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Strategic trading in the wrong direction by a large institutional insider

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ABSTRACT

Many theoretical papers suggest that large informed traders should make misleading or random trades to disguise their trading. Alternatively, informed traders may trade purely on their estimate of stock value. This paper examines the trading behavior of a large institutional insider that periodically trades in the wrong direction, i.e., makes occasional sell (buy) trades within packages of buy (sell) trades. Using a hand-collected data set, we find that three quarters of the trade packages include wrong-direction trades. Wrong trades appear to be used mostly to disguise right-direction trades. We find that the wrong-trade stocks are larger and have less noisy returns, hence, they lack natural disguise. Wrong trades are relatively small, used to accentuate return volatility, distributed evenly during a package of trades, and are not consistently profitable.

1. Introduction

The strategic trading models of Allen and Gale (1992), John and Narayanan (1997), Fishman and Hagerty (1995), Huddart et al. (2001), and Chakraborty and Yilmaz (2004) suggest that informed traders should sometimes make misleading or random trades, but there has been little empirical work documenting such trading behavior. This could be because traders are unlikely to freely disclose such trades. This paper considers a large institutional insider who must disclose individual trades, and occasionally trades in the wrong direction (hereafter "wrong trades"). To our knowledge, this is the first empirical study of wrong trades. We examine the firm characteristics, profitability, and return volatility associated with wrong trades to infer whether they are made to disguise right-direction trades, or to exploit profit opportunities.

Why would an investor who is accumulating a substantial number of shares occasionally sell some shares? The sell trade is in the wrong direction from his goal, and we call it a wrong trade. Conversely, a wrong trade buy occurs when the investor is liquidating a position during a package of mostly sell trades. Earlier studies of institutional investors' trades do not report that their proprietary databases contain wrong-direction trades[2]. One reason that they may not include wrong trades is that they examine relatively small trade packages[3]. We study large packages of trades made by Gabelli Asset Management Company (GAMCO). These

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[2] These include Holthausen, Leftwitch, and Mayers (1987, 1990), Chan and Lakonishok (1993, 1995), Keim and Madhavan (1995), Gemmill (1996) and Chiyachantana et al. (2004).
[3] Their trade packages are typically completed within one to four trading days and average about 30,000 shares worth $1.2million. GAMCO's average package covers 24 trading days and involves 600,000 shares worth $15.2million.

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long-duration packages of large trades could make wrong trades more effective, either because the large trades have more price impact, or because a longer execution period provides more opportunity to exploit profitable market conditions for wrong trades[4].

Data on GAMCO's wrong trades are available because of several unique circumstances. First, GAMCO manages a relatively large amount of assets ($27 billion in 2003) concentrated in relatively few companies, consequently, its shareholdings are often so large that they are subject to insider disclosure regulations[5]. Second, GAMCO is the only large institutional insider of which we are aware that does not file the simple insider disclosures designed for "passive" institutional insiders. Active insiders must file more frequent insider disclosures, with less delay, and disclose the sizes and prices of individual trades.

Why would GAMCO bear the cost of extra disclosure? GAMCO claims to benefit from the additional management monitoring flexibility that active insiders are allowed, and could obtain greater management influence and better access to firm information[6]. Bozcuk and Lasfer (2006) and Faure-Grimaud and Gromb (2004) show that large shareholders' monitoring efforts can increase firm value. GAMCO could reap return benefits quickly if the market quickly impounds into stock prices the expected value of GAMCO's monitoring.

Theory suggests that wrong trades can help reduce the costs associated with GAMCO's more frequent disclosures. First, Huddart et al. (2001) show how disclosure strips away some of the natural disguise created by noise traders' trades, so that an insider's information advantage dissipates quicker. Germain (2005) shows how informed traders may create noise to slow the dissipation of their advantage, and Furfine (2007) finds that trade direction reversals are associated with less informed trading. GAMCO could use wrong trades as decoys to create trade direction reversals and noise, both of which disguise their right trades from traders who watch the order flow for evidence of informed trading. We call this the disguise hypothesis.

Second, Jarrow (1992) and Fishman and Hagerty (1995) show how uninformed traders can free-ride on an informed traders' trades and buy (sell) after insiders disclose their buys (sells), further driving up (down) prices[7]. GAMCO can discipline uninformed free-riders by occasionally trading against them when they push the stock price too far away from GAMCO's current estimate of share value. We call this the value hypothesis[8].

Our descriptive model of wrong trades shows that the disguise and value hypotheses are not mutually exclusive. Indeed, we find evidence of both, but most of the evidence supports disguise. First, we find that GAMCO makes wrong trades in stocks whose returns are naturally less noisy. Second, wrong trades appear to create greater return volatility than right trades. Third, wrong trades are distributed evenly throughout trade packages as opposed to towards the end when prices for stocks being bought (sold) are relatively high (low). Fourth, wrong trades are unprofitable. Fifth, wrong trades are significantly smaller in size than right trades. Finally, consistent with Saar's (2001) model and Hu's (2009) empirical work, we analyze buy packages separate from sell packages and find differences in size between wrong trade buys and sells.

Focusing solely on GAMCO means that the results may not apply to other traders, hence, this study is just a first step toward explaining wrong trades. As noted below, some much smaller institutional insiders file the more detailed insider forms necessary for the analysis, but they held only a handful of insider positions. An advantage of studying only GAMCO's trade strategies is that they are likely to be uniform, because the same person has overseen the portfolio holdings throughout our sample period[9].

The paper is organized as follows. Section 2 presents the theoretical intuition behind the empirical tests. Section 3 describes the data and the sample. Section 4 reports the results and Section 5 is a conclusion.

2. The theoretical intuition

The intuition behind this paper's empirical tests is based on the theoretical models of Kyle (1985), Bertsimas and Lo (1998), and Huddart et al. (2001). Consider a simplified presentation of these trading models. The stock price at time t is P_t. An informed trader places orders equal to $O_{i,t}$, and uninformed liquidity traders place orders equal to $O_{u,t}$. The uninformed traders' orders are distributed with mean zero and variance s_u^2. The informed trader knows the true value of the stock (V), and submits orders according to:

$$O_{i,t} = \beta(V - P_{t-1}) + z_t, \tag{1}$$

[4] Bozcuk and Lasfer (2006) find that large block trades made by mutual funds have relatively large stock price impacts compared to earlier studies of smaller trades.

[5] John and Narayanan (1997), Fishman and Hagerty (1995) and Huddart et al. (2001) use forced trade disclosure to motivate their informed trading strategies.

[6] The following paragraph appears in each of GAMCO's insider filings. The persons referred to are GAMCO, its subsidiaries, and investment officers. The foregoing persons in the aggregate often own beneficially more than 5% of a class of a particular issuer. Although several of the foregoing persons are treated as institutional investors for purposes of reporting their beneficial ownership on the short-form Schedule 13G, the holdings of those who do not qualify as institutional investors may exceed the 1% threshold presented for filing on Schedule 13G or implementation of their investment philosophy may from time to time require action which could be viewed as not completely passive. In order to avoid any question as to whether their beneficial ownership is being reported on the proper form and in order to provide greater investment flexibility and administrative uniformity, these persons have decided to file their beneficial ownership reports on the more detailed Schedule 13D form rather than on the short-form Schedule 13G and thereby to provide more expansive disclosure than may be necessary.

[7] Allen and Gale (1992) describe similar behavior except without disclosure.

[8] A third potential reason for wrong trades is stock price manipulation, Merrick et al. (2005) and Khwaja and Mian (2005) show that large traders can impact market liquidity and manipulate prices, although Jiang et al. (2005) provide a counter-example. We do not consider price manipulation as an explanation for GAMCO's wrong trades because we find that they are too small to produce significant liquidity effects. Furthermore, because price manipulation is illegal and GAMCO must disclose its trades, it is highly unlikely that they would try to use large wrong trades to manipulate prices.

[9] This person is Mario Gabelli, GAMCO's chairman of the board, chief executive officer, chief investment officer, and primary portfolio manager according to the filings.

where $\beta>0$ is the informed trader's trading intensity, and the noise component of her trade, z_t, is distributed with mean of zero and variance s_z^2. A market maker changes the price each period based on the pooled order flow so that,

$$P_t - P_{t-1} = \lambda\left(O_{i,t} + O_{u,t}\right) = \lambda\left[\beta(V - P_{t-1}) + z_t + O_{u,t}\right], \tag{2}$$

where $\lambda>0$ is the market maker's price adjustment factor, representing antiselection or the inverse of market depth. V, z_t, and $O_{u,t}$ are assumed to be mutually independent.

Kyle's (1985) model assumes no disclosure. In this case, the uninformed orders provide sufficient noise to conceal the informed trader's orders from the market maker, hence, $z_t=0$. But when the informed trader must disclose her orders, Huddart et al. (2001) show that it is optimal for her to help disguise her trades by adding some noise ($z_t\neq 0$).

Eq. (1) can produce wrong trades based on value or disguise. Disguise produces a wrong trade sell within a buy package if the noise portion of a trade is large and negative ($z_t<<0$), completely overwhelming the positive value-based portion ($\beta(V-P_{t-1})>0$). A disguise-based wrong trade is the net result of two opposing effects; therefore, if wrong trades are mostly disguise-based, then they could be relatively small compared to right trades. Hence, we propose;

Hypothesis 1. The disguise hypothesis implies that wrong trades will be smaller than right trades on average.

A wrong trade could also be value-based. For example, suppose GAMCO initiates a buy package because it believes $(V-P_{t-1})>0$ but the stock price occasionally spikes above V. In those cases, $(V-P_{t-1})<0$ and GAMCO could place a sell order among its buys. A price spike could be due to uninformed momentum traders who try to buy when they observe GAMCO's series of buy trades (see Jarrow (1992) and Fishman and Hagerty (1995)). There is nothing “wrong” with these sell trades, indeed, they should be profitable (the argument is analogous for infrequent buys in a sell package).

We cannot differentiate value-based from disguise-based wrong trades ex ante, but both look “wrong” because they do not appear to help fulfill the goal of a trade package. Therefore, we use the term “wrong trade” for both. Each hypothesis is stated with respect to disguise-based wrong trades, with the implied alternative that value-based wrong trades do not produce the same effect. For example, there is no reason to believe that value-based wrong trades will differ in size from right trades, hence, Hypothesis 1 will be rejected if wrong trades are value-based.

Eq. (2) illustrates how the price change, i.e., stock return, could be comprised of two effects. Based solely on the value effect, we expect wrong trades to be profitable because GAMCO reverses the direction of its trades only when stock price moves far above (below) expected value during a buy (sell) package. Alternatively, based solely on disguise, we expect wrong trades to be unprofitable, because GAMCO will be trading against its own information. By unprofitable we mean that, during a buy package, GAMCO forfeits a larger average return to the buyer of its wrong trade sells than it earns on its right trade buys. The converse holds during a sell package. Therefore, we propose;

Hypothesis 2. The disguise hypothesis implies that wrong trades will be unprofitable.

Eq. (2) also illustrates how wrong trades could affect return volatility. Based solely on the value effect, we expect little effect on volatility. This follows from Kyle (1985), who shows that the noise traders' trades drive return volatility (along with some prior fixed level of business-related volatility). The positively correlated insider's trades have a smoothing effect because her information is gradually incorporated into prices at a constant rate. Conversely, wrong trades are used to create noise similar to noise trader's trades. Therefore, we propose;

Hypothesis 3. The disguise hypothesis implies that wrong trades will create more return volatility than right trades.

Our hypotheses are not precise tests of the simple models of Kyle (1985) and Huddart et al. (2001), although those models help to illustrate the general intuition of our hypotheses[10]. GAMCO's wrong trade strategy could be more complex. For example, wrong trades could create uncertainty in the minds of uninformed traders, increasing the volatility of their trades and enhancing disguise. This type of correlation between z_t and $O_{u,t}$ is excluded from their models but could enhance the effect of wrong trades on return volatility.

Our hypotheses will be tested for packages of buy and sell trades separately because GAMCO could behave differently for buys and sells. Saar (2001) suggests this could happen because GAMCO does not short stocks. When it sells stocks, it can only sell the ones it already owns, limiting its choice set. This implies that the effect of $(V-P_{t-1})$ in Eq. (1) could differ systematically between buys and sells, which in turn, could lead GAMCO to select different distributions of z_t for buys and sells. Hu (2009) suggests market conditions could lead to buy–sell differences so we will control for these in the multivariate results.

[10] We do not have the data required to test them precisely. Hypothesis 1 is relatively precise because it only requires us to have the size of GAMCO's trades. Hypotheses 2 and 3 are less precise because Eq. (2) requires net orders, that is, the net difference between GAMCO's orders and noise trader orders at a point in time. Nevertheless, the intuition is clear, when GAMCO makes a wrong trade purely for disguise, it is likely to create additional return noise but at some cost to GAMCO in the form of suboptimal returns.

The model of Bertsimas and Lo (1998) deals with the more practical aspects of trading. It models the common practice that a certain number of shares must be traded over a fixed time horizon (see Chan and Lakonishok (1993, 1995) and Keim and Madhavan (1995)). This fits GAMCO's position of having to trade a large number of shares over a limited time period.

Bertsimas and Lo show that stock price change will be a direct function of market conditions around the time of the insider's trade, as well as an indirect function (through her trades) of her private information about those conditions. They find that wrong trades are possible but unusual, because they delay progress toward accumulating or liquidating a given position[11].

