Overreaction, Delayed Reaction, and Contrarian Profits

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This article examines the contribution of stock price overreaction and delayed reaction to the profitability of contrarian strategies. The evidence indicates that stock prices overreact to firm-specific information, but react with a delay to common factors. Delayed reactions to common factors give rise to a size-related lead-lag effect in stock returns. In sharp contrast with the conclusions in the extant literature, however, this article finds that most of the contrarian profit is due to stock price overreaction and a very small fraction of the profit can be attributed to the lead-lag effect.

The evidence that individual stock returns exhibit negative serial correlation has been well known for almost 30 years [see for example, Fama (1965)]. However, these return reversals have only recently been considered economically important. The extant view is due mainly to empirical estimates that indicate that short-horizon contrarian strategies consistently make substantial profits. For example, Jegadeesh (1990)

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documents profits of about 2 percent per month from a contrarian strategy that buys and sells stocks based on their prior month returns and holds them one month. A similar strategy applied to weekly portfolio formation and holding periods examined by Lehmann (1990) generates positive profits in every six-month period in his sample.

These short-term contrarian profits were initially regarded as evidence that market prices tend to overreact to information, which would have important policy implications. For example, some have argued that the overreaction is caused by speculative trading and recommend policy initiatives to discourage short-term speculation [e.g., Stiglitz (1989) and Summers and Summers (1989)]. Another possibility is that the return reversals indicate that the market lacks sufficient liquidity to offset short-term price swings caused by unexpected buying and selling pressure [e.g., Grossman and Miller (1988) and Jegadeesh and Titman (1995)].

A recent article by Lo and MacKinlay (1990) suggests that these earlier interpretations may be premature and demonstrates that return reversal is not the only source of contrarian profits. They identify a second potential source of contrarian profits that arises when some stocks react more quickly to information than do others, or equivalently, when the returns of some stocks lead the returns of others. For example, if price changes of stock A lead that of stock B, a contrarian strategy may profit from buying stock B subsequent to an increase in stock A and selling stock B subsequent to a decline in stock A, even if neither overreacts to information.

Lo and MacKinlay's analysis makes the important point that one cannot draw definitive inferences about how stock prices react to information based on the observed profitability of contrarian strategies. Indeed, both overreaction and underreaction (or equivalently delayed reaction) of prices to information can in theory lead to contrarian profits.

To analyze the importance of various sources of contrarian profits, Lo and MacKinlay examine the returns of a portfolio with weights inversely proportional to each stock's past returns less the return on the equally weighted index. This portfolio has the property that its expected profits can be easily decomposed into three components: a component due to the dispersion of expected returns, a component due to the serial covariances of returns, and a final component due to the cross-serial covariances of returns. Lo and MacKinlay posit that the cross-serial covariances measure the contribution of the lead-lag structure to contrarian profits.

The pattern of cross-serial covariances documented by Lo and MacKinlay implies a size-dependent lead-lag structure. They find large positive covariances between the returns of small stocks and lagged returns of large stocks, but virtually no correlation between returns of large stocks and lagged small stock returns. Based on this evidence, as well as other empirical tests, Lo and MacKinlay conclude that "a systematic lead-lag relationship among returns of size-sorted portfolios is an important source of contrarian profits." They further argue that "less than 50 percent of the profit from a contrarian investment rule may be attributed to overreaction."

The evidence documented in this article, however, indicates that contrarian strategies applied to size-sorted portfolios do not generate significant abnormal profits. Specifically, the Lo and MacKinlay contrarian strategy applied to 50 size-sorted portfolios actually generates small negative returns despite the fact that the cross-serial covariances between these portfolios are significantly positive (see Table 1). This finding indicates that the average cross-serial covariance may be a misleading measure of the contribution of the lead-lag structure to the profitability of contrarian strategies.

This article separately examines stock price reactions to common factors and firm-specific information and presents a decomposition that directly relates the different components of contrarian profits to their sources, identified based on how stock prices respond to information. This decomposition, therefore, enables us to directly evaluate the economic significance of any overreaction or delayed reaction that we may find. We consider the factor model based decomposition for two reasons. First, by definition, the lead-lag structure in stock returns arises because of differences in the timeliness of stock price reactions to common factors and not because of over- or underreactions to firm-specific information. Therefore, by measuring the contrarian profits due to price reactions to common factors, we directly assess the relation between the observed lead-lag structure and contrarian profits. Our analysis also illustrates that over- or underreaction to common factors affect contrarian profits differently from over- or underreaction to firm-specific information. For instance, systematic overreactions to firm-specific information always contribute to contrarian profits, whereas systematic overreactions to common factors can either reduce or increase such profits. Hence, to assess the extent to which overreaction results in contrarian profits, we separate the contributions of over- or underreaction to firm-specific information and over- or underreaction to common factors.

