is used directly, rather than its share in total trading volume[7]. Further, the results with n=10 are stronger than those with n=5, though both provide the same qualitative conclusion[8]. Overall, results suggest that up to 26.5% of the variation in daily returns can be explained by the net buys of biggest net traders.

Table 1: Results of the test for a contemporaneous association between the "net inflow" and ISE-100 returns on daily data from 3.3.2004 to 19.10.2004.

		b_1	sig(b_1)	F	adj. R-sqrd
Equation 1:	n=5	0.440	0.000	38.4	0.189
	n=10	0.520	0.000	59.2	0.265
Equation 2:	n=5	0.343	0.000	21.3	0.112
	n=10	0.434	0.000	37.2	0.184

The columns: b_1 is the estimate of the standardized value of coefficient b_1
sig(b_1) is the significance level of this estimate.
F is the F statistic of the regression fit.
Adj. R-sqrd is explained variation over total variation.

Note: As "**a**" coefficients of these regressions are neither of interest nor meaningful, we do not need to report them.

These findings confirm that the "net inflow" variable is a relevant one, strongly associated with current returns. In more accurate words, the net trades of big investors, to the extent they are proxied by this variable, do tend to explain a considerab-

(7) *This finding, interesting at the face value, may suggest that volume puts some noise onto the association between net trades and returns, and may be consistent with the argument that informed traders tend to conceal in crowd (see Admati and Pfleiderer, 1988, for a theoretical discussion of this argument).*

(8) *Normally, both of the independent variables with n=5 and n=10 cannot be entered into the regression simultaneously, because of severe multicollinearity. When we tried this off record, we've seen that the coefficient with n=5 came out negative and borderline significant. This may lend some support in favor of the argument that big players sometimes try to mislead.*

le portion of variation in daily returns of the ISE-100 index. Hence, it is not surprising that it has drawn attention of market participants in ISM.

Now, does it have the predictive ability to justify its use in market commentaries whose primary task is forecasting, or is its use just an illusion stemming from this contemporaneous association with no clue for the future? This question is addressed next by estimating equations 3 and 4. Results are presented in Table 2 below:

Table 2: Results of the test for the predictive ability of the "net inflow" on daily data from 3.3.2004 to 20.10.2004

		b_2	sig(b_2)	F	R-sqrd
Equation 1:	n=5	-0.094	0.232	1.4	0.003
	n=10	-0.058	0.460	0.5	0.000
Equation 2:	n=5	0.003	0.966	0.0	0.000
	n=10	0.040	0.615	0.3	0.000

The columns: b_2 is the estimate of the standardized value of coefficient b_2

sig(b_1) is the significance level of this estimate.

F is the F statistic of the regression fit.

Adj. R-sqrd is explained variation over total variation.

Note: As "a" coefficients of these regressions are neither of interest nor meaningful, we do not need to report them.

All b_2 coefficients are insignificant. Indeed, as is clear from Table 2, all of them are far from significance. Those with the monetary value of the net buys (version 1) are even negative. This suggests that the "net inflow" information has no value at all in predicting next day's return.

Our conclusion based on these findings is that the "net inflow" data has no predictive power. Market participants' emphasis on it seems to be just an illusion stemming from its contemporaneous association with returns. Further, a strong contemporaneous association with current returns and no relation with future returns are consistent with the price pressure hypothesis or big investors' trading being correlated with public information, rather than asymmetrically informed trading.

Here, we also address some econometric issues: First, some empirical studies report a positive first order positive autocorrelation (i.e.; findings consistent with an AR(1) model) of market index returns. If daily returns are positively autocorrelated by first order and the "net inflow" variable is associated with current returns, then part of any possible predictive ability of Equation 3 or 4 should have been attributed to AR(1) in returns. Note that this would only diminish any result favoring the efficacy of this information set and is irrelevant here as we have found no efficacy. Moreover, in our sample period the first order autocorrelation in daily returns of ISE-100 index turned out to be insignificant (+0.054, t=0.682, p=0.496), suggesting that there is no need to correct for this possibility.