The goal in the Bertsimas and Lo model is to minimize the trade cost of a series of trades, which is equivalent to earning high weighted average returns on the trades. At the margin, the optimal decision to make a trade on day t as opposed to days $t-1$ or $t+1$, depends upon market return conditions observed by the insider on days $t-1$ and t, and her expectations for conditions on $t+1$. If the decision processes for wrong trades and right trades are the same, then their returns will be the same. But if wrong trades are made primarily to create noise, then they could have smaller returns than right trades on average.

Based on this structure, we propose two empirical models. To test whether GAMCO earns smaller returns on wrong trades than on right trades, we use,

$$R_{i,t} = f\left(W_{i,t},\ X_{i,t-1},\ X_{i,t},\ X_{i,t+1}\right), \tag{3}$$

where for each trade i on trade day t, $R_{i,t}$ is GAMCO's trade day return, $f(\bullet)$ is some function, $W_{i,t}$ is an indicator variable for wrong trades, and $X_{i,t}$ is a set of variables representing market conditions on day t.

To test whether wrong trades create more return noise on the trade day we use,

$$\sigma_{i,t} = g\left(W_{i,t}, Y_{i,t}\right), \tag{4}$$

where $\sigma_{i,t}$ is the traded stock's return volatility on day t, $g(\bullet)$ is some function, and $Y_{i,t}$ is a set of market variables that could impact return volatility on day t. Here, $W_{i,t}$ captures any difference in return volatility effects between wrong trades and right trades, after controlling for $Y_{i,t}$.

3. The data source and the sample

3.1. Background on regulatory filings and GAMCO

We construct our sample using GAMCO's Schedule 13D filings from the Securities and Exchange Commission's (SEC's) Electronic Data Gathering, Analysis and Retrieval (EDGAR) database covering January 1994 to April 2003. Sections 13(d) and 13(g) of the Securities and Exchange Act of 1934 define institutions as insiders under certain conditions, and require them to disclose their shareholdings. Filings under section 13(g) are called 13Gs and filings under section 13(d) are called 13Ds.

Section 13(d) requires an institution to disclose its daily trades over the previous 60 days as well as its total holdings, whenever its holdings reach 5% or more of a firm's outstanding shares and for subsequent material holdings changes. The disclosure must occur no later than ten days after a change. The extra costs and inconvenience of 13D filings compared to 13G filings imply that 13D filers could be better informed than other institutions or investors[12]. The primary benefits to 13D filers are that 13Ds are a safe harbor for insiders who intend to actively influence or replace management, and perhaps provide better access to firm information.

Section 13(g) is more lenient than 13(d). Disclosure is not required until holdings reach a 10% threshold instead of five, disclosure is delayed a month, and individual trades are not disclosed. But the 13G filer cannot actively work to change management. Almost all large institutional investors file under 13(g). GAMCO is an exception because 99% of its filings are 13Ds. They filed 2647 13Ds during our sample period, far more than any other filer[13].

GAMCO is an investment advisory company controlled and directed by Mario Gabelli, through his ownership of about 97% of the voting shares of GAMCO's parent. GAMCO controlled about \$27 billion in stocks in 2003. Mr. Gabelli is well-known for his value investment style and his willingness to engage the management of the companies in which he invests[14].

[11] Unusually large or small right trades also impact this progress, but their size could reflect any number of influences, including the preferred transaction size of GAMCO's counterparty. Wrong trades, however, are not driven by influences like counterparty preferences.

[12] One of those costs is that of early disclosure compared to 13Gs. Fidrmuc, Goergen, and Renneboog (2006) show that there is greater market reaction when insiders' trades are disclosed faster. Because GAMCO makes more than one filing during each package on average, the market reaction implies that they likely trade at less advantageous prices after the first filing.

[13] Some other large institutions occasionally file 13D's, but they mostly file 13G's. Some smaller institutions file 13D's exclusively, but they are not large enough to own many five-percent position. For example, FMR Corp., Fidelity funds' management company, controlled \$484billion in stocks in 2003. FMR owns more "insider" positions than any other institution. FMR filed 13,371 13Gs and only 517 13Ds during the sample period. Merrill Lynch & Company, which controlled \$21billion, filed 1453 13Gs and only 10 13Ds. Steel Partners, which controlled \$249million and specializes in purchasing insider-sized holdings in order to influence management, filed 334 13Ds and no 13Gs.

[14] GAMCO's investment strategy is articulated on its website (www.gabelli.com). "In the tradition of Graham and Dodd, we utilize fundamental research to identify undervalued companies with dominant industry positions… we add our assessment of the private market value of the business. In other words, what would this company be worth to an informed industrialist attempting to create or purchase a business with similar characteristics? …We continually visit hundreds of company managements and integrate their input with our knowledge base. Our goal is to understand management's motivations and expectations. Given our long term approach, we want to know who our partners are and if they are working to enhance shareholder value. This process, coupled with our financial analysis, helps us select the most attractive investment candidates for our clients."

We assume that Mr. Gabelli sets the investment and trading strategies, including when to accumulate large positions, which types of stocks to wrong-trade, and when to confront management. The boilerplate language found in the 13D filings confirms that GAMCO's trading decisions are centralized in Mr. Gabelli[15]. Mr. Gabelli started his business as a brokerage company, funded from capital he accumulated from trading stock. Given that he approves all new stock holdings, we assume that any systematic trading strategy like wrong-trading is approved by him. His style is to accumulate large positions in relative few companies so that he can know and influence their management[16].

Large holdings are parceled out among GAMCO's many funds. It is possible that wrong-trades are not part of a conscious strategy, but rather reflect one or more of GAMCO's fund managers' preferences to sell (buy) while most of the other managers buy (sell). But Mr. Gabelli's oversight of insider holdings implies that such behavior would be infrequent because it allows one manager to trading against the others. Furthermore, internal differences cannot account for all wrong trades because GAMCO's initial 13D filings often contain wrong trades. Even if some wrong trades are due to managers' conflicting objectives, it is still reasonable to assume that GAMCO uses these wrong trades to its strategic advantage when it executes them.

Information in each 13D filing includes the traded company's name, state, SIC code, and CUSIP number, the date on which GAMCO records its total shareholdings (the holding date), the filing date, total shareholdings, and GAMCO's shareholdings as a percentage of shares outstanding. More important, each filing reports the number of shares and price of the individual trades on each day over the period of up to 60 days preceding the holding date. Unfortunately, the time of day is not reported; consequently, we cannot analyze intraday trading[17].

3.2. The data sample

The initial data set of 2647 filings is reduced to 2238; including 1472 that contain mostly buy trades and 766 that contain mostly sell trades. Filings are excluded from the sample when they cover stocks, convertible securities, or foreign stocks which do not appear in the Center for Research in Security Prices (CRSP) database. Some trade entries in the filings represent canceled trades, stock splits, or changes in dispositive power or beneficial ownership as opposed to market trades. These 3416 entries are eliminated. The final sample consists of 71,283 individual trades.

Trades are grouped into "packages". A buy (sell) package always results in a significant increase (decrease) in GAMCO's total shareholdings. A buy (sell) package is defined as a sequence of mostly buy (sell) trades with less than eight trading days between chronologically adjacent trades. The package groupings are not sensitive to the selection of the eight-day break because most are separated by much longer periods (the average break between packages is 151 days). The long breaks between trade packages is apparently due to GAMCO's long-term value orientation and commitment to actively influence management, which of course, takes time.

A "package" can include two or more filings if there is less than eight trading days between the trades disclosed in consecutive filings. Each filing does not necessarily represent a package because once a series of trades significantly changes GAMCO's holdings, they must file even if they continue to trade. Consequently, the sample summary statistics in Table 1 cover 2238 filings in Panels A and B, but only 1428 packages in Panels C and D. The number of companies with at least one package equals 303, including 191 traded on the NYSE, 34 on the AMEX, and 78 on the NASDAQ. This means that there are about five trade packages per firm on average during the sample period.

About two thirds of the packages are buy packages (911) and one third (517) are sell packages reflecting GAMCO's growth in equity holdings from $7.7 billion in 1994 to $27 billion in 2003. Panel C shows that the average package covers 24 trading days, with a range of one to 207 days. Panel D shows that the average number of trades per package is 50, with a range of one to 543. This implies that GAMCO makes about two trades per day on average. Sell packages are executed faster than buy packages on average, covering fewer trading days (20 vs. 26) and fewer trades (38 vs. 57).

Chan and Lakonishok (1993, 1995) and Keim and Madhavan (1995) also find that sells are executed faster than buys. But as shown below, this is because individual sell trades are about twice as large as buy trades; the average total number of shares

[15] For example, the following is taken from GAMCO's December 30, 2002 initial 13D filing for Baycorp.
This statement is being filed by Mario J. Gabelli ("Mario Gabelli") and various entities which he directly or indirectly controls or for which he acts as chief investment officer. … the Reporting Persons analyze the operations, capital structure and markets of companies in which they invest, including the Issuer, on a continuous basis through analysis of documentation and discussions with knowledgeable industry and market observers and with representatives of such companies (often at the invitation of management). The Reporting Persons do not believe they possess material inside information concerning the Issuer. As a result of these analytical activities one or more of the Reporting Persons may issue analysts reports, participate in interviews or hold discussions with third parties or with management in which the Reporting Person may suggest or take a position with respect to potential changes in the operations, management or capital structure of such companies as a means of enhancing shareholder values … most portfolio decisions are made by or under the supervision of Mario Gabelli … With respect to voting of the Securities, the Reporting Persons have adopted general voting policies relating to voting on specified issues affecting corporate governance and shareholder values.

[16] See en.wikipedia.org/wiki/Mario_Gabelli for more details on his trading strategies.

[17] We treat the separate daily entries of trades in the 13Ds as separate trades, but we cannot be sure that each is a single trade for two reasons. First, as Chakravarty (2001) and Alexander and Peterson (2007) note, NYSE specialists can report a combination of trades on at least one side of a transaction as one trade. For example, a 10,000 buy share order could be filled with two 5000 share sells and reported as a single 10,000 share trade. Second, we found that some large orders are filled with more than one trade. For example, GAMCO reports a 100,000 share trade at $5 for Baldwin Technology on August 17, 1994 but all trades listed on the TAQ data set for that day are smaller than 100,000 shares. However, the first two trades that day are 25,000 shares at 9:50AM and 75,000 shares at 9:54AM, both at $5. Because 13D's do not require traders to report the time of day of trades, we cannot be sure that these were GAMCO's trades. Although regulations clearly state that each trade should be disclosed separately, apparently some large trades reflect combined trades on a particular day. Nevertheless, like Chakravarty (2001) and Alexander and Peterson (2007), we find that our results are not very sensitive to these large trades. Our results for the buy (sell) packages hold even when all trades larger than 1000 (2000) shares are eliminated.

Table 1
Summary statistics for GAMCO's insider filings and trade packages.

Sample	Number of Filings or packages	Mean	Median	Standard deviation	Min	Max	Skewness
Panel A: Number of trading days in a filing							
All	2238	15	13	10.86	1	96	0.83
Buys	1472	16	14	10.91	1	69	0.67
Sells	766	14	12	10.63	1	96	1.17
Panel B: Number of trades in a filing							
All	2238	32	23	30.13	1	263	2.23
Buys	1472	35	25	31.89	1	263	2.03
Sells	766	26	20	25.49	1	250	2.78
Panel C: Number of trading days in a package							
All	1428	24	19	22.83	1	207	2.81
Buys	911	26	21	23.92	1	207	2.59
Sells	517	20	16	20.26	1	197	3.41
Panel D: Number of trades in a package							
All	1428	50	29	61.59	1	546	3.28
Buys	911	57	34	67.18	1	546	3.01
Sells	517	38	24	48.10	1	468	3.90

Summary statistics are computed for GAMCO's insider trades reported in Schedule 13D filings on the SEC's Electronic Data Gathering, Analysis and Retrieval (EDGAR) database covering January 1994 through April 2003. Section 13(d) of the Securities and Exchange Act of 1934 requires an institution to disclose its daily trades over the previous 60 days as well as its holdings, whenever its holdings reach 5% or more of a firm's outstanding shares. Subsequent large holdings changes must also be disclosed. Daily trades reported in filings are grouped into buy and sell packages. A buy (sell) package is defined as a sequence of mostly buy (sell) trades with less than eight trading days between chronologically adjacent trades. A package ends if GAMCO fails to trade in the company's stock for at least seven trading days.

traded per package is about the same for buys and sells. We present empirical results after grouping trades into buy and sell packages to investigate whether GAMCO's trade strategy differs between buys and sells. Earlier studies by Chan and Lakonishok (1993, 1995), Keim and Madhavan (1995), and Gemmill (1996) found significant differences.

4. The empirical results

Whether GAMCO uses wrong trades to disguise its trading intentions or as a way to exploit its informed stock valuation is explored in the following sections. Section 4.1 compares the characteristics of the stocks with wrong trades to those without wrong trades. Section 4.2 compares GAMCO's average trade prices for wrong trades and right trades. Section 4.3 does the same for returns and Section 4.4 does the same for trade size. These univariate analyses are used to guide the multivariate regressions in Section 4.5. The regressions examine whether wrong trades earn better returns than right trades, and whether they create more return noise, after controlling for market conditions.