The results of our tests indicate that stock prices on average react with a delay to common factors, but overreact to firm-specific information. The differences in the timeliness of price reactions to common factors give rise to the size-related lead-lag relation in stock returns. We find, however, that the delayed reactions contribute little to contrarian profits. Our estimates indicate that most of the short-horizon contrarian profits arise because of the tendency of stock prices to overreact to firm-specific information.

The rest of the paper is organized as follows: The next section presents the model used to analyze stock price reactions to common factors and firm-specific information. Section 2 describes the contrarian strategy we analyze and presents a decomposition of the profits into various sources related to specific types of stock price reactions. Section 3 presents empirical tests based on this model, and Section 4 concludes the paper.

1. A Multifactor Model

Consider the following K-factor model of stock returns. This factor model, described in the following equation, allows stock prices to react instantaneously as well as with a one-period lag to factor realizations. Let

$$r_{i,t} = \mu_i + \sum_{k=1}^{K}(b^t_{0,i,k} f_{t,k} + b^t_{1,i,k} f_{t-1,k}) + e_{i,t}, \tag{1}$$

where μ_i is the unconditional expected return of stock i, $f_{t,k}$ is the unexpected kth factor realization, $e_{i,t}$ is the firm-specific component of return at time t, and $b^t_{0,i,k}$ and $b^t_{1,i,k}$ are the sensitivities of stock i to the contemporaneous and lagged realizations of the kth factor at time t. The factor sensitivities are indexed by t since the timeliness of a stock's price reaction to a common factor need not be constant over time. However, we assume for now that the factor sensitivities are uncorrelated with factor realizations; that is, $\mathrm{E}(b^t_{0,i,k} \mid f_{t,k}, f_{t-1,k}, k = 1 \text{ to } K) = b_{0,i,k}$ and $\mathrm{E}(b^t_{1,i,k} \mid f_{t,k}, f_{t-1,k}, k = 1 \text{ to } K) = b_{1,i,k}$.

Without loss of generality we consider orthogonal factors so that $\mathrm{E}(f_{t,i}\ f_{t,j}) = 0$ for $i \neq j$ and $\mathrm{E}(f^2_{t,k}) = \sigma^2_{f_k}$. In addition, since $f_{t,k}$ is defined as the unexpected factor realization $\mathrm{cov}(f_{t,k}, f_{t-1,j}) = 0$, and since the comovements in stock returns are entirely captured by the common factor,

$$\mathrm{cov}(e_{i,t}, e_{j,t-1}) = 0 \ \forall\ i \neq j.$$

This model is similar to conventional multifactor models except that we allow for the lagged factor sensitivities to be different from zero. If stock i reacts with a delay to common factor k then $b_{1,i,k} > 0$, and if this stock overreacts to the factor then $b_{1,i,k} < 0$. Stock price overreaction to firm-specific information will induce negative serial covariance in e_i and underreaction will induce positive serial covariance. Negative serial correlation in e_i will also be observed if stock prices move in the absence of information and subsequently revert to their fundamental values. Consistent with prior literature, we refer to negative serial covariance in stock returns as overreaction irrespective of the underlying source of pricing error.

Given this return-generating model, the cross-serial covariance between the returns of i and j is

$$\text{cov}(r_{i,t}, r_{j,t-1}) = \sum_{k=1}^{K} \text{E}(b_{1,i,k}^{t} b_{0,j,k}^{t-1})\sigma_{f_k}^2. \tag{2}$$

As can be seen from the above expression, Equation (1) allows for the cross-serial covariances to be asymmetric. For instance, if j reacts instantaneously to $f_{t,k} \forall\, k$ but i reacts partially with a delay to at least one factor, that is, if $b_{1,j,k}^{t} = 0$ and $b_{1,i,k}^{t} > 0$, then $\text{cov}(r_{i,t}, r_{j,t-1}) > 0$ but $\text{cov}(r_{j,t}, r_{i,t-1}) = 0$. In this case, j leads i since j's return predicts i's return but the reverse is not true.[1]