Second, if the "net inflow" series is positively autocorrelated, then one would attribute any predictive ability to the execution of large trades spread over time rather than informed trading. As we found no predictive ability, this is not a relevant issue. However, if the "net inflow" can be forecast from its past values, then a forecasting model for ISE-100 index can be devised. Hence it is interesting to see the autocorrelation characteristics of the "net inflow" variable. For this purpose, we estimate the following autoregression:

$$N^{10}_{t} = \alpha + \beta 1 N^{10}_{t-1} + ,2N^{10}_{t-2} + ,3N^{10}_{t-3} + ,5N^{10}_{t-5} + \varepsilon_{t} \quad (5)$$

where N^{10}_{t} is the net buys ($N^{n}_{t} = LNB^{n}_{t} - LNS^{n}_{t}$). Lags are selected to include last three trading days and the same day of the past week. Results suggest that the net buys follow almost a random walk at the daily frequency, with no significant dependency on its past values: β_1 = 0.055 (p=0.491), β_2 = 0.091 (p=0.251), β_3 = β_0.026 (p=0.744), β_5 = 0.103 (p=0.105); F=1.08 (p=0.366), adj.R^2= 0.002. Though insignificant positive autocorrelation at lags 1, 2 and 5 are noteworthy, we have no clear evidence that net buys are autocorrelated on a daily basis nor that they are forecastable using their lagged values. Hence, it is not possible to devise a forecasting model for ISE-100 index daily returns by using the past daily values of the net buys variable.

Next, we repeat the same test out-of-sample: After Turkey received green light to start talks for EU full membership on 17.Dec.2004, a large inflow of foreign portfolio investment into ISM was observed during the subsequent few months. Consequently, the share of foreign investor holdings of Turkish stocks has increased to about 58%. Foreign investors, mostly institutional, are big and typically informed traders. So, we choose the sample period from 11.March.2005 to 29.April.2005 for an out-of-sample confirmation. This period was characterized by dominance of foreign investors and large fluctuations in ISE-100 index driven by trends in global and emerging equity markets; hence these big foreign investors did have an informational advantage. If the "net money inflow" information has any predictive value, it is more likely to show up in this period.

Results from estimating Equations 1 and 2 on daily data from this sample is reported in Table 3 below:

Table 3: Results of the test for a contemparenous association between the "net inflow" and ISE-100 returns on daily data from 11.3.2005 to 29.4.2005.

		b_1	sig(b_1)	F	R- sqrd
Equation 1:	n=5	0.59	0.000	18.3	0.330
	n=10	0.72	0.000	36.1	0.500
Equation 2:	n=5	0.52	0.001	12.4	0.246
	n=10	0.68	0.000	28.5	0.440

See explanations in Table 1.

The association between current returns and the “net inflow” variable (or net buys) is stronger in this sample period, as we expected. The net buys variable with n=10 accounted for as much as 50% of variation in daily returns of ISE-100 index in this sample period. The lower F values are due to loss of power because of shorter sample period. All of the findings are similar to those in our original sample: The version with n=10 provided stronger association with current returns than that with n=5. Again, the version with the numeric value of net buys provided stronger association than that with its ratio to total trading volume. Overall, the results reinforced our conclusion that the net buys are significantly associated with current returns, and perhaps added that the degree of association is stronger when the share of foreign investors (a group of big, informed traders) is higher.

As to the predictive value of this information, results from estimating equations 3 and 4 on this sample, reported in Table 4 below, suggest that it has still no predictive ability. Stronger association with current returns did not translate into improved ability to forecast future returns. Thus, our main conclusion that the net buys information has no predictive ability is confirmed.

Table 4: Results of the test for the predictive ability of the "net buys" on daily data from 11.3.2005 to 29.4.2005.

		b_2	sig(b_2)	F	adj. R-sqrd
Equation 1:	n=5	-0.016	0.591	0.4	0.002
	n=10	-0.002	0.786	0.1	0.000
Equation 2:	n=5	0.017	0.572	0.5	0.004
	n=10	0.029	0.431	0.8	0.007

See the explanations in Table 2.