4.1. Characteristics of the stocks that GAMCO trades

Most stock characteristics are gleaned from the following four-factor return model, estimated for the stock involved in each trade package, over the one-year (255 trading day) period before GAMCO starts to trade the stock.

$$\left(R_{i,t} - R_{f,t}\right) = \alpha + \beta_m\left(R_{m,t} - R_{f,t}\right) + \beta_s \mathrm{SML}_t + \beta_h \mathrm{HML}_t + \beta_u \mathrm{UMD}_t + \varepsilon_t, \tag{5}$$

where for each trading day t, $R_{i,t}$ is stock i's return, $R_{f,t}$ is the risk-free return, $R_{m,t}$ is the CRSP value-weighted stock index return, and SML_t, HML_t, and UMD_t are the size, book-to-market, and momentum factors, respectively; and β_m, β_s, β_h, and β_u are the associated factor loadings. α is the alpha, and ε_t is a residual error term. The four factor model, developed by Fama and French (1992, 1993) and Carhart (1997), is widely used to capture the systematic risk characteristics of a firm's stock. The factor data are taken from Kenneth French's website. The market value of the shares outstanding for the firms involved in the trades is also calculated as a measure of firm size.

Table 2 lists the average alphas, factor loadings, residual return standard deviations and equity market values for GAMCO's insider stocks. Averages are calculated across companies grouped by trade type (buy, sell, wrong-trade, no-wrong-trade). Note that about three-quarters of the packages, both buys and sells, involve wrong trades.

Panel A shows that for all 1428 packages, the average market (beta), size, book-to-market, and momentum factor loadings are 0.88, 0.71, 0.52, and −0.13, respectively[18]. Carhart's (1997) averages for equity mutual funds are 0.90, 0.30, −0.05, and 0.08, respectively. Comparison shows that GAMCO's average size loading is more than twice that of the average mutual fund. GAMCO's

[18] We calculate the characteristics of the stocks by package and average these. If we measure using only each stock's first package, we find very similar results. However, because the average time between packages for a stock can be quite long, and a stock's characteristics can change over time, we average by package to capture any changes in characteristics.

Table 2
Average characteristics of GAMCO's insider stocks grouped by trade package type.

Sample	α-Alpha	β_m market	β_s size	β_h Bk/Mkt	β_u moment.	St. dev. residuals	Value of shares outstanding (1,000,000)
Panel A. All packages							
All 1428 packages	0.02	0.88	0.71	0.52	−0.13	2.70	502.26 average
	(0.17)	(0.51)	(0.58)	(0.65)	(0.51)	(1.53)	(268.43) median
							(728.80) st.dev.
1085 Packages with wrong trades	0.02	0.91*	0.70	0.53	−0.14	2.54*	590.97*
	(0.17)	(0.48)	(0.56)	(0.65)	(0.51)	(1.34)	(799.48)
							(364.82)
343 Packages without wrong trades	0.03	0.78*	0.74	0.48	−0.12	3.19*	221.65*
	(0.17)	(0.58)	(0.64)	(0.66)	(0.50)	(1.93)	(118.72)
							(293.98)
Panel B. Buy packages							
All 911 buy packages	0.01	0.84	0.69	0.52	−0.13	2.74	422.61
	(0.16)	(0.48)	(0.56)	(0.63)	(0.46)	(1.49)	(249.22)
							498.18
700 Buy packages with wrong trades	0.003	0.90*	0.69	0.53	−0.14	2.54*	502.14*
	(0.16)	(0.47)	(0.54)	(0.63)	(0.47)	(1.28)	(339.09)
							526.61
211 Buy packages without wrong trades	0.02	0.66*	0.67	0.49	−0.10	3.41*	158.76*
	(0.18)	(0.49)	(0.60)	(0.63)	(0.45)	(1.89)	(93.36)
							247.74
Panel C. Sell packages							
All 517 sell packages	0.05	0.94	0.75	0.52	−0.14	2.63	642.61
	(0.18)	(0.54)	(0.61)	(0.68)	(0.58)	(1.59)	(321.73)
							(1000.14)
385 Sell packages with wrong trades	0.05	0.93	0.71***	0.54	−0.13	2.55	752.47*
	(0.19)	(0.50)	(0.58)	(0.67)	(0.58)	(1.44)	(419.06)
							(1,122.03)
132 Sell packages without wrong trades	0.06	0.96	0.84***	0.45	−0.15	2.85	322.17*
	(0.16)	(0.65)	(0.69)	(0.71)	(0.58)	(1.94)	(171.29)
							(332.70)

* (**, ***) Average differences between wrong-trade package companies and no-wrong-trade companies statistically significant at the 1 (5, 10)% level.
Standard deviations (and medians for shares value) in parentheses.
Most characteristics are gleaned from the following four-factor return model, estimated for the stock involved in each trade package, over the one-year (255 trading day) period before GAMCO starts the trade package.

$$\left(R_{i,t} - R_{f,t}\right) = \alpha + \beta_m\left(R_{m,t} - R_{ft}\right) + \beta_s \mathrm{SML}_t + \beta_h \mathrm{HML}_t + \beta_u \mathrm{UMD}_t + \varepsilon_t,$$

where for each trading day t, $R_{i,t}$ is stock i's return, $R_{f,t}$ is the risk-free return, $R_{m,t}$ is the CRSP value-weighted stock index return, and SML_t, HML_t, and UMD_t are the size, book-to-market, and momentum factors, respectively, and β_m, β_s, β_h, and β_u are the associated factor loadings. α is the alpha and ε_t is a residual error term. The factor data are taken from Kenneth French's website. The value of a firm's shares outstanding is obtained from the CRSP database. Alpha, loadings, and residual return standard deviation and firm stock values are averaged across package types, including buy or sell, and whether the trade package includes wrong trades. Characteristic differences between groups of packages with wrong trades and those without wrong trades are tested with t-tests (F-tests for residual standard deviations).

value style shows up in its relatively large average book-to-market factor loading and negative momentum factor loading. The average equity value of shares outstanding is about $500 million. Overall, these results show that GAMCO's insider stocks are small-cap value stocks.

Panel A also shows that compared to no-wrong-trade stocks, wrong-trade stocks have significantly larger betas and equity values, and smaller residual return standard deviations. Panels B and C show that the beta difference is driven by buy-package stocks. Furthermore, wrong-trade sell package stocks have smaller size factor loadings than no-wrong-trade sell package stocks. These differences suggest that GAMCO selects stocks with certain characteristics to wrong-trade, and the characteristics could vary between buy and sell packages.

The relatively small average residual return standard deviation and large average equity market value of wrong-trade stocks support the disguise hypothesis. Large size and small standard deviation are associated with less noisy stock returns. Any noise generated by GAMCO's wrong trades could help to disguise their right trades. Furthermore, GAMCO could produce more noise if it wrong-trades on a day when the stock price is already falling or rising considerably. This possibility is considered next.

4.2. Average trade prices for GAMCO's wrong-trade and no-wrong-trade packages

Fig. 1 shows the average trade prices of GAMCO's trades grouped by trade type (buy or sell within a wrong-trade or no-wrong-trade package) compared to high, low, and close prices on the trade day, the day before and the day after. eGAMCO denotes an

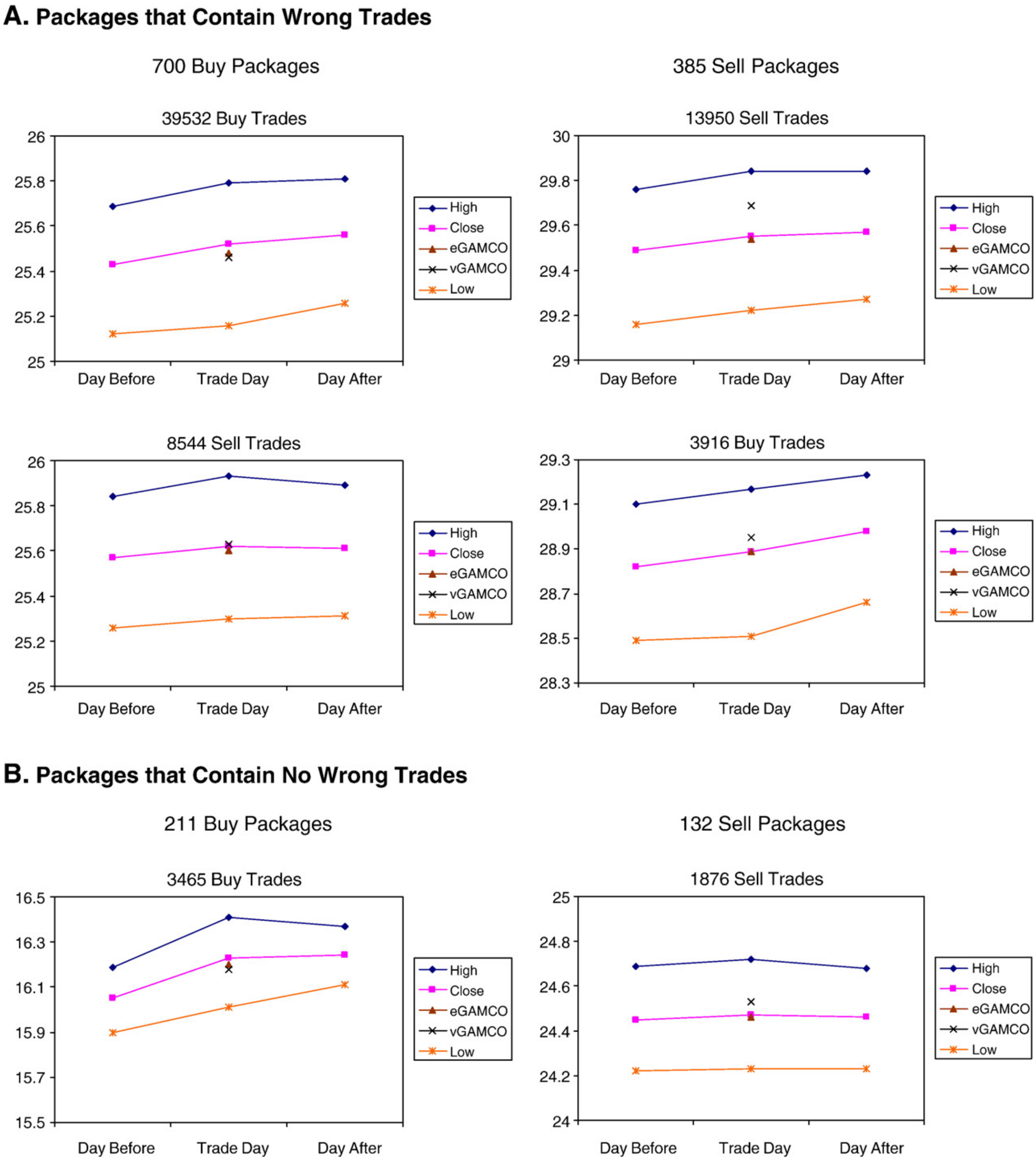

Fig. 1. Comparing average prices for GAMCO's trades, with high, low, and close market prices for the stocks that GAMCO trades. GAMCO's trade packages are grouped by whether the package contains a wrong trade or not, and further subset into buy packages and sell packages. For each subgroup of trade packages, a graph plots two points that mark GAMCO's equally-weighted average trade price (denoted eGAMCO) and its trade-size weighted average trade price (vGAMCO) for the subgroup. One can compare those trade prices to each other and to the average high, low, and close prices for the same group of stocks on the day GAMCO trades as well as the day before and the day after. For example, GAMCO's trade price is better than the close price, and vGAMCO is usually better than eGAMCO, showing that GAMCO gets better prices (i.e., lower buy prices and higher sell prices) on its larger trades.

equal-weighted average price and vGAMCO denotes a trade-size weighted average price. Trade-size weight is the market value of a trade divided by the total value of all trades in the group. Admati and Ross (1985) show that when a trader is better informed, he should make larger trades, hence, large trades could perform better than small ones.

First, compare GAMCO's average equal-weighted and trade-size-weighted prices. In each group, the trade-size-weighted price is better (except for the buy trades in the 385 sell packages). That is, GAMCO's larger buy (sell) trades come at lower (higher) prices on average. The differences between equal- and trade-size-weighted prices are statistically significant for the sell package trades (see Appendix A for the numbers and statistical test results).

Note that GAMCO's average prices are almost exactly midway between the average highs and lows for each group, and slightly better than the average closing prices. Closing prices are rising on the days around the trades except for two cases where average close price falls by one cent. Panel A shows the prices for trades in packages where GAMCO is both buying and selling, i.e. wrong-trade packages. Among the 700 buy packages, GAMCO's size-weighted sell price ($25.63) is higher than its size-weighted buy price ($25.46). Similarly, among the 385 sell packages, GAMCO sells at a higher average price ($29.54) than it buys ($28.89). Therefore, ignoring transactions costs, GAMCOs wrong trades appear to be profitable.

Lastly, note that the average trade prices for the 211 buy packages without wrong trades ($16.18) are much lower than those of the other groups. This means that GAMCO tends to avoid wrong trades when it is trading low-priced stocks. This could be because these stocks are naturally volatile (see Table 2), hence, GAMCO does not need to use wrong trades to disguise its trades in those stocks.

Fig. 1 results mostly support the value hypothesis. GAMCO makes wrong trades at favorable prices. One explanation for what appears to be a profitable strategy is that GAMCO makes wrong trades towards the end of its buy (sell) packages, when its own trades have pushed prices up (down). This possibility is considered in Fig. 2. The figure shows the timing of wrong trades across the time-ordered quintiles of package trade days[19]. Wrong trades are a bit more common early in the trade packages and are clearly not made mostly at the end of the packages.