2. The Contrarian Strategy and Sources of Contrarian Profits

2.1 The strategy

The contrarian strategy we consider buys and sells stocks based on their returns in week $t-1$ and holds the stocks in week t. Because of its analytic tractability, we examine the strategy proposed by Lo and MacKinlay (1990). With this strategy, the portfolio weight ($w_{i,t}$) assigned to stock i at time t is

$$w_{i,t} = -\frac{1}{N}(r_{i,t-1} - \overline{r}_{t-1}), \tag{3}$$

where N is the number of stocks and $\overline{r}_{t-1}$ is the equally-weighted index return at time $t-1$. By construction, the total investment at any given time is zero. However, the dollar investments in the long and short sides of the portfolio vary over time depending on the return realizations at time $t-1$. The time t profit of this contrarian strategy,

[1] In our specification, stock return predictability arises either because of serial correlation in the firm-specific component of returns or because of delayed reactions to common factors. It is also possible that the return predictability arises because of predictable changes (e.g., serial correlation) in factor risk premia, which would be represented as time variation in μ. We do not, however, consider time variation in μ for two reasons. First, Jegadeesh (1990) reports that time-varying risk premia cannot account for the profitability of contrarian strategies. Secondly, time-variation in μ would give rise to symmetric cross-serial correlation. The evidence presented here and in Lo and MacKinlay (1990) indicates that the cross-serial correlation is asymmetric; small firm returns are correlated with lagged large firm returns, but large firm returns are not correlated with lagged small firm returns. Our statistical specification is consistent with this pattern of asymmetric cross-serial correlation.

denoted as π_t, is

$$\pi_t = -\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - \overline{r}_{t-1})r_{i,t}. \tag{4}$$

2.2 Decomposition of contrarian profits

This subsection decomposes the profits from the contrarian strategy described in Equation (3) into components attributable to stock price reactions, to firm-specific information, and to common factor realizations. The decomposition of contrarian profits, derived under the assumption that stock returns are generated by the process described by Equation (1), is given below:

$$\begin{aligned} E(\pi) &= -E\left(\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - \overline{r}_{t-1})r_{i,t}\right) \\ &= -\sigma_\mu^2 - \Omega - \sum_{k=1}^{K}\delta_k\sigma_{f_k}^2 \end{aligned} \tag{5}$$

where

$$\sigma_\mu^2 = \frac{1}{N}\sum_{i=1}^{N}(\mu_i - \overline{\mu})^2,$$

$$\Omega \equiv \frac{1}{N}\sum_{i=1}^{N}\operatorname{cov}(e_{i,t}, e_{i,t-1}) \tag{6}$$

$$\delta_{t,k} \equiv \frac{1}{N}\sum_{i=1}^{N}(b_{0,i,k}^{t-1} - \overline{b}_0^t)(b_{1,i,k}^t - \overline{b}_1^t) \quad \text{and} \tag{7}$$

$$\delta_k \equiv E(\delta_{t,k})$$

and $\overline{b}_{0,k}^t$ and $\overline{b}_{1,k}^t$ are the cross-sectional averages of $b_{0,i,k}^t$ and $b_{1,i,k}^t$.

Equation (5) decomposes expected contrarian profits into three components. The first component, $-\sigma_\mu^2$, is the cross-sectional variance of expected returns. Stocks that have higher expected returns tend to experience higher-than-average returns during both portfolio formation and holding periods and thus reduce contrarian profits. The second component, $-\Omega$, which is the negative of the average serial covariance of the idiosyncratic component of returns, is determined by stock price reactions to firm-specific information. If stock prices tend to overreact to firm-specific information and then correct the overreaction in the following period, Ω will be negative and will thus contribute to contrarian profits. The last term in Equation (5) is the component of contrarian profits attributable to differences in the timeliness of stock price reactions to common factors. When $\delta_k < 0$, stock price reactions to the kth-factor realizations contribute positively to contrarian profits while the reverse is true if $\delta_k > 0$.

2.3 Lo and MacKinlay decomposition

Lo and MacKinlay (1990) present a different decomposition of contrarian profits, which is described below. They show that

$$\mathrm{E}(\pi_t) = C - O - \sigma_{\mu}^2, \tag{8}$$

where

$$C = \mathrm{E}(\overline{r}_t \overline{r}_{t-1}) - \overline{\mu}^2 - \frac{1}{N^2} \sum_{i=1}^{N} \mathrm{E}(r_{i,t} r_{i,t-1} - \mu_i^2) \tag{9}$$

$$O = \frac{N-1}{N^2} \sum_{i=1}^{N} \mathrm{E}(r_{i,t} r_{i,t-1} - \mu_i^2), \tag{10}$$

and where $\overline{\mu}$ is the expected return on the equally weighted index. In words, C is the average cross-serial covariance, and O is the average autocovariance of raw returns.