Before ruling out the predictive ability of the net buys information, however, we must conduct additional tests with alternative unit periods of observation. Ülkü (2001) reports a significant ability of monthly net buys of foreign investors to forecast the next month's return of ISE-100 index for the sample period 1999-2001. That the data set in this study has common ingredients as the monthly foreign investors' trades data used in Ülkü (2001) suggests the possibility that the net buys of big investors may have predictive value for future returns over a more flexibly defined, longer horizon. To assess this possibility, we convert our daily data into weekly and repeat the same tests on our main sample[9].

Results are reported in Table 5 below (to save space, hereafter, results with the ratio version are omitted, and tests for contemporaneous association with current ISE-100 returns, equation 1, and for predictive ability, equation 3, are presented together).

Table 5: Results of the test for contemporanous association between the "net inflow" and ISE-100 returns (Equation 1) and test for the predictive ability of the "net inflow" (Equation 3) on weekly data from 3.3.2004 to 20.10.2004

		b_1	sig(b_1)	F	adj. R-sqrd
Equation 1:	n=5	0.627	0.000	19.4	0.372
	n=10	0.521	0.002	11.2	0.247
		b_2	sig(b_2)	F	adj. R-sqrd
Equation 3:	n=5	-0.173	0.846	0.9	0.000
	n=10	-0.143	0.779	0.6	0.000
See explanations in Tables 1 and 2.					

Again there is a strong association between the weekly cumulative net buys of big investors and current weekly returns of ISE-100 index, as results of Equation 1 suggest. Up to 1/3 of variation in weekly returns of ISE-100 index can be explained by the weekly net buys variable. Results of Equation 3 suggest that the net buys over a week has no ability to forecast next week's return of ISE-100 index. Thus, our main conclusion is reinforced again with weekly data.

We also repeat the same tests over a unit period of 2-days. Results are reported in Table 6 below:

(9) *Because our second sample is too small for weekly data, the tests are conducted only on the main sample.*

Table 6: Results of the test for contemporanous association between the "net inflow" and ISE-100 returns (Equation 1) and test for the predictive ability of the "net inflow" (Equation 3) on 2-daily data from 3.3.2004 to 20.10.2004

		b1	sig(b1)	F	adj. R-sqrd
Equation 1:	n=5	0.537	0.000	31.9	0.279
	n=10	0.411	0.000	16.0	0.158
		b2	sig(b2)	F	adj. R-sqrd
Equation 3:	n=5	-0.005	0.965	0.0	0.000
	n=10	-0.013	0.906	0.0	0.000

See explanations in Tables 1 and 2.

Again, there is a significant association (weaker than that on weekly test) between the net buys and current returns, while net buys over the last 2 days has no ability to forecast the returns for the next 2 days. These repeated similar results strengthen our main conclusion that the net buys information is associated with current returns, not with future returns.

A complementary inquiry with the available data would be whether the net buys can be forecast from lagged returns of the ISE-100 index. Such an analysis would also shed some light on whether big investors condition their trades on past market returns. For this purpose we estimate the following regression:

$$(LNB_t^n - LNS_t^n) = N_t^{10} = \alpha + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_5 R_{t-5} + e_t \qquad (6)$$

Lags are selected to include the last three trading days and the same day of the past week. Results for the version with n=10 suggest that the net buys is positively related to previous day's ISE-100 index return (β_1 = 0.260, t=3.31, p=0.001), while coefficients at other lags are insignificant (β_2=0.078, t=1.00, p=0.318; β_3= -0.044, t= -0.569, p=0.570; β_5=0.116, t=1.47, p=0.144)[10]. Overall, 5.8% of the daily variation of in the net buys can be forecast by the model in Equation 6 (F=3.39, p=0.11)[11].