An alternative explanation is that wrong trades look profitable based upon average trade prices, but not when returns are considered. Average price differences do not translate directly into returns because price changes are not necessarily distributed proportionately across stocks of different prices; therefore, returns are examined next.

4.3. Average returns for GAMCO's wrong-trade and no-wrong-trade packages

Fig. 3 illustrates GAMCO's average trade day returns following Fig. 1's format. GAMCO's trade day return is computed as the closing price, minus GAMCO's transaction price, divided by GAMCO's transaction price. GAMCO earns this return on its buys and forfeits this return on its sells. A large positive return implies good performance for a buy, but poor performance for a sell. Profitability of wrong trades can be judged by whether GAMCO earns more on its buys than it forfeits on its sells, on average.

Using this criterion, wrong-trade sells are profitable but wrong-trade buys are not. In Panel A for 700 buy packages, GAMCO earns 0.20% on buys and forfeits 0.12% on sells. For 385 sell packages, GAMCO earns 0.15% on buys and forfeits 0.18% on sells. These differences, however, are not statistically significant (see Appendix B). For the 700 buy packages, GAMCO appears to be informed for its buy trades because the difference between trade-size-weighted and the equal-weighted returns (0.20 vs. 0.14) is statistically significant. Keim and Madhavan (1995) also find that institutional investors perform better on buy trades than sell trades.

Bertsimas and Lo (1998) suggest that optimal trading decisions depend on market conditions around the trade day. Market conditions could differ systematically between right and wrong trades, partly explaining return differences. Therefore, we examine the average close-to-close returns for the traded stocks as well as the value-weighted CRSP Index return.

Market conditions appear to be important. Compare the traded stocks' average close-to-close returns to the average CRSP returns on the same days. The close-to-close returns are almost always much larger (adding the affects of size, book-to-market, and momentum factors makes little difference). The minimum average trade-day close-to-close return on stocks GAMCO is buying is 0.76% compared to the maximum CRSP return on the same day of 0.20. Clearly, firm-specific returns are large on the days that GAMCO trades.

Given that firm-specific returns are large, one way to judge wrong trade performance is to measure the portion of close-to-close returns that GAMCO earns or forfeits. For buy packages, buy trades earn less than one fourth of the close-to-close returns (0.20 of 0.91), and wrong trade sells forfeit almost half (0.12 of 0.21). For sell packages, sell trades forfeit more than half of the close-to-close returns (0.18 of 0.26), and wrong trade buys earn only about one sixth (0.15 vs. 0.76). Judged from this perspective, all of the wrong trades perform poorly.

The daily patterns in average close-to-close and CRSP returns differ between all buys and all sells, whether or not they are right-direction or wrong direction trades. GAMCO buys while both the close-to-close and CRSP average returns increase from the day before to the trade day, and both drop significantly on the day after the trade. GAMCO sells while the close-to-close returns fall on each day around the trade, and average CRSP returns rise on each day.

Overall, wrong-trade performance appears to be poor after one considers the trade-day close-to-close-returns of the traded stocks. GAMCO's decision to buy or sell appears to depend on market conditions on the days around the trades. The pattern of close-to-close returns is the same as (opposite from) the CRSP returns when GAMCO buys (sells). The close-to-close returns are also larger on days when GAMCO is buying than when it is selling. Therefore, multivariate analysis in Section 4.5 reconsiders wrong-trade return performance after controlling for market conditions.

[19] If a package covers less than five trading days, wrong trades are assigned to the closest quintile. For example, if a three-day package has a wrong trade on the second day, it goes into the third quintile. If it has a wrong trade on the third day, it is randomly assigned to either the fourth or fifth quintile.

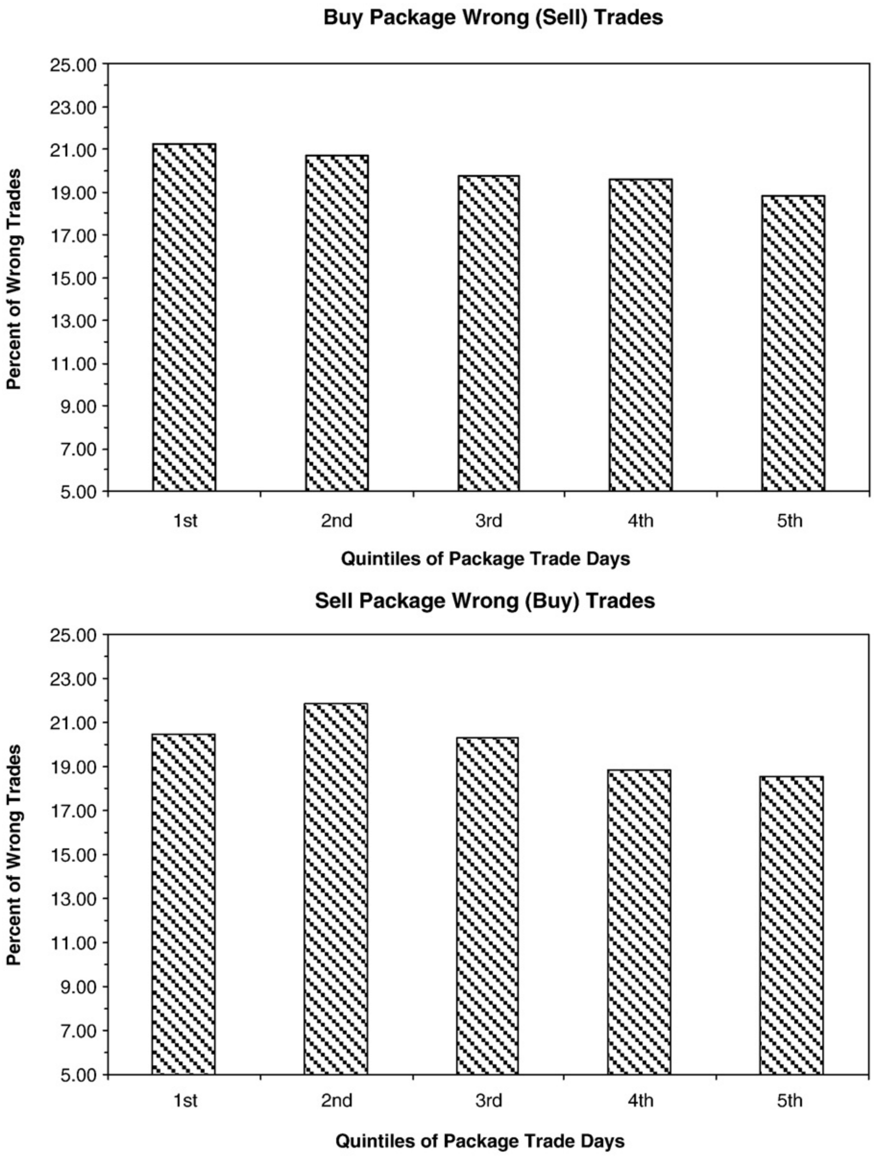

Fig. 2. The timing of wrong-direction trades during buy and sell packages. GAMCO makes groups of mostly buy (sell) trades adjacent in time, which we group into buy (sell) packages. A trade package ends when GAMCO makes no trade in the stock for more than seven trading days. Wrong-direction buy (sell) trades are occasional buy (sell) trades interspersed within a package of mostly sell (buys) trades. The trading days covered by each package are divided into quintiles, and each wrong trade in the package is placed in the quintile according to the package trade day on which it was executed.

4.4. Average trade size for GAMCO's wrong-trade and no-wrong-trade packages

Table 3 reports GAMCO's average trade size and its standard deviation along with the average number of shares outstanding for the traded firms. Hypothesis 1 proposes a simple test of the disguise hypothesis. Wrong-direction trades should be smaller than right-direction trades. Results in Table 3 support this hypothesis. For buy packages that include wrong trades, the average wrong trade size is 4286 shares compared to the average right trade size of 8737 shares. For sell packages that include wrong trades, the average wrong trade size is 6807 shares compared to the average right trade size of 20,458 shares. Means tests of the size differences between wrong and right trades show that the differences are statistically significant beyond the 1% level. The variation in trade size is also smaller for wrong trades than right trades.

These conclusions do not change if wrong trades are compared to right trades in packages that contain no wrong trades. And small wrong trade size is not due to wrong trade firms having fewer shares outstanding than right trade firms. Furthermore, trade-day volume differences cannot explain why wrong trades are less than half the size of right trades on average (see Appendix C). The trade size differences also hold up if trade size is measured in dollars.

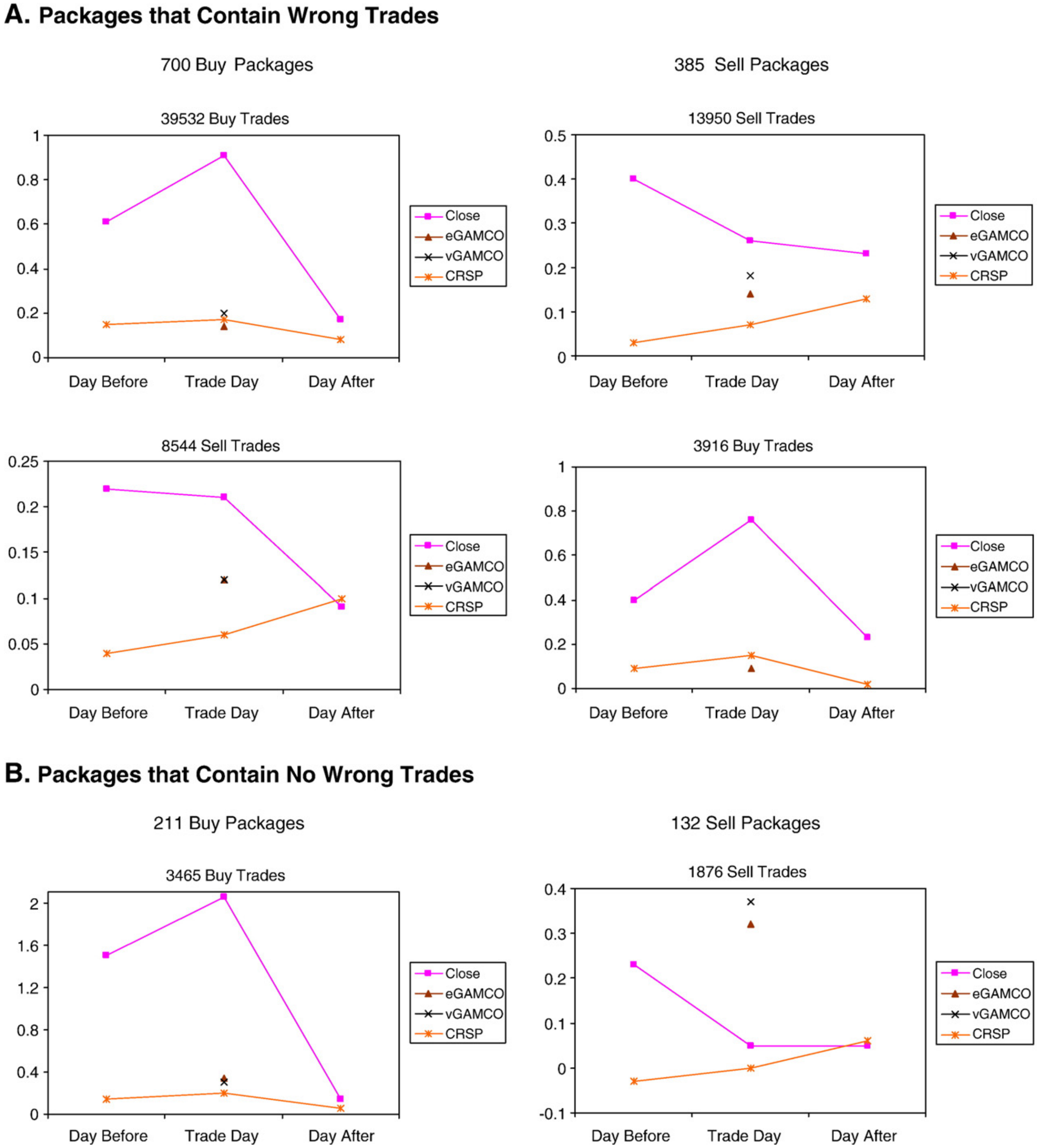

Fig. 3. Comparing average daily percent returns for GAMCO's trades, with close-to-close market returns for the stocks that GAMCO trades and the CRSP index returns. GAMCO's trade packages are grouped by whether the package contains a wrong trade or not, and further subset into buy packages and sell packages. For each subgroup of trade packages, a graph plots two points that mark GAMCO's equally-weighted average return (denoted eGAMCO) and its trade-size weighted average return (vGAMCO) for the subgroup. One can compare those returns to each other and to the average close-to-close return for the same group of stocks and the CRSP Index return on the day GAMCO trades as well as the day before and the day after. For example, the average close-to-close returns for the stocks bought is always much larger than GAMCO's return or the CRSP Index return, showing that GAMCO trades on days when the particular stocks it buys have large firm-specific returns.