Since Equation (8) is a mathematical identity, the sum of the above three components must equal the contrarian profits irrespective of the sources of the cross-serial covariances and autocovariances. However, as we later show, the cross-serial covariance and autocovariance do not in general relate systematic stock price over- or underreactions to contrarian profits. Briefly, this is because any delayed reactions to common factors that give rise to the lead-lag structure will in general affect autocovariances as well as cross-serial covariances.

2.4 Two examples

To illustrate why the average cross-serial covariance and autocovariance given by Equations (9) and (10) cannot in general be related to specific types of stock price reactions, we consider two examples. The first example illustrates the intuition behind the Lo and MacKinlay (1990) decomposition and is similar to Example 2.3 used in their article. The second example illustrates why this intuition fails in the general case. In both examples we assume that stock prices are subject to factor risk, but not firm-specific risk, and that all stocks have the same expected returns so that in these examples the contrarian profits arise solely from the assumed lead-lag structure.

For these illustrative examples assume a single-factor model, that is, $K = 1$. In the first example, stock A, the leading stock, reacts instantaneously to the common factor with assumed factor sensitivities of $b^t_{0,A} = 1$ and $b^t_{1,A} = 0$ for all t. For stock B, the lagging stock, the sensitivities to the contemporaneous and lagged factor realizations are specified as $b^t_{0,B} = 0$ and $b^t_{1,B} = .3$. These parameters imply that $\delta = -.015$, and the average contrarian profit equals $.015\sigma_f^2$, which from Equation (2) equals the average cross-serial covariance.

In the second example, the factor sensitivities of A are the same as in the first example, but the factor sensitivities of B are specified as $b^t_{0,B} = 1.2$ and $b^t_{1,B} = .3$. In other words, B reacts partially to the information in the contemporaneous period and partially with a lag. As in the last example, A leads B, and the average cross-serial covariance is $C = .015\sigma_f^2 > 0$. However, in this example, since $\delta = .015 > 0$, the expected contrarian profit is negative, and equals $-.015\sigma_f^2$. To understand this, note that when the factor realization is high the return of stock B will be higher than the return of stock A, implying that a contrarian strategy will sell B and buy A. Since part of stock B's reaction to the positive factor realization is delayed, its return in the following period will on average be higher than the return of stock A.

In the second example, as in the first, there is only a single source of contrarian profits, the delayed reaction of stock B to the common factor. The Lo and MacKinlay decomposition, however, identifies two distinct sources of contrarian profits based on the autocovariances and cross-serial covariances but attributes only the latter to the lead-lag effect. Since the average autocovariance is positive in the second example, the average cross-serial covariance overestimates the contrarian profit due to the lead-lag effect. As we show in the next subsection, the average cross-serial covariance will in general equal the contribution of the lead-lag relation to contrarian profits only in the cases illustrated by the first example, that is, when some stocks react instantaneously to the common factor while others do not react to common factors contemporaneously, but react completely with a lag.

2.5 Delayed reactions, cross-serial covariances, and autocovariances

This subsection derives the average cross-serial covariances and average serial covariances given the return-generating process described by Equation (1). These derivations allow us to relate the Lo and MacKinlay (1990) decomposition with the decomposition given in Equation (5).

We first examine the average cross-serial covariances using the return generating process described in Equation (1). From Equations (1), (2), and (9), we find

$$C = \sum_{k=1}^{K} \mathrm{E}(\overline{b}_{0,k}^{t}\overline{b}_{1,k}^{t})\sigma_{f_k}^2 - \frac{1}{N^2}\sum_{k=1}^{K} \mathrm{E}\left(\sum_{i=1}^{N} b_{0,i,k}^{t} b_{1,i,k}^{t}\right)\sigma_{f_k}^2. \tag{11}$$