(10) *The constant α was significantly positive, indicating net buying by large traders over the sample period at an average rate of 3.555 million YTL per day.*

(11) *However, this sample period was characterized by an uptrend in ISE-100 index and a trend of persistent foreign inflows from foreign investors; hence it is likely that positive coefficients are a byproduct of these trends. Not surprisingly, the results of the same regression over our second sample did not coincide with those over the original sample, though the signs were similar: β_1 = 0.040, t=0.23, p=0.820; β_2=-0.219, t=-1.26, p=0.220; ,3=-0.429, t=-2.49, p=0.020; β_5=0.043, t=0.25, p=0.808; F=1.94 (p=0.135), R^2=0.111. Note that, as previously reported results suggest that net trades almost follow a random walk (i.e.; exhibited no serial correlation), VAR results would not significantly differ from the simple model in Equation 6.*

We can conclude that there is weak evidence that big investors in ISM condition their trades on past market returns, and that only a very small portion of the variation in the "net inflow" variable can be forecast reliably using past returns of the index.

Following suggestions of Barclay and Warner (1992) that most of the stock price change is due to medium-size trades (rather than large-size), we estimated equation 3 excluding days with overtly large "net in- or outflows" (i.e.; days with a net flow in excess of 20 million YTL, or 5% of the trading volume), with a hope to see some improvement in predictive ability.

However, all attempts (not reported) ended up in weaker contemporaneous association between current returns and "net inflows", and no considerable improvement in forecast ability. Interestingly, some of the b_2 coefficients turned into negative, still insignificant. Thus, attempts to sort out extreme net trades seemed to wipe out the essential part of the relation between market returns and "net inflows". It may be the case that the "net inflow" variable does not capture trade size in sufficient detail to differentiate between overt large trades with no information content and informative medium-size trades or that overt large size trades in ISM are not different from medium-size trades (i.e., Barclay and Warner's suggestion does not apply in ISM).

Does the "net inflow" have no information content at all beyond its co-movement with ISE-returns? If the answer is "no", any emphasis put on this information by market participants would totally be an illusion. Our discussions with some individual traders and portfolio managers in ISM on why they so much care about this information suggested they insist on their claim that the net inflows do have some information content. This led us to further explore any possible information content.

It might be that any information content of this variable becomes unnoticeable as part of it is priced-in on the same day, and part of it remains to the next day. Then, market participants' emphasis on the net trades may somewhat be justified even if the predictive power does not appear in univariate regressions as in Equations 3 and 4. To inquire this possibility, we computed the expected value of the net buys, $E(N_t^{10})$, as a function of its contemporaneous relationship with the ISE-100 index return. From the estimation of a regression of N_t^{10} on R_t we obtained the following contemporaneous relationship:

$E(N_t^{10}) = 350523.7 + 32000000\ R_t$. Then, we computed the unexpected (i.e.; not priced-in on the current day) values of the net buys: $U(N_t^{10}) = N_t^{10} - E(N_t^{10})$.

Finally, we tested the predictive value of $U(N_t^{10})$ by estimating[12]:

$$R_{t+1} = a + b_2\, U(N_t^{10}) + e_t \qquad (7)$$

Results were interesting: b_2 was significantly positive (standardized value of b_2 was 0.263, significant at p=0.001, F=11.8). 6.3% of the variation in next day's return of ISE-100 index could be accounted for by today's "net inflow" not incorporated to ISE-100 index value on the same day. Although this is a quite low level of predictive ability (and probably, market participants do not compute $U(N_t^n)$), this finding suggests that market participants' emphasis on the "net inflow" data is not totally unjustified. Rather, it has some information content, though perhaps not sufficiently large for forecasting.

Tests on Intraday Data

Another possibility for the "net inflow" information to have predictive value is to be assessed with intraday data. Spreading the execution of large orders over time may be across hours rather than across days, and the information on which big investors trade may be perishable within hours rather than days (i.e.; other market participants inferring from the trades of big investors may cause the prices to adjust to this information on the same trading day). For these reasons, as well as the results of empirical tests with intraday data such as Lee et al. (1999), one would expect the "net flow" information to have more predictive value on intraday basis.

Results of the tests with intraday data with observations at approximately 60 minutes intervals for the 4-29.April.2005 sample period (93 observations) are presented in Table 7 below. Because intraday volume data was not collected, the versions using ratio of "net inflow" to total trading volume (Equations 2 and 4) are omitted.