Wrong trade sells are 50% smaller than wrong trade buys on average. This is puzzling because, like earlier studies such as Chan and Lakonishok (1993, 1995) and Keim and Madhavan (1995), we find that right trade sells are about twice as large as right trade buys. This puzzle can be explained by the disguise component of a trade (see Eq. (1)). A wrong trade is a combination of a value component and an offsetting disguise (noise) component, and the noise component distribution will be scaled to the value

Table 3
Comparison of the average size of GAMCO's trades between right trades and wrongs trades.

Variable	Buy packages			Sell packages		
	39,532 buy trades for 700 buy packages with wrong trades	8544 sell trades for 700 buy packages with wrong trades	3465 buy trades for 211 buy packages without wrong trades	13,950 sell trades for385 sell packages with wrong trades	3916 buy trades for 385 sell packages with wrong trades	1876 sell trades for 132 sell packages without wrong trades
GAMCO's trade size (shares)	8737.08	4286.27 [a]	12,678.67	20,458.78	6807.08 [a]	10,913.13
Standard deviation of GAMCO's trade size	11,602.14	4570.10	14,013.32	34,237.70	8205.28	12,717.85
Shares outstanding for traded firms (1000)	22,893.38	22,923.01	10,774.88	24,162.70	24,001.93	14,448.70

Figures are all averages measured in shares. GAMCO's trades are grouped by package type (buy or sell) and trade type (buy or sell and wrong-trade or no-wrong-trade). GAMCO's average trade size is the number of shares in an average transaction.
[a] Indicates that average wrong trade size is smaller than average right trade size at least at the 1% level.

component distribution. Right trade buys are smaller than right trade sells, hence, wrong trade sells are scaled to match the size of right trade buys. That is, wrong trades take on the relative sizes of the right trades. This is evidence that GAMCO could select the average size of wrong trades strategically.

Fig. 4 shows how the volume for the stocks that GAMCO trades is relatively large on the trade day and drops sharply on the day after. This suggests that GAMCO is interested in disguising its trades because, on average, it chooses to trade on high-volume days. Volume on the trade day remains high compared to the adjacent day's volume even if we remove GAMCO's trades from each stock's market volume. We call the volume after subtracting the volume accounted for by GAMCO's trades “clean volume”.

GAMCO's volume drops substantially on the day after. This could reflect a tendency by GAMCO to occasionally stop trading for a day or so in order to break up its trades. To consider this possibility, we calculated the number of days between each trade within a package, and then computed averages for right trades and wrong trades, for buy packages and sell packages. For buy packages, the average for right (wrong) trades is 0.68 (0.76) days. For sell packages, the average for right (wrong) trades is 0.84 (0.89) days. A t-test of the differences between right and wrong trades is significant beyond the 1% level for both buy and sell packages. This shows that GAMCO waits a bit longer after making a wrong trade, perhaps as a way to enhance the disguise effects of its wrong trades.

NYSE volume is larger on average during buy package trading than during sell package trading. It also increases slightly across trade days except for the day after buys in the 700 buy packages, and sells in the 385 sell packages (see Appendix C). The volume of the traded stocks is larger on average when GAMCO is buying, even when the buys are part of sell packages.

These volume regularities could reflect GAMCO's trading strategy or simply the changes in the amount of assets GAMCO manages over time. GAMCO's investors could be depositing (withdrawing) funds when market trade volume rises (falls). Fig. 5 illustrates the possible effects of investor deposits and withdrawals on the types of trades GAMCO makes over time. GAMCO's assets increased by about \$1 billion per year except for larger increases in 1998 (\$3 billion) and 1999 (\$5.5 billion), and a decrease in 2002 (−\$3 billion). Consistent with this pattern in asset growth, GAMCO substantially increased (decreased) the number of buy (sell) trades in 1998 and 1999, and decreased (increased) the number of buys (sells) in 2002. But wrong trades do not follow assets in a consistent way. For example, the number of wrong trades decreases for both buy and sell packages in 1998 and 1999, even though the number of right trades increases. Conversely, in 2001, the number of buy-package wrong trades increases while the number of trades falls for the other groups.

The volume regularities associated with GAMCO's trading are not accounted for by asset inflows and outflows, but could instead relate to GAMCO's trade strategy. Therefore, we will account for these regularities in the multivariate analysis.

4.5. Multivariate analysis of wrong trade returns and volatility

In this section, we present a multivariate analysis of GAMCO's trade-day returns and return volatility. In particular, we wish to test Hypotheses 2 and 3, respectively, that wrong trades are unprofitable but produce larger return volatility, after controlling for market conditions.

For GAMCO's trade-day returns, we use a regression model based on model (3).

$$R_{i,t} = \alpha + \delta W_{i,t} + \beta_0 X_{i,t-1} + \beta_1 X_{i,t} + \beta_2 X_{i,t+1} + \varepsilon_{i,t}, \tag{6}$$

where for each trade i on trade day t, $R_{i,t}$ is GAMCO's return, $W_{i,t}$ is a dummy variable equal to one if trade i is a wrong trade, and zero otherwise, $X_{i,t}$ is a matrix of explanatory variables including logarithm of GAMCO trade size[20], close-to-close return, CRSP

[20] Trade size is included in the regression models (6) and (7) because Eq. (2) suggests that return and return volatility could be affected by net trade size. We do not have data on net trade size but instead use GAMCO's trade size.

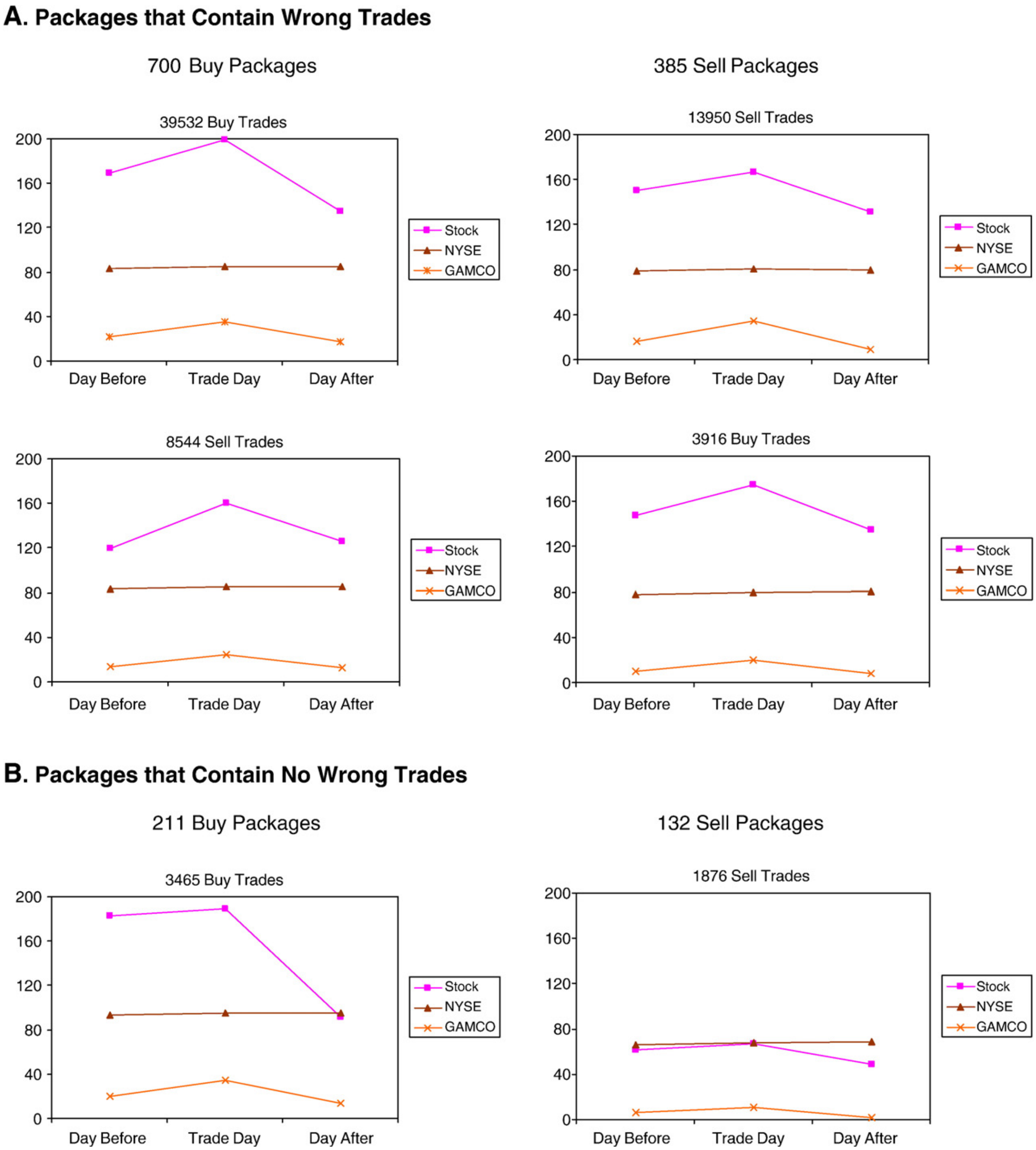

Fig. 4. Comparing average daily share volume of the stocks GAMCO trades (1000s), with volume of all stocks traded on the NYSE (10MM), and volume of GAMCO's trades (1000s). GAMCO's trade packages are grouped by whether the package contains a wrong trade or not, and further subset into buy packages and sell packages. One can compare the average total volume of the stocks that GAMCO trades, to the average volume accounted for by GAMCO's trades, and the market volume of all NYSE stocks on the day that GAMCO trades, as well as on the day before and on the day after. For example, the average volume for the stocks that GAMCO trades is larger on the day that GAMCO trades than the day before or the day after, and this holds even if GAMCO's trades are removed from the stocks' total volume. This shows that GAMCO tends to trade on days when a stock experiences high volume.

value-weighted index return, size factor, book-to-market factor, momentum factor, the logarithm of clean volume for the traded firm, and the logarithm of NYSE volume. The natural logarithm transformation is used to normalize variables whose distributions are skewed. The matrices $X_{i,t-1}$ and $X_{i,t+1}$ include the same variables as $X_{i,t}$ (except for trade size) on the day before and the day after the trade day t, respectively. α, δ, β_0, β_1, β_2 are vectors of regression coefficients and $\varepsilon_{i,t}$ is an error term.

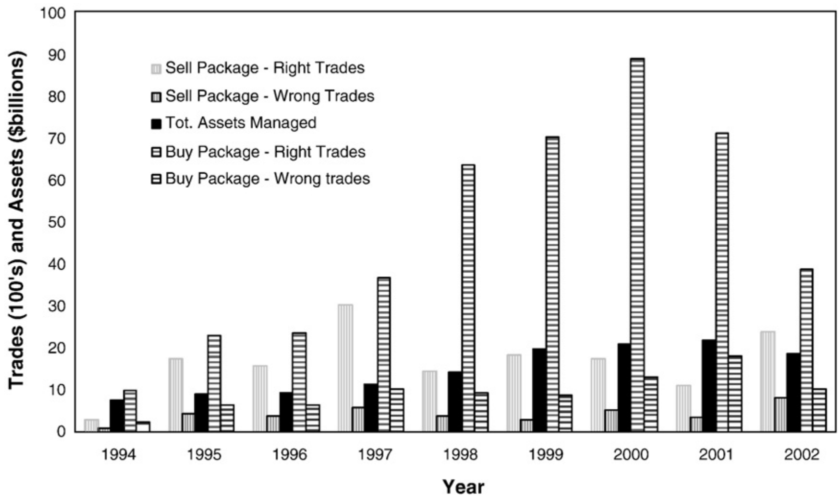

Fig. 5. Growth in assets managed by GAMCO and the numbers of right-direction and wrong-direction trades in each year of our sample. GAMCO makes groups of mostly buy (sell) trades adjacent in time, which we group into buy (sell) packages. A trade package ends when GAMCO makes no trade in a stock for more than seven trading days. Wrong-direction buy (sell) trades are occasional buy (sell) trades interspersed within a package of mostly sell (buys) trades. Packages are identified by type (buy or sell) and by year, and the number of right-direction and wrong-direction trades in each year is computed for each type. Assets are the total assets managed by GAMCO at year-end, listed in GAMCO Investors Inc. 10 K reports.

To examine the effect of a wrong trade on trade-day return volatility, we propose the following regression model based on model (4).

$$\sigma_{i,t} = \alpha + \delta W_{i,t} + \beta_0 Y_{i,t} + \mu_{i,t}, \tag{7}$$

where for each trade i on trade day t, $\sigma_{i,t}$ is return volatility, $W_{i,t}$ is a dummy variable equal to one if trade i is a wrong trade, and zero otherwise, $Y_{i,t}$ is a matrix of explanatory variables including logarithm of trade size, close-to-close return, CRSP value-weighted index return, size factor, book-to-market factor, momentum factor, the logarithm of clean volume for the traded firm, the logarithm of NYSE volume, and the Russell 3000 volatility. α, δ, β_0 are vectors of regression coefficients and $\mu_{i,t}$ is an error term.

Following Alizadeh et al. (2002)[21], a stock's return volatility on a particular day is estimated as the logarithm of the day's high price minus low price divided by the low price. We control for general market volatility by including the volatility of the Russel 3000, which is estimated using the same range-based method.