The contrarian profit due to the lead-lag structure in Equation (5) is

$$-\sum_{k=1}^{K} \delta_k \sigma_{f_k}^2 = -\frac{1}{N}\sum_{k=1}^{K} \mathrm{E}\left(\sum_{i=1}^{N} b_{0,i,k}^{t} b_{1,i,k}^{t}\right)\sigma_{f_k}^2 + \sum_{k=1}^{K} \mathrm{E}(\overline{b}_{0,k}^{t}\overline{b}_{1,k}^{t})\sigma_{f_k}^2. \tag{12}$$

A comparison of the above expressions indicates that the contribution of the lead-lag structure to contrarian profits equals the average cross-serial covariance only when the second term in Equation (11) equals the first term in Equation (12). This condition will generally be met only when either $b_{0,i,k}^{t}$ or $b_{1,i,k}^{t}$ equal zero for all stocks. In other words, in general, cross-serial covariances measure the contribution of delayed reactions to contrarian profits only when some stocks react instantaneously to the common factor (for these stocks $b_{0,i,k}^{t} \neq 0$ and $b_{1,i,k}^{t} = 0$), and other stocks exhibit no contemporaneous reaction (not even partially) to the common factor but react with a one-period lag (for these stocks $b_{0,i,k}^{t} = 0$ and $b_{1,i,k}^{t} \neq 0$).

We next examine the average autocovariance. From Equation (10) and the return-generating process given in Equation (1), we get the following expression for the average autocovariance:

$$O = \frac{1}{N}\sum_{k=1}^{K} \mathrm{E}\left(\sum_{i=1}^{N} b_{0,i,k}^{t} b_{1,i,k}^{t}\right)\sigma_{f_k}^2 + \frac{1}{N}\sum_{i=1}^{N} \mathrm{cov}(e_{i,t}, e_{i,t-1}) \tag{13}$$

The overreaction component of contrarian profit Ω given in Equation (6) equals O only if for some stocks $b_{0,i,k}^{t} \neq 0$ and $b_{1,i,k}^{t} = 0$ and for the others if $b_{0,i,k}^{t} = 0$ and $b_{1,i,k}^{t} \neq 0$. When some stocks react to the common factor partly contemporaneously and partly with a delay so that $b_{0,i,k}^{t} > 0$ and $b_{1,i,k}^{t} > 0$, the delayed reaction induces a positive autocovariance in returns. Therefore, delayed reaction at least partly masks the contribution of overreaction to contrarian profits when O is used as a measure of market overreaction.

The crux of the difference between our decomposition and the Lo and MacKinlay decomposition is as follows. Our decomposition allows us to tie down the importance of the different components of contrarian profits to their sources, identified based on how stock prices respond to information. The Lo and MacKinlay decomposition, however, counts the effect of delayed reactions twice; once in the own-autocovariance term and once in the cross-serial covariance term. This double counting in general leads to misleading inferences. For instance, as we have shown, delayed reaction at least partly masks the contribution of overreaction to contrarian profits and hence O is not useful for measuring the profit due to overreaction. Also, in our decomposition, we tie down the contribution of the lead-lag component to its source, which is delayed reactions to common factors.[2]

3. Empirical Tests

This section presents empirical tests that examine stock price reactions to different types of information and their relative importance for contrarian profits. The sample period is 1963 to 1990. All firms traded on the New York Stock Exchange and the American Stock Exchange that had at least 260 consecutive weeks of return data are included in the sample. The 260-week data availability requirement is imposed because we examine autocovariance estimates in some of the tests, and it is well known that these estimates are biased downward in small samples. In addition, stocks with prices below \$1 are also excluded because a large fraction of the price changes of these stocks is due to the bid-ask bounce.[3] On average, there are 1987 firms in the sample each week.

Table 1 reports the average profits of the Lo and MacKinlay (1990) contrarian strategy described in the last section implemented on the

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[2] Considering own- and cross-serial covariances as separate effects could potentially cloud certain other issues as well. For instance, Lo and MacKinlay (1990) observe that the estimates of cross-serial covariances and autocovariances are negatively correlated and conjecture that this occurs "perhaps as a result of co-skewness or kurtosis." The analysis here indicates that this correlation arises because of the functional relation between C and O. To see this, let the expected values of the cross-serial covariances and autocovariances at time t conditional on the factor realizations at time $t-1$ be C_t and O_t, respectively. Given the return generating process Equation (1), C_t and O_t equal

$$C_t = \sum_{k=1}^{K}\left(\bar{b}^t_{0,k}\bar{b}^t_{1,k}f^2_{t-1,k} - \frac{1}{N^2}\sum_{i=1}^{N} b^t_{0,i,k}b^t_{1,i,k}f^2_{t-1,k}\right) \quad \text{and}$$

$$O_t = \sum_{k=1}^{K}\left(\frac{1}{N}\sum_{i=1}^{N}(b^t_{0,i,k}b^t_{1,i,k})f^2_{t-1,k}\right) + \frac{1}{N}\sum_{i=1}^{N}\operatorname{cov}(e_{i,t}, e_{i,t-1}).$$