Table 7: Results of the test for contemporaneous association between the "net inflow" and ISE-100 returns (Equation 1) and test for the predictive ability of the "net inflow" (Equation 3) on intraday data from 4.4.2005 to 29.4.2005

		b1	sig(b1)	F	adj. R-sqrd
Equation 1:	n=5	0.338	0.001	11.5	0.105
	n=10	0.335	0.001	11.2	0.102
		b2	sig(b2)	F	adj. R-sqrd
Equation 3:	n=5	0.147	0.168	1.9	0.010
	n=10	0.163	0.125	2.4	0.015

See explanations in Tables 1 and 2.

(12) *Notice that b_2 in Equation 7 is equivalent to b_2 in the multivariate regression: $R_{t+1} = a + b_1 R_t + b_2 N_t^{10} + e_t$*

As seen in the upper part of Table 7, the contemporaneous association between the "net inflow" variable and the current returns of ISE-100 index is somewhat weaker than observed on daily data, but still significant. The results with predictive ability test, seen in the lower part of Table 7, suggest some signs of predictive ability, though not statistically significant: The b_2 values were of expected sign and close to borderline levels of significance. The net buys during an intraday interval of 1 hour can help forecast up to 1.5% of the variation in ISE-100 index return in the next interval.

To see if this small degree of predictability is due to hourly autocorrelation of N_t^n (i.e.; large trades split over hours), we estimated an autoregression of N_t^n on its lagged values of up to 5 lags. Results for both n=5 and n=10 suggested no significant autoregressive coefficients at all (not reported). So, the net buys do not seem to be forecastable using its lagged values, even on an intraday basis, nor the small degree of predictability on intraday version seems to come from large net trades in an hour signaling further large net trades in the same direction in the next hours. Note that the aggregate nature of our data set does not allow us to provide direct evidence on whether large trades are indeed being split across hours in a trading day or not.

We also estimated Equation 7 on this intraday data, with a hope to see stronger predictive ability. The b_2 coefficient on $U(N_t^{10})$ (i.e.; "net inflow" unreflected into ISE-100 level in the current period) was positive (standardized b_2=0.102), but insignificant (p=0.313, F=1.0), with an R^2 near zero. Thus, we cannot confirm our interesting finding on daily data.

We also repeated the tests over this sample period with a unit period of one session or 150 minutes[13]. Results are presented in Table 8 below:

Table 8: Results of the test for contemporaneous association between the "net inflow" and ISE-100 returns (Equation 1) and test for the predictive ability of the "net inflow" (Equation 3) on 150 min. session data from 4.4.2005 to 13.5.2005

		b1	sig(b1)	F	adj. R-sqrd
Equation 1:	n=5	0.381	0.003	9.3	0.133
	n=10	0.439	0.001	13.1	0.178
		b2	sig(b2)	F	adj. R-sqrd
Equation 3:	n=5	0.061	0.654	0.2	0.000
	n=10	0.067	0.622	0.3	0.000

See explanations in Table 1 and 2.

(13) *The test with 1 session as the unit period would avoid any critcism for our intaday data not consisting of intervals with exactly equal length*

The contemporaneous association of buys with current market returns seems to be slightly stronger than that with approximately 60 minute intervals, but there is no sign of predictive ability at all. From this analysis, we obtain the view that signs of predictive ability, if any, are to be sought at high frequency data with observation intervals of 60 minutes or shorter.

Upon this observation, we added a high-frequency analysis into this study and collected the same data at 15 minutes intervals for a sample period between 4.May.2005 to 13.May.2005 (87 observations)[14].

Results of estimating Equations 1 and 3 on this high-frequency data are reported in Table 9 below:

Table 9: Results of the test for contemporanous association between the "net inflow" and ISE-100 returns (Equation 1) and test for the predictive ability of the "net inflow" (Equation 3) on high-frequency data from 4.5.2005 to 13.5.2005

		b1	sig(b1)	F	adj. R-sqrd
Equation 1:	n=5	0.100	0.362	0.84	0.00
	n=10	0.042	0.702	0.15	0.00
		b2	sig(b2)	F	adj. R-sqrd
Equation 3:	n=5	0.067	0.55	0.36	0.00
	n=10	-0.016	0.89	0.02	0.00

See explanations in Table 1 and 2.