Models (6) and (7) are first estimated by ordinary least squares regression (OLS). But OLS regression requires wrong trades to be determined exogenously, otherwise, estimates of δ could be biased. Earlier results show that GAMCO may decide to make a wrong trade based upon stock characteristics or market conditions, and at least some of these could be related to stock returns or volatility. One way to handle part of this problem is to use a fixed effects (FE) panel regression to control for the average return or volatility of each firm (see Verbeek and Nijman, 1992a,b, and Vella, 1998). Indeed, a fixed-effects specification allows us to control for those unobserved characteristics that are fixed within each firm but changing between firms. It is still possible that some unobserved firm-specific characteristic changes, however. For this reason, we will combine fixed-effects with an instrumental variable specification below.

To further control for market conditions and the magnitude of characteristics differences between right- and wrong-trade stocks, we combine FE with a two-stage instrumental variable (IV) approach (see Faulkender and Petersen, 2006). Instead of the dummy variable $W_{i,t}$, we substitute the estimated probability of a wrong trade. The wrong-trade probability for each trade is estimated with the following probit regression.

$$P_{i,t} = \gamma Z_{i,t} + \pi I_{i,t} + v_{i,t}, \tag{8}$$

where for each trade i on trade day t, $P_{i,t}$ equals one if i is a wrong trade and zero otherwise, γ and π are vectors of coefficients, $\nu_{i,t}$ is an error term, and $Z_{i,t}$ is a matrix of stock characteristics or market variables including market, size, book-to-market, and momentum factor loadings (all estimated from the four factor model over one year before i's trade package begins), the close-to-close return on the trade day, and the logarithm of clean volume on the trade day. $I_{i,t}$ is a matrix of instrumental variables including alpha, the standard deviation of residual returns from the four factor model, the logarithm of the value of shares outstanding for

[21] These authors show theoretically and in simulation that the log of the price range generates a volatility proxy that is about normally distributed, less noisy than alternative volatility proxies (e.g., the log squared returns) and unaffected by non-synchronous trading or bid-ask bounce effects. This proxy is particularly handy when the price dynamics over the interval of interest is not completely observable.

Table 4
Probability that GAMCO makes a wrong-trade (first stage of instrumental variable regressions).

Independent variables	Buy package trades	Sell package trades
α-Alpha	−0.6996*	−0.3933
	(0.000)	(0.114)
Residual return standard deviation	−0.0280	0.1289*
	(0.219)	(0.005)
Log of value of shares outstanding	−0.0451	0.0717
	(0.121)	(0.165)
S&P 500 dummy	0.1401***	0.0184
	(0.074)	(0.932)
NYSE dummy	−0.0654	−0.0901
	(0.280)	(0.461)
β_m − Market	0.0683	−0.1231
	(0.410)	(0.243)
β_s − Size	0.0877	−0.1261
	(0.202)	(0.212)
β_h − Bk/Mkt	−0.0590	0.0173
	(0.183)	(0.805)
β_u − Moment.	−0.0925***	0.0001
	(0.065)	(0.999)
Close-to-close return (trade day)	−0.0114*	0.0066***
	(0.000)	(0.076)
Log of clean volume for the traded firm (trade day)	−0.0065	−0.0768**
	(0.561)	(0.011)
Intercept	−0.0271	−1.4796
	(0.961)	(0.109)
Pseudo-R^2	0.0154	0.0190
Chi-square statistic: H_0: all instruments = 0	27.05*	13.73**
Number of observations	48,861	18,350

This table reports estimates for the following probit model,

$$P_{i,t} = \gamma Z_{i,t} + \pi I_{i,t} + v_{i,t},$$

where for each trade i on trade day t, $P_{i,t}$ equals one if i is a wrong trade and zero otherwise, γ and π are vectors of coefficients, $\nu_{i,t}$ is an error term, $Z_{i,t}$ a matrix of stock characteristics including market, size, book-to-market, and momentum factor loadings (all estimated from the four-factor model over one year before the trade i's trade package begins), and trading conditions including the firm's market return and clean volume, and $I_{i,t}$ is a matrix of instruments including alpha, the standard deviation of residual returns from the four factor model, the value of shares outstanding for the stock of trade i, and two dummy variables to indicate if the stock is in the S&P 500 Index or traded on the NYSE. Clean volume is the total volume for the traded firm minus GAMCO's trade volume. Reported p-values are based on bootstrapped standard errors corrected for correlation across observations of a given firm (Davidson and Mackinnon, 2004). * (**, ***) Indicates significance at the 1 (5, 10)% level.

the stock, an indicator variable equal to one if the stock is in the S&P 500 and zero otherwise, and an indicator variable equal to one if the stock is traded on the NYSE, and zero otherwise.

Identification for the IV approach requires at least one instrument that is correlated to the probability of a wrong trade, but uncorrelated with GAMCO's return and stock return volatility. Assuming that the four factor model is properly specified, alpha and standard deviation of residual returns could serve as instruments. They should be unrelated to future expected return and are estimated prior to the start of the trade package. Firm size, measured by the value of shares outstanding, could also serve as an instrument, assuming that the size factor loading controls for the effects of size on returns. Finally, like Faulkender and Petersen (2006), we include S&P 500 and NYSE indicator variables as proxies for how well-known a firm is to stock market participants. The better-know the firm, the more likely that GAMCO could use wrong trades to disguise its trades. These proxies should not be related to trade-day returns[22].

Table 4 reports the coefficient estimates for the wrong-trade probability model separately for buy packages and sell packages. First, note that some of the instruments are statistically significant, but the small pseudo-R-squareds indicate that they do not account for a great deal of variation[23]. Nevertheless, a chi-square test of the hypothesis that the instruments are jointly insignificant is rejected. We also performed Olsen's (1980) procedure to determine whether the nonlinearity in the probit model, rather than significant instruments, could account for the second-stage model identification. Results showed that the nonlinearity of the probit is not the identification mechanism.

Table 4 regression estimates often differ in sign between buy and sell packages. Seven of the eleven pairs of coefficient estimates differ in sign, although the close-to-close return estimates are the only ones that are both statistically significant.

[22] Size, S&P 500, and NYSE variables are not measuring the same thing. Estimated correlations between size and the other two for buy and sell package groups are less than 0.30, and the correlations between S&P 500 and NYSE variables are less than 0.19.

[23] Estimate significance tests are based on bootstrapped standard errors to account the fact that some of the regressors are estimated and observations for each firm could be cross-correlated (see Davidson and MacKinnon, 2004). Most of the estimates are significant when using ordinary standard errors.

GAMCO is more likely to make a wrong trade sell (buy) on a low (high) return day. We do not have sign expectations for each estimate; however, there are plausible reasons for each. For example, the negative estimate on clean volume implies that the greater the clean volume, the less likely that GAMCO makes a wrong trade. This could reflect the notion that GAMCO does not need to disguise its trades when there are many other traders (including noise traders) submitting orders. Similarly, the negative alpha estimate can be interpreted to mean that less disguise is required when trading less efficiently-priced stocks. And the positive S&P 500 estimate implies that GAMCO is more likely to make wrong trades in better known stocks, where more disguise could be useful.

Table 5 reports the coefficient estimates for the return regressions. The focus of the analysis is the wrong trade dummy (or wrong-trade probability for IV), which measures the difference in returns between right trades and wrong trades, after controlling for trade size and market conditions. Compared to OLS, FE and IV estimates are smaller, but the signs are maintained. To make the interpretation of the estimates clearer, recall that GAMCO's trade-day return is the return one would earn by purchasing at GAMCO's trade price. For buy packages, the positive estimate means that the wrong-trade sells are costly because GAMCO is selling the stock at a price that earns the buyer a larger return than GAMCO earns on its right-trade buys. Similarly, the negative estimates for the sell packages imply that wrong trades in those packages are costly on average. Here, GAMCO makes wrong-trade buys at prices that earn it a smaller return than the return it gives up when it makes sell trades. These results support Hypothesis 2. The IV estimate for buy packages is positive but not statistically significant[24]. Nevertheless, we can still reject the value hypothesis that wrong trades will out-perform right trades.

Plausible explanations for the signs of the estimates of the other coefficient can also be given, although we do not have explicit expectations for them[25]. Many will depend upon how GAMCO bases its trade strategy on market conditions. But, for example, the positive estimates on trade-day close-to-close return make sense. The larger the close-to-close return on the day of the trade, the larger is GAMCO's return.

Comparatively more of the trade day estimates are statistically significant, but quite a few day-after and day-before estimates are as well. Trade size has little significant impact, except in the buy packages OLS regression, where larger size implies smaller return. This perhaps reflects the greater price impact of GAMCO's larger trades. The positive (although insignificant) trade size estimates for sell packages are also consistent with a greater price impact of larger trades.

The multivariate evidence shows that wrong trades are not profitable. But we also consider some complementary evidence concerning wrong-trade profitability. Suppose that GAMCO is informed and other traders believe that GAMCO is informed. Then one should observe a positive (negative) abnormal return when GAMCO files a 13D for a buy (sell) package, because other traders buy (sell) after GAMCO buys (sells).

Table 6 Panel A reports the cumulative average abnormal returns (CAARs) for GAMCO's filings for various windows around the filing date, day 0[26]. The sample includes only the last filing of each package. Filings made during the trade package are excluded because GAMCO continues to trade around the filing date. GAMCO's trades themselves could cause abnormal returns around the intermediate filings, hence, we exclude those filings. This is not a problem for the final filing because it typically comes ten days after the last trade of a package.

Results show that there are significant positive CAARs around buy packages, but insignificant CAARs around sell packages. Therefore, the market appears to believe that GAMCO is informed for buy packages, but not for sell packages. These results are consistent with Faure-Grimaud and Gromb (2004), who show that public trading increases share prices after a large shareholder buys. Bozcuk and Lasfer (2006) find similar results for block trades when the trader holds, or recently held, a significant percentage of the firm's shares outstanding.

For comparison, Table 6 Panel B reports CAARs for the 13G filings of Fidelity Funds (FMR Corp) during our sample period. Recall that most large institutional insiders file these forms because they can make fewer disclosures; they file only after they accumulate

[24] The panel data structure implies that firm-specific errors could be correlated across time, causing OLS standard errors to be underestimated. Therefore, following White (1980) and Rogers (1993), we use heteroscedasticity consistent errors, adjusted for residual correlation across firm observations to compute the probability values for significance tests of coefficient estimates in Tables VII and IX.

[25] One unusual result would appear to be the negative estimates for the momentum factor coefficients. But recall from Table II that GAMCO's traded stocks have a negative average momentum factor loading, hence, their returns should be negatively related to the momentum factor.

[26] Cumulative abnormal returns (CARs) are calculated using the following four-factor return model, estimated for each stock over the 5-month (100 trading day) period before GAMCO starts to trade the stock.

$$\left(R_{i,t} - R_{f,t}\right) = \alpha + \beta_m\left(R_{m,t} - R_{f,t}\right) + \beta_s \mathrm{SML}_t + \beta_h \mathrm{HML}_t + \beta_u \mathrm{UMD}_t + \varepsilon_t,$$

where for each trading day t, $R_{i,t}$ is stock i's return, $R_{f,t}$ is the risk-free return, $R_{m,t}$ is the CRSP value-weighted stock index return, and SML_t, HML_t, and UMD_t are the size, book-to-market, and momentum factors, respectively, and β_m, β_s, β_h, and β_u are the associated factor loadings. α is the alpha and ε_t is a residual error term. The factor data are taken from Kenneth French's website. The abnormal return (AR) on day t is:

$$\mathrm{AR}_{i,t} = R_{i,t} - \left[\hat{\alpha} + \hat{\beta}_{i,m}\left(R_{mt} - R_{f,t}\right) + \hat{\beta}_{i,s}\,\mathrm{SML}_t + \hat{\beta}_{i,h}\,\mathrm{HML}_t + \hat{\beta}_{i,u}\,\mathrm{UMD}_t\right].$$

The announcement dates, $t=0$, are the public filing dates for the last filing for each package of trades. ARs are summed over the event period to produce CARs. CARs are grouped into portfolios and averaged by group to obtain cumulative average abnormal returns (CAARs).

Table 5
Regression estimates for multivariate analyses of GAMCO's trade-day returns.