The second component of C_t becomes arbitrarily small in large samples. The changes in both C_t and O_t are driven by the common factor realizations at time $t-1$. If $b^t_{0,i,k} > 0$ and $b^t_{1,i,k} > 0$ (i.e., if there is partial reaction to the kth-factor), then both C_t and O_t are monotonically increasing functions of $f^2_{t-1,k}$. As a result, C_t and $-O_t$ will be negatively correlated.

[3] Our conclusions are not sensitive to any of these exclusion criteria although the contrarian profits were larger when these conditions were not imposed.

Table 1
Contrarian profits

	Size-sorted subsamples	$\pi \times 10^3$	ψ
Small	1	0.6150	0.0243
		(36.11)	(43.31)
	2	0.3246	0.0150
		(25.76)	(31.04)
Medium	3	0.2261	0.0116
		(20.45)	(24.84)
	4	0.1475	0.0085
		(17.87)	(21.92)
Large	5	0.0839	0.0060
		(16.12)	(19.02)
	All	0.2619	0.0137
		(27.83)	(36.73)
50 size-sorted portfolios		−0.0036	−0.0002
		(−2.04)	(−0.69)

This table presents the estimates of profits to the Lo and MacKinlay (1990) contrarian strategy. π is the average weekly contrarian profit and ψ is the average weekly contrarian profit per dollar long. The contrarian strategy is implemented with the full sample of stocks as well as within size-sorted quintiles. The t-statistics are reported in parentheses. The sample period is 1963 to 1990. The last two rows report the profits and the corresponding t-statistics to the contrarian strategy implemented with 50 size-sorted portfolios.

full sample as well as on five size-sorted subsamples.[4] To put these profits in perspective we also report the profits to a contrarian strategy that normalizes the investments in the long and short positions to $1. With the latter strategy, the average contrarian profit is 1.37 percent *per week* per dollar long for the entire sample and are monotonically related to size; the contrarian profits for the small and large firm subsamples are 2.43 percent and 0.6 percent, respectively.

Table 1 also reports the profits of the contrarian strategy implemented on 50 size-sorted portfolios. As we stated at the outset, if the size-related lead-lag structure is an important source of contrarian profits then we expect this contrarian strategy to be profitable. The average profit of the contrarian strategy implemented on these portfolios, however, is not different from zero (−0.02 percent).[5] This observation implies that the lead-lag structure across size-sorted portfolios cannot be exploited using the contrarian strategy. The contrarian strategy fails in this case because, as we report later, small firms tend to have higher-than-average betas both with respect to contem-

[4] Stocks are assigned to size-sorted subsamples when they first enter the sample.

[5] The average profit for the Lo and MacKinlay (1990) strategy is significantly below zero while the average profit per dollar long is not reliably less than zero. This result is due to the fact that the dollar investment in the long or short side of the Lo and MacKinlay contrarian portfolio is correlated with the rate of return per dollar long.

Table 2
Sensitivities to contemporaneous and lagged value-weighted index returns

	Size-sorted subsamples	$\overline{b}_0$	$\overline{b}_1$	$\hat{\delta}$
Small	1	1.0952	0.2355	−0.0112
	2	1.0899	0.2065	−0.0105
Medium	3	1.0886	0.1712	−0.0071
	4	1.0209	0.1139	−0.0013
Large	5	0.9509	0.0272	0.0019
	All	1.0595	0.1631	−0.0033

This table presents the average estimates of the sensitivities of stock returns to current and lagged value-weighted index (VWI) returns based on the following time-series regression:

$$r_{it} = a_i + b_{0,i} r_{VWI,t} + b_{1,i} r_{VWI,t-1} + e_{i,t},$$

where r_{it} and $r_{VWI,t}$ are the returns on stock i and the VWI, respectively. $\hat{\delta} \equiv \frac{1}{N}\sum_{i=1}^{N}(b_{0,i} - \overline{b}_0)(b_{1,i} - \overline{b}_1)$. These estimates are presented for the full sample and also for five size-sorted subsamples. The sample period is 1963 to 1990.

poraneous and lagged common factor realizations. In other words, contemporaneous and lagged betas are positively correlated for the size-based portfolios so that the lead-lag structure does not increase contrarian profit but actually reduces it.