A surprising first note is that the contemporaneous association between the net buys and ISE-100 returns disappears on high-frequency data. Predictive ability is again nonexistent, disappointing any hopes flourished based on the results with hourly data.

The intriguing loss of association with current returns needs some explanation: One possibility (our view) is that it is a by-product of the noise caused by extremely large tick-sizes (i.e.; bid-ask spreads) in ISM. Average tick-sizes between 0.5-1.0% in ISM lead to excessive fluctuations in stock prices and the index measured in high-frequency, which are not necessarily associated with actual stock price changes. The noise created by such trades especially interferes with high-frequency returns.

Results of an autoregression of N_t^{10} and N_t^{5} on its lagged values (as in Equation 5) suggest no significant autocorrelation (not reported), providing no support for the argument that large trades are executed in increments during a trading day.

(14) *Some difficulties in collecting intraday data manually from real-time broadcast apply here. This cumbersome task, especially the need to watch live data every 15 minutes, kept the author from obtaining a longer sample. However, our sample size is sufficently long for statistical inference. Yet, consistency across samples is a remaining issue.*

Tests on Individual Stocks

A final possibility is that the net buys may have some predictive value on individual stock basis, which is lost in our data aggregated marketwide. To check for this, we repeated estimation of Equation 1 and Equation 3 on a sample of 15 selected individual stocks . Working with panel data, we first report the pooled estimator, as we have no a priori reason to expect the error terms to be correlated with the coefficient. However, as our time series sample size is sufficient (n=37 days), we also report independent regression results without constraining the coefficient to be equal across stocks[15]. Results, presented in Table 10 below[16], are no different than those with marketwide data and ISE100 index: The net buys are significantly associated with current returns, but have no significant ability to predict next day's returns. The coefficient b_1 (contemporaneous association) was significantly positive for all of the 15 stocks, though it exhibited some variation across stocks[17].

On marketwide tests we had found no significant autocorrelation pattern in "net inflows"; however, it may be that large trades on individual stocks are split over days while marketwide aggregation prevents this to be detected. Therefore, individual stocks are the best place to check whether large net trades are autocorrelated. For this purpose, we estimate Equation 5 with n=5 on the pooled panel data. Results suggest some evidence in favor of large net trades being spread across days: β_1=+0.142 (p=0.002), β_2=-0.042 (p=0.376), β_3=+0.122 (p=0.009), β_5=+0.002 (p=0.974), F=4.01 (p=0.003), R^2 = 0.025. Significantly positive autocorrelation coefficients at lag 1 and 3 suggest that large trades are spread across days, and sometimes, possibly as a trading tactic, they are alternated by 1 day. However, the predictive value is too low to be used as a forecasting tool.

Note that the aggregated nature of our data may have kept us from discovering more complex relationships between trades, trading parties and the information content of the first two.

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(15) *The selected stocks are Isctr, Ykbnk, Tuprs, Turkcell, Garan, Kchol, Ereğli DÇ, Dohol, Sahol, Vestel, Thyao, ŞişeCam, Ülker, BatıSöke Çimento, Gsray. They are mainly the most active stocks in ISM representing the most weighted sectors in the index. We also added some small and thinly traded stocks from different sectors to check for any possible impact of different characteristics such as market capitalization and trading volume.*

(16) *Only regressions with N_t^5 are performed, because the data vendor supplied the stock-based "net inflow" data only for the 5 largest net buyers and sellers.*

(17) *While our insight suggests that this variation is a result of information dynamics rather than stock-specific characteristics, a characterization of the differences across stocks in terms of the return sensitivity to "net inflow" is beyond the scope of this paper.*

Table 10: Results of the test for contemporaneous association between the "net inflow" and stock retums (Equation 1) and the test for the predictiv ability of the "net inflow" (Equation 3) on daily panel data of individual stocks (sample from 5.4.2005 to 26.05.2005)