Independent variables	Buy package trades			Sell package trades		
	OLS	Fixed-effects (FE)	Instrumental variables (IV)	OLS	Fixed-effects (FE)	Instrumental variables (IV)
Dummy for wrong trade	0.1980*	0.1661*	0.0792	−0.2581**	−0.3253**	−0.4038***
	(0.000)	(0.001)	(0.186)	(0.036)	(0.034)	(0.053)
Log of trade size	−0.0253**	−0.0093	−0.0155	0.0627	0.0281	0.0291
	(0.038)	(0.426)	(0.149)	(0.167)	(0.518)	(0.492)
Close-to-close return	0.1179*	0.1299*	0.1299*	0.3445*	0.3461*	0.3467*
(Trade day)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Close-to-close return	−0.0008	−0.0018	−0.0019	−0.0471**	-0.0477**	-0.0478**
(Day after)	(0.966)	(0.927)	(0.924)	(0.047)	(0.038)	(0.038)
Close-to-close return	0.0041	0.0119	0.0119	−0.0613	−0.0560	−0.0559
(Day before)	(0.728)	(0.334)	(0.348)	(0.210)	(0.250)	(0.237)
Value-weighted CRSP return	0.3200*	0.3073*	0.3068*	0.0428	0.0394	0.0395
(trade day)	(0.000)	(0.000)	(0.000)	(0.524)	(0.562)	(0.570)
Value-weighted CRSP return	0.0947**	0.0994**	0.1001**	0.1293**	0.1215**	0.1221**
(day after)	(0.033)	(0.019)	(0.015)	(0.033)	(0.038)	(0.031)
Value-weighted CRSP return	−0.2073*	−0.2153*	−0.2167*	0.0556	0.0682	0.0682
(Day before)	(0.000)	(0.000)	−(0.000)	(0.409)	(0.366)	(0.346)
SML (trade day)	0.1176**	0.0950***	0.0957***	−0.0450	−0.0449	−0.0444
	(0.032)	(0.076)	(0.067)	(0.501)	(0.467)	(0.487)
SML (day after)	0.1624*	0.1355*	0.1365*	0.1408***	0.1150***	0.1160***
	(0.004)	(0.006)	(0.004)	(0.071)	(0.089)	(0.095)
SML (day before)	−0.1047**	−0.1327*	−0.1330*	0.0896***	0.0953***	0.0962***
	(0.032)	(0.006)	(0.004)	(0.071)	(0.095)	(0.077)
HML (trade day)	0.2441*	0.2283*	0.2287*	−0.0229	−0.0429	−0.0418
	(0.003)	(0.005)	(0.004)	(0.662)	(0.425)	(0.466)
HML (day after)	0.1111***	0.1106**	0.1115**	0.1175***	0.1070***	0.1082***
	(0.055)	(0.046)	(0.041)	(0.053)	(0.060)	(0.060)
HML (day before)	−0.2457*	−0.2568*	−0.2582*	0.0435	0.0671	0.0676
	(0.000)	(0.000)	(0.000)	(0.526)	(0.445)	(0.431)
UMD (trade day)	−0.0644**	−0.0544**	−0.0548**	−0.0736**	−0.0674**	−0.0672**
	(0.024)	(0.049)	(0.043)	(0.016)	(0.031)	(0.034)
UMD (day after)	−0.0018	−0.0069	−0.0070	−0.0136	−0.0209	−0.0209
	(0.944)	(0.763)	(0.752)	(0.803)	(0.715)	(0.715)
UMD (day before)	0.0030	−0.0033	−0.0031	0.0287	0.0318	0.0318
	(0.909)	(0.900)	(0.900)	(0.457)	(0.405)	(0.404)
Log of clean volume for the traded firm (trade	−0.1591*	−0.1435*	−0.1425*	−0.1505*	−0.1719*	−0.1783*
day)	(0.000)	(0.000)	(0.000)	(0.003)	(0.001)	(0.001)
Log of clean volume for the traded firm (day after)	−0.0561*	−0.0701**	−0.0695**	0.0383*	−0.0104	−0.0091
	(0.010)	(0.011)	(0.013)	(0.191)	(0.784)	(0.806)
Log of clean volume for the traded firm (day	0.1408*	0.1413*	0.1419*	0.1002	0.0549	0.0559
before)	(0.000)	(0.000)	(0.000)	(0.053)	(0.301)	(0.298)
Log of NYSE volume (trade day)	−0.0413	−0.0644	−0.0606	0.0693	0.0649	0.0665
	(0.823)	(0.715)	(0.724)	(0.718)	(0.741)	(0.757)
Log of NYSE volume (day after)	−0.1412	−0.1225	−0.1192	−0.1443	−0.0923	−0.0904
	(0.192)	(0.262)	(0.262)	(0.324)	(0.561)	(0.579)
Log of NYSE volume (day before)	0.1364	0.1349	0.1346	0.1668	0.1136	0.1170
	(0.427)	(0.399)	(0.387)	(0.296)	(0.492)	(0.487)
Intercept	1.9038	1.8646	1.7569	−2.1289	−0.4783	−0.5096
	*(0.050)	(0.185)	(0.228)	(0.217)	(0.822)	(0.815)
R^2	0.1406	0.1394	0.1387	0.3075	0.3034	0.3027
Number of observations	48,861	48,861	48,861	18,350	18,350	18,350

* (**, ***) Indicates significance at the 1 (5, 10)% level.
The regression model is;

$$R_{i,t} = \alpha + \delta W_{i,t} + \beta_0 X_{i,t-1} + \beta_1 X_{i,t} + \beta_2 X_{i,t+1} + \varepsilon_{i,t},$$

where for each trade i on trade day t, $R_{i,t}$ is GAMCO's return (equal to GAMCO's trade price minus close price divided by GAMCO's trade price), $W_{i,t}$ is a dummy variable equal to one if trade i is a wrong trade, and zero otherwise, $X_{i,t}$ is a matrix of explanatory variables including trade size, close-to-close return, CRSP value-weighted index return, size factor (SML), book-to-market factor (HML), momentum factor (UMD), clean volume for the traded firm, and NYSE volume, and $X_{i,t-1}$ and $X_{i,t+1}$ are matrices of the same variables as $X_{i,t}$ (except for trade size) on the day before and the day after the trade day t, respectively. α, δ, β_0, β_1, β_2 are vectors of regression coefficients and $\varepsilon_{i,t}$ is an error term. The numbers in parentheses are the estimated p-values, which for the OLS and the firm fixed-effects regressions are based on White heteroscedasticity consistent errors adjusted for the residuals correlation across observations of a given firm (White, 1980; Rogers, 1993). Because a generated regressor is used in the instrumental variables models, reported p-values in this case are based on bootstrapped standard errors corrected for correlation across observations of a specific firm over time (Davidson and Mackinnon, 2004).

Table 6
Percent cumulative average abnormal returns around GAMCO's 13D insider trade filings and Fidelity funds' 13G institutional insider trade filings.

Sample	Event period		
	Day 0	Day −1 to +1	Day 0 to +5
Panel A. CAARs for GAMCO's 13D filings			
All 911 buy packages (886 with required data)	0.51	0.88	1.10
	(4.65)***	(4.30)***	(4.64)***
700 buy packages with wrong trades (675 with required data)	0.49	0.71	1.22
	(4.00)***	(3.08)***	(4.44)***
211 buy packages without wrong trades (211 with required data)	0.57	1.40	0.70
	(2.36)**	(3.28)***	(1.52)
All 517 sell packages (453 with required data)	−0.15	0.17	0.35
	(−0.97)	(0.61)	(1.01)
385 sell packages with wrong trades (333 with required data)	−0.24	0.22	0.54
	(−1.23)	(0.64)	(1.24)
132 sell packages without wrong trades (120 with required data)	0.11	0.01	−0.18
	(0.55)	(0.02)	(−0.37)
Panel B. CAARs for Fidelity funds' 13G filings			
All filings (3822 observations)	0.18	0.24	0.21
	(2.268)**	(2.058)**	(1.340)
Buy filings (2150 observations)	−0.03	−0.27	−0.64
	(−0.384)	(−1.944)*	(−3.462)***
Sell filings (1672 observations)	0.46	0.90	1.30
	(2.993)***	(4.473)***	(4.991)***

* (**, ***) CAAR different from zero at the 1 (5, 10)% level. t-statistics in parentheses.
Cumulative abnormal returns (CARs) are calculated using the following four-factor return model, estimated for each stock over the 5-month (100 trading day) period before GAMCO starts to trade the stock.

$$\left(R_{i,t} - R_{f,t}\right) = \alpha + \beta_m\left(R_{m,t} - R_{f,t}\right) + \beta_s \mathrm{SML}_t + \beta_h \mathrm{HML}_t + \beta_u \mathrm{UMD}_t + \varepsilon_t,$$

where for each trading day t, $R_{i,t}$ is stock i's return, $R_{f,t}$ is the risk-free return, $R_{m,t}$ is the CRSP value-weighted stock index return, and SML_t, HML_t, and UMD_t are the size, book-to-market, and momentum factors, respectively, and β_m, β_s, β_h, and β_u are the associated factor loadings. α is the alpha and ε_t is a residual error term. The factor data are taken from Kenneth French's website. The abnormal return (AR) on day t is:

$$\mathrm{AR}_{i,t} = R_{i,t} - \left[\hat{\alpha} + \hat{\beta}_{i,m}\left(R_{mt} - R_{f,t}\right) + \hat{\beta}_{i,s}\mathrm{SML}_t + \hat{\beta}_{i,h}\mathrm{HML}_t + \hat{\beta}_{i,u}\mathrm{UMD}_t\right].$$

The announcement dates, $t = 0$, are the public filing dates for the last 13D filing for each package of trades. ARs are summed over the event period to produce CARs. CARs are grouped into portfolios and averaged by group to obtain cumulative average abnormal returns (CAARs).

10% or more of a stock (instead of five for 13Ds), and then again only for large changes in holdings. Filings are delayed by a month and only the total trade size is revealed, not the day-to-day trades. To qualify, the institutional insider must agree to be a passive investor. Results for Fidelity show that investors do not believe that Fidelity is informed. Indeed, prices fall when they file a buy and rise when they file a sell. We cannot tell if Fidelity uses wrong trades, but it is possible that GAMCO's use of wrong trades could partly explain GAMCO's better CAARs.

Finally, we consider tests of Hypothesis 3, that wrong trades produce more return volatility than right trades. Table 7 reports the coefficient estimates for the return volatility regressions. The wrong trade dummy (or wrong-trade probability for IV) measures the difference in trade-day return volatility between right trades and wrong trades, after controlling for trade size and market conditions. Except for the OLS estimate for sell packages, the estimates are positive. A positive estimate implies that wrong trades produce more volatility than right trades. The FE and IV estimates for buy packages are smaller than the OLS estimate, but have the same sign. FE and IV estimation actually changes the estimate's sign for sell packages because they account for endogeneity.

Explanations for the signs of the other estimates are straightforward. For example, the larger the market (Russell 3000) volatility on the trade day, the larger is the traded stock's volatility. Trade volume is also positively related to volatility. The buy package regressions have smaller intercept estimates than the sell package regressions. This means that, all else equal, buy package stocks are less volatile than sell package stocks, on average (the negative intercept estimates reflect the fact that volatility is measured as a logarithm of a number less than one).

Overall, the multivariate results support the disguise hypothesis over the value hypothesis. Wrong trades are not profitable when compared to right trades, and they produce more return volatility than right trades. This shows that GAMCO is willing to bear the low returns of wrong trades in exchange for their disguise benefits.

Table 7
Regression estimates for multivariate analyses of GAMCO's traded stock volatility on the trade day.

Independent variables	Buy package trades			Sell package trades		
	OLS	Fixed-effects (FE)	Instrumental variables (IV)	OLS	Fixed-effects (FE)	Instrumental variables (IV)
Dummy for wrong trade	0.0759*	0.0292*	0.0483*	−0.0572*	0.0227**	0.0250***
	(0.000)	(0.000)	(0.000)	(0.005)	(0.019)	(0.054)
Log of trade size	−0.0160*	0.0008	0.0010	0.0034	−0.0011	−0.0013
	(0.000)	(0.733)	(0.651)	(0.629)	(0.741)	(0.703)
Close-to-close return (trade day)	−0.0030*	−0.0006	−0.0005	0.0024	0.0019	0.0019
	(0.006)	(0.519)	(0.596)	(0.372)	(0.314)	(0.308)
Value-weighted CRSP return (trade day)	0.0061	−0.0006	−0.0005	−0.0009	0.0003	0.0003
	(0.188)	(0.840)	(0.860)	(0.899)	(0.939)	(0.935)
SML (trade day)	0.0060	0.0012	0.0012	−0.0078	0.0049	0.0049
	(0.305)	(0.712)	(0.712)	(0.428)	(0.351)	(0.367)
HML (trade day)	−0.0163**	−0.0110**	−0.0110**	−0.0004	0.0001	0.0001
	(0.032)	(0.024)	(0.025)	(0.974)	(0.992)	(0.999)
UMD (trade day)	−0.0028	0.0003	0.0003	−0.0067	−0.0032	−0.0032
	(0.446)	(0.896)	(0.891)	(0.215)	(0.259)	(0.250)
Log of clean volume for the traded firm (trade day)	0.0479*	0.0735*	0.0738*	0.0589*	0.0724*	0.0727*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log of NYSE volume (trade day)	0.0847*	0.0505**	0.0506**	0.0269	−0.0095	−0.0099
	(0.001)	(0.031)	(0.030)	(0.402)	(0.711)	(0.700)
Russell 3000 volatility (trade day)	0.1232*	0.2167*	0.2161*	0.2134*	0.2177*	0.2179*
	(0.010)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)
Intercept	−1.6265*	−1.3661*	−1.3825*	−0.7124	−0.1011	−0.0986
	(0.002)	(0.006)	(0.004)	(0.254)	(0.844)	(0.848)
R^2	0.1567	0.1314	0.1332	0.1911	0.1753	0.1770

* (**, ***) Indicates significance at the 1 (5, 10)% level.
The regression model is;

$$\text{Volatility}_{i,t} = \alpha + \delta W_{i,t} + \beta_0 X_{i,t},$$

where for each trade i on trade day t, $\text{Volatility}_{i,t}$ is GAMCO's traded stock volatility estimated as the logarithm of the day's high price minus low price divided by the low price, $W_{i,t}$ is a dummy variable equal to one if trade i is a wrong trade, and zero otherwise, $X_{i,t}$ is a matrix of explanatory variables including trade size, close-to-close return, CRSP value-weighted index return, size factor (SML), book-to-market factor (HML), momentum factor (UMD), clean volume for the traded firm, NYSE volume, and the volatility of the Russell 3000 Index. α, δ, β_0 are vectors of regression coefficients and $\varepsilon_{i,t}$ is an error term. The numbers in parentheses are the estimated p-values, which for the OLS and the firm fixed-effects regressions are based on White heteroscedasticity consistent errors adjusted for the residuals correlation across observations of a given firm (White, 1980; Rogers, 1993). Because a generated regressor is used in the IV models, reported p-values in this case are based on bootstrapped standard errors corrected for correlation across observations of a specific firm over time (Davidson and Mackinnon, 2004).