3.1 A one-factor model

We first present our analysis in the context of a single-factor model. Since the CRSP value-weighted index (VWI) exhibits very little serial correlation (factor innovations are required to be unexpected), it serves as an appropriate proxy for the factor. Previous studies have shown that most of the comovements in stock returns are captured by a single factor [e.g., see Trzcinka (1986)]. In a later section we will generalize our analysis to multiple factors.

We estimate the sensitivities of weekly individual stock returns to contemporaneous and lagged factor returns using the following time-series regression:

$$r_{it} = a_i + b_{0,i} r_{VWI,t} + b_{1,i} r_{VWI,t-1} + e_{i,t}, \tag{14}$$

where $r_{i,t}$ and $r_{VWI,t}$ are the time t returns of security i and the VWI, respectively.

Table 2 presents the average estimates of the slope coefficients in Equation (14) for the entire sample and for size-sorted quintiles. The average contemporaneous beta is 1.0594 and the average lagged beta is .1631. These estimates indicate that, on average, stock prices do not fully react to common factor realizations contemporaneously. Part of the effect of common factors is incorporated into prices with a one-

Table 3
Decomposition of contrarian profits

	Size-sorted subsamples	$-\hat{\delta}\sigma^2_{VWI}$ $\times 10^3$	$-\Omega$ $\times 10^3$	$-\sigma^2_{\mu}$ $\times 10^3$
Small	1	0.0052	0.4814	−0.0061
		[0.008]	[0.783]	[−0.010]
	2	0.0048	0.3546	−0.0056
		[0.015]	[1.092]	[−0.017]
Medium	3	0.0033	0.2606	−0.0036
		[0.015]	[1.153]	[−0.016]
	4	0.0006	0.1645	−0.0037
		[0.004]	[1.115]	[−0.025]
Large	5	-0.0009	0.0932	−0.0014
		[-0.011]	[1.111]	[−0.017]
	All	0.0015	0.2881	−0.0044
		[0.006]	[1.100]	[−0.017]

This table presents estimates of various sources of contrarian profits. $-\hat{\delta}\sigma^2_{VWI}$, $-\Omega$, and $-\sigma^2_{\mu}$ are the estimates of contrarian profits due to the lead-lag structure, overreaction to the firm-specific component of returns and the cross-sectional dispersion of expected returns, respectively. The results are presented for the full sample as well as for five size-sorted subsamples. The numbers within brackets are the ratios of each of these components relative to the contrarian profit (π) reported in Table 1. These ratios do not add up to one due to estimation errors.

week lag. The delayed response is relatively more pronounced for the small firms. The lagged beta for the quintile of the smallest firms is .2350, while that for the quintile of largest firms is close to zero. Since the large firms react almost instantaneously to common factor realizations, while the small firms react with a delay, the large firms lead the small firms, but the reverse is not true.

To examine whether the lead-lag structure in stock returns could potentially contribute to contrarian profits, we examine the cross-sectional covariance of contemporaneous and lagged betas, defined as

$$\hat{\delta} \equiv \frac{1}{N}\sum_{i=1}^{N} \mathrm{E}\{(b_{0,i} - \overline{b}_0)(b_{1,i} - \overline{b}_1)\}. \tag{15}$$

$\hat{\delta}$ defined above provides an estimate of δ defined in Equation (7) under the assumption that the contemporaneous and lagged betas do not vary over time.[6] As reported in Table 2, $\hat{\delta}$ is negative for all size quintiles except the large firm quintile and it is also negative for the full sample, suggesting that the lead-lag structure could potentially contribute to contrarian profits. Our subsequent tests assess the magnitude of this contribution.

[6] Since we use a single-factor model here we omit the factor subscript.

The average autocovariance of the error terms from Equation (14) is $-.2881 \times 10^{-3}$ (see Table 3). The negative autocovariance indicates that a part of stock returns in one week is, on average, reversed the following week. In other words stock prices seem to overreact to firm-specific information.[7] The contrarian profit due to overreaction to firm-specific information, given by Equation (6), is $.2881 \times 10^{-3}$. In comparison, the contrarian profit due to delayed reaction, given by $-\hat{\delta}\sigma^2_{VWI}$, is $-.0015 \times 10^{-3}$, which accounts for less than 1 percent of the total contrarian profits. The effect of the cross-sectional dispersion in average returns (σ^2_μ) on contrarian profits is also small, consistent with the earlier findings of Jegadeesh (1990) and Lo and MacKinlay (1990).