Panel A: Estimation Resilts of Equation 1:

	b_1	sig(b_1)	F	adj. R-sqrd
The pooled estimator	0.401	0.000	103.2	0.016
Isctr	0.711	0.000	30.6	0.489
Ykbnk	0.307	0.088	3.1	0.064
Tüpraş	0.509	0.003	10.5	0.234
Tcell	0.743	0.000	37.0	0.537
Garan	0.535	0.001	14.4	0.266
Kchol	0.742	0.000	44.2	0.538
Eregl	0.460	0.004	9.7	0.190
Dohol	0.404	0.013	6.8	0.140
Sahol	0.669	0.000	29.2	0.433
Vestel	0.308	0.060	3.88	0.069
Thyao	0.554	0.000	15.1	0.276
Şişe Cam	0.498	0.001	11.8	0.227
Ülker	0.419	0.009	7.7	0.153
Bsoke	0.616	0.000	22.0	0.362
Gsray	0.368	0.038	4.7	0.106

Panel B: Estimation Resilts of Equation 3:

	b_1	sig(b_1)	F	adj. R-sqrd
The pooled estimator	0.002	0.965	0.0	0.000
Isctr	-0.014	0.940	0.1	0.000
Ykbnk	0.000	0.999	0.0	0.000
Tüpraş	0.142	0.446	0.6	0.000
Tcell	-0.006	0.972	0.0	0.000
Garan	0.082	0.630	0.2	0.000
Kchol	-0.001	0.997	0.0	0.000
Eregl	-0.021	0.900	0.1	0.000
Dohol	-0.194	0.264	1.3	0.008
Sahol	0.126	0.458	0.6	0.000
Vestel	-0.141	0.406	0.7	0.000
Thyao	-0.126	0.457	0.6	0.000
Şişe Cam	0.085	0.618	0.3	0.000
Ülker	0.129	0.448	0.6	0.000
Bsoke	0.260	0.121	2.5	0.041
Gsray	-0.059	0.754	0.1	0.000

See explanations in Table 1 and 2.

6. Conclusion

All of our test results reported in the previous section lead to, more or less, the same conclusion: There is significant contemporaneous association between the net buys of largest net trading brokers in ISM and current returns of the ISE-100 index (the association is monotonically increasing in the length of interval). This association seems to have triggered market participants' attention to the data about the net trades of largest net buyers or sellers. However, it seems to provide little clue for the future: Net buys of largest net traders, or "the net money inflow" as most market commentaries inaccurately refer, has little value in predicting future returns to justify its frequent mention in market forecast commentaries. It is just a coincident variable, co-moving with (possibly, but not necessarily, causing) returns. It seems to have some additional information content, but not sufficient to be used as a reliable forecasting tool alone.

Versions of the test with intraday data, and daily data on individual stocks provide similar results. Two points are worth noting: First, we observed some low level of predictive ability with hourly marketwide data. Second, we found some evidence of large net trades on individual stocks being spread (i.e.; significantly positively autocorrelated) across days.

The use of this information set in market forecast commentaries is mostly redundant: ISE-100 returns itself can capture most of the variation in the "net inflow" variable, while the component of the information contained in net buys which is not priced-in on the same day has some predictive value for the next day's index return. Overall, our results are consistent with market efficiency in the sense that very little information contained in large net trades remains to be discounted in the future periods.

Our findings are more likely consistent with "big investors' trading being correlated with current information arrivals", rather than "asymmetric information", as contemporaneous relationship between net buys and returns is far more significant than the ability of net buys to predict future returns. Absence of a negative relationship between current net trades and future returns rules out price pressure hypothesis.

Because of the aggregated nature of our data in this study, we were not able to directly test hypotheses pertaining to whether the execution of large trades is spread over time, or whether trades sorted by size or the identity of the actual trader rather than brokerage house have the ability to predict future returns. With the availability of data sorted by the size of trades and identity of trader, future research is likely to shed more light on the relationship between trades and price changes in ISM.

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