5. Conclusion

Many theoretical studies of large informed traders show that they should sometimes make misleading trades, but there is little work documenting such trade behavior. This paper examines the wrong-direction trades of a large institutional insider (GAMCO) to decide whether it uses wrong-direction trades to disguise its right-direction trades, or to exploit attractive prices.

Overall, the evidence supports disguise. First, GAMCO makes wrong trades in stocks of larger companies with smaller residual return variation. That is, GAMCO makes wrong trades in stocks whose returns may not otherwise be volatile enough to naturally disguise its trades. Second, wrong-direction trades are small compared to right-direction trades. If wrong direction trades were based on valuation as opposed to disguise, one would expect them to be at least as large as right-direction trades. Third, wrong-direction trades are evenly distributed throughout trade packages. If they were motivated primarily by valuation, one would expect GAMCO to wait to execute them at the end of trade packages, when they would likely receive better prices.

The multivariate analyses of GAMCO's trade-day returns and stock return volatility show that wrong trades are unprofitable compared to right trades, but produce greater return volatility. The poor returns of wrong trades make sense if GAMCO possesses valuable information because they are essentially trading against that information when they make wrong trades. But if the volatility produced by wrong trades helps disguise GAMCO's right trades, they may earn greater returns on right-direction trades than they would otherwise. Because we cannot observe what right trades would have earned without wrong trades, we cannot prove that wrong trades are valuable. Nonetheless, the evidence shows that GAMCO is more likely to make wrong trades when a stock lacks natural disguise, and it accepts low wrong-trade returns in exchange for enhanced disguise.

One potentially profitable trading strategy is based upon our result that GAMCO's wrong trades earn poor returns. Conversely, the other side of the trade earns good returns. The strategy is as follows. After GAMCO files its first 13D showing a new buy (sell) package, one can buy (sell) the stock when a sell order appears after a series of buy order-initiated trades. Our work can be extended by comparing GAMCO's wrong trade strategy to that of other large traders, however, we found that publicly-available trade-by-trade data are scarce. One possibility is to identify a willing proprietary data source.

Appendix A

GAMCO's equal-weighted and trade-size-weighted average trade prices by type of trade package compared to equal-weighted and trade-size-weighted average high, low, and close prices.

Figures are all averages measured in dollars, either equal-weighted or trade-size weighted, where trade size is measured as the dollar value of GAMCO's trade divided by the total dollar value of all trades in the group. Trades are grouped by package type (buy or sell) and trade type (buy or sell and wrong-trade or no-wrong-trade). Average prices are calculated for the day of the trade, the day before the trade, and the day after the trade. Daily high, low, and close prices are obtained from the CRSP database.

Panel A. Buy packages

Variable	39,532 buy trades for 700 buy packages with wrong trades			8544 sell trades for 700 buy packages with wrong trades			3465 buy trades for 211 buy packages without wrong trades		
	Day before	Trade day	Day after	Day before	Trade day	Day after	Day before	Trade day	Day after
GAMCO Trade Price		25.48***			25.60***			16.20	
Trade-Size-Weighted GAMCO Trade Price		25.46**			25.63**			16.18	
Close Price	25.43#	25.52Δ	25.56♦	25.57##	25.62ΔΔΔ	25.61	16.05#	16.23	16.24
Low Price	25.12###	25.16	25.26♦	25.26###	25.30	25.31	15.90	16.01	16.11♦♦♦
High Price	25.69#	25.79	25.81♦♦♦	25.84#	25.93	25.89♦♦	16.19#	16.41	16.37

Panel B. Sell packages

Variable	13,950 sell trades for 385 Sell packages with wrong trades			3916 buy trades for 385 sell packages with wrong trades			1876 sell trades for 132 sell packages without wrong trades		
	Day before	Trade day	Day after	Day before	Trade day	Day after	Day before	Trade day	Day after
GAMCO Trade Price		29.54♀,*			28.89*			24.46♀♀	
Trade-Size-Weighted GAMCO Trade Price		29.69♀,*			28.95*			24.53♀♀	
Close Price	29.49#	29.55ΔΔ	29.57♦♦♦	28.82##	28.89	28.98♦	24.45	24.47	24.46
Low Price	29.16#	29.22	29.27♦	28.49	28.51	28.66♦	24.22	24.23	24.23
High Price	29.76#	29.84	29.86	29.10##	29.17	29.23♦	24.69##	24.72	24.68♦♦

(##, ###) indicates that the price on the trading day is statistically different from the price on the day before the trading day at the 1 (5, 10)% level.
♦ (♦♦, ♦♦♦) indicates that the price on the trading day is statistically different from the price on the day after the trading day at the 1 (5, 10)% level.
Δ (ΔΔ, ΔΔΔ) indicates that GAMCO's equal-weighted (trade-size-weighted) prices are statistically different from the close price (trade-size-weighted close price) on the trading day at the 1 (5, 10)% level.
♀ (♀♀, ♀♀♀) indicates that GAMCO's equal-weighted price is statistically different from GAMCO's trade-size-weighted price at the 1 (5, 10)% level.
* (**, ***) indicates that GAMCO's equal-weighted (or trade-size-weighted) price for the buy (sell) trades for buy (sell) packages with wrong trades is statistically different from GAMCO's equal weighted (or trade-size-weighted) price for the sell (buy) trades for buy (sell) packages with wrong trades at the 1 (5, 10)% level.
Variables' definitions: GAMCO Trade Price is the price at which GAMCO trades the stock as reported in the 13D,Trade-Size-Weighted GAMCO Trade Price is the price at which GAMCO trades the stock scaled by trade size, Close Price is the CRSP close price for the stock GAMCO is trading, Low Price is the low price for the stock GAMCO is trading, High Price is the high price for the stock GAMCO is trading.

Appendix B

GAMCO's equal-weighted and trade-size-weighted average trade-day returns by type of trade package compared to average close-to-close stock returns, CRSP value-weighted index returns, and size (SML), book-to-market (HML), and momentum (UMD) factors.

Figures are all averages measured in percent, either equal-weighted or trade-size weighted, where trade size is measured as the dollar value of GAMCO's trade divided by the total dollar value of all trades in the group. GAMCO's trade-day return is computed as the closing price, minus GAMCO's transaction price, divided by the GAMCO's transaction price. GAMCO earns this return on its buys and forfeits this return on its sells. Close-to-close return is the share return from the day-before close price to the trade-day close price. GAMCO's trades are grouped by package type (buy or sell) and trade type (buy or sell and wrong-trade or no-wrong-trade). Average returns are calculated for the day of the trade, the day before the trade, and the day after the trade. Close-to-close and CRSP index returns are obtained from the CRSP database and the factors are from Kenneth French's website.

Panel A. Buy packages

Variable	39,532 buy trades for 700 buy packages with wrong trades			8544 sell trades for 700 buy packages with wrong trades			3465 buy trades for 211 buy packages without wrong trades		
	Day before	Trade day	Day after	Day before	Trade day	Day after	Day before	Trade day	Day after
GAMCO Return		0.14♀♀			0.12			0.34	
Trade-Size-Weighted GAMCO Return		0.20♀♀			0.12			0.30	
Close-to-Close Share Return	0.61#	0.91Δ	0.17♦	0.22	0.21	0.09	1.50##	2.05Δ	0.14♦
CRSP Value-Weighted Index Return	0.15	0.17	0.08♦	0.04	0.06	0.10	0.14	0.20	0.06♦♦

Appendix B (*continued*)

Panel B. Sell packages

Variable	13,950 sell trades for 385 sell packages with wrong trades			3916 buy trades for 385 sell packages with wrong trades			1876 sell trades for 132 sell packages without wrong trades		
	Day before	Trade day	Day after	Day before	Trade day	Day after	Day before	Trade day	Day after
GAMCO Return		0.14			0.09			0.32	
Trade-Size-Weighted GAMCO Return		0.18			0.15			0.37	
Close-to-Close Share Return	0.40##	0.26	0.23	0.40##	0.76Δ	0.23♦♦	0.23	0.05ΔΔΔ	0.05
CRSP Value-Weighted Index Return	0.03	0.07	0.13	0.09	0.15	0.02♦♦	−0.03	0.00	0.06

(##, ###) indicates that the return on the trading day is statistically different from the return on the day before the trading day at the 1 (5, 10)% level.
♦ (♦♦, ♦♦♦) indicates that the return on the trading day is statistically different from the return on the day after the trading day at the 1 (5, 10)% level.
Δ (ΔΔ, ΔΔΔ) indicates that GAMCO's equal-weighted (trade-size-weighted) returns are statistically different from the close-to-close return on the trading day at the 1 (5, 10)% level.
♀ (♀♀; ♀♀♀) indicates that GAMCO's equal-weighted return is statistically different from GAMCO's trade-size-weighted return at the 1 (5, 10)% level.
Variables' definitions: GAMCO Return is defined as the closing price, minus GAMCO's transaction price, divided by GAMCO's transaction price. Trade-Size-Weighted GAMCO Return is GAMCO return scaled by market value of shares traded, Close-to-Close Share Return is the daily return on the stock. Value-Weighted Index Return is the value-weighted return on the CRSP index.

Appendix C

Average daily total trade volume for the stocks GAMCO trades, total volume excluding GAMCO's trades (clean volume), GAMCO's trade volume, the ratio of GAMCO's trade volume to total volume, and NYSE volume.

Figures are all averages measured in shares. GAMCO's trades are grouped by package type (buy or sell) and trade type (buy or sell and wrong-trade or no-wrong-trade). Averages are calculated for the day of the trade, the day before the trade, and the day after the trade. Total volume for a traded firm is the total number of the firm's shares traded on a particular day, clean volume is total volume minus GAMCO's trade volume, GAMCO's trade volume is the number of shares GAMCO traded on a particular day (can include multiple transactions), and NYSE volume is the total volume of shares traded on the NYSE. Total volume for traded firms is taken from the CRSP database, GAMCO's volume is taken from its 13D filings, and NYSE volume is obtained from the NYSE website. Note that the ratio of GAMCO's trade volume to total volume is not the ratio of trade size to market volume because GAMCO makes about two trades per day. Also, the distribution of the ratio is skewed, with GAMCO taking a greater share of low volume stocks across all package types.

Panel A. Buy packages

Variable	39,532 buy trades for 700 buy packages with wrong trades			8544 sell trades for 700 buy packages with wrong trades			3465 buy trades for 211 buy packages without wrong trades		
	Day before	Trade day	Day after	Day before	Trade day	Day after	Day before	Trade day	Day after
Total volume for traded firms (1000)	169.14#	199.04	135.00♦	119.14	160.38	125.84	182.80	189.34	91.49♦
Clean volume for traded firms (1000)	147.72###	163.81	118.15♦	105.60	135.72	113.19	162.92	155.25	78.02♦
GAMCO's trade volume	21.42#	35.23	16.85♦	13.54#	24.66	12.65♦	19.88#	34.09	13.47♦
GAMCO's trade volume/total volume for traded firms (%)	29.14#	31.35	28.02♦	27.16#	28.44	25.58♦	39.05##	40.85	39.43♦♦♦
NYSE volume (1,000,000)	832.93#	849.14	848.18	832.91#	851.43	853.57	931.24##	945.82	948.36

Panel B. Sell packages

Variable	13,950 sell trades for 385 sell packages with wrong trades			3916 buy trades for 385 sell packages with wrong trades			1876 sell trades for 132 sell packages without wrong trades		
	Day before	Trade day	Day after	Day before	Trade day	Day after	Day before	Trade day	Day after
Total volume for traded firms (1000)	150.01#	166.18	130.99♦	147.75##	174.75	134.53♦	61.52###	66.69	49.13♦
Clean volume for traded firms (1000)	133.95	131.48	122.07♦♦♦	137.40	154.92	126.06♦	54.95	55.55	47.03♦♦♦
GAMCO's trade volume	16.06#	34.70	8.92♦	10.35#	19.83	8.47♦	6.57#	11.14	2.1♦
GAMCO's trade volume/total volume for traded firms (%)	23.39#	27.90	22.30♦	23.79##	25.41	22.50♦	23.39	24.67	23.19
NYSE volume (1,000,000)	790.22#	806.20	794.37♦	779.90#	795.84	801.38	664.40#	676.34	684.06

Only 802 (426) buy (sell) packages had the required data to calculate standard deviations of trade size. Only 855 (444) buy (sell) packages had the required data to calculate ratios of shares traded to market volume for traded firms.
(##, ###) indicates that the market volume for traded firms (or GAMCO's volume or NYSE volume) on the trading day is statistically different from the market volume for traded firms ((or GAMCO's volume or NYSE volume) on the day before the trading day at the 1 (5, 10)% level.
♦ (♦♦, ♦♦♦) indicates that the market volume for traded firms ((or GAMCO's volume or NYSE volume) on the trading day is statistically different from the market volume for traded firms ((or GAMCO's volume or NYSE volume) on the day after the trading day at the 1 (5, 10)% level.

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