These results suggest that although, on average, stocks react with a delay to common factors, the resulting lead-lag relation contributes little to contrarian profits. Most of the contrarian profits are attributable to market overreaction to firm-specific information. It should be noted, however, that if factor sensitivities change over time, the contribution of the lead-lag structure estimated above is likely to be biased downwards and the contribution of overreaction to firm-specific information is likely to be biased upwards. To illustrate this, consider the example where stock A always reacts instantaneously to the common factor (*i.e.*, $b^t_{0,A} = 1$ and $b^t_{1,A} = 0 \,\forall\, t$) and stock B reacts to the common factor instantaneously half of the time but with a one period lag the other half of the time (*i.e.*, $b^t_{0,B} = 1$ and $b^t_{1,B} = 0$ half the time and $b^t_{0,B} = 0$ and $b^t_{1,B} = 1$ the other half). In this case, the unconditional estimates from Equation (14) will be $b_{0,A} = 1$ and $b_{1,A} = 0$; and $b_{0,B} = .5$ and $b_{1,B} = .5$. From the decomposition in Equation (5), it follows that the contrarian profit due to the lead-lag effect is underestimated by the above procedure by $\frac{3}{16}\sigma^2_f$ and the profit due to overreaction is overestimated by $\frac{1}{8}\sigma^2_f$.

The next subsection provides estimates of the relative contribution of the different sources of contrarian profits, allowing for time-varying factor sensitivities.

3.2 Contrarian profits conditional on lagged factor realizations

Let Equation (1) describe the return generating process. If in addition we assume that the e_{it}s are normally distributed and let $\text{corr}(e_{i,t}, e_{i,t-1}) = \rho, \forall i$, the expected contrarian profit at time t conditional on f_{t-1}

[7] Rosenberg, Reid, and Lanstein (1985) report that a contrarian strategy based on firm-specific component of return yields significant profits.

and each $e_{i,t-1}$, can be shown to be

$$E(\pi_t \mid f_{t-1}, e_{i,t-1}) = \sigma_\mu^2 - \delta_t f_{t-1}^2 - \rho\theta_{t-1}, \tag{16}$$

where

$$\theta_t = \frac{1}{N_t}\sum_{i=1}^{N_t} e_{i,t}^2.$$

Intuitively, this expression captures the fact that if the stock price reactions to factor realizations are important for the profitability of contrarian strategies, then large factor realizations should lead to large contrarian profits. Likewise, if the contrarian profits are related to overreaction to firm-specific-information, then π_t will be larger following periods with large cross-sectional dispersion in the firm-specific components of returns. To measure the contribution of the different components of contrarian profits we estimate the following time-series regression:

$$\pi_t = \alpha_0 + \alpha_1(r_{VWI,t-1} - \bar{r}_{VWI})^2 + \gamma\theta_{t-1} + u_t \tag{17}$$

The estimates of contrarian profits due to delayed reactions to the common factor and to overreaction are given by $\alpha_1\sigma_{VWI}^2$ and $\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$, respectively. This decomposition does not require that $b_{0,i}^t$ and $b_{1,i}^t$ be constant through time. The estimates of the $e_{i,t}$s used to compute θ are estimated from Equation (14). Sampling error and possible changes in factor sensitivities will induce measurement errors in the estimated $e_{i,t}$s, and consequently θ used in Equation (17) will be measured with error. Therefore, the estimate of the contrarian profit due to overreaction obtained from this regression will be biased downwards. Our empirical results, however, indicate that most of the contrarian profit is attributable to overreaction, which suggests that this bias is probably not severe.

Table 4 presents the estimates of Equation (17). The estimates of the slope coefficient, α_1, are significant in the regression on the sample of small firms, but not in the regressions on the samples of the larger firms. For instance, the estimate (t-statistic) of α_1 for the small and large firm quintiles are .07 (8.55) and .002 (.68), respectively. The contrarian profit due to the lead-lag structure is statistically significant for the full sample, but the magnitude is small; only about 3.89 percent of the contrarian profits can be attributed to the lead-lag relation in stock prices, and the point estimate of the contribution due to overreaction to firm-specific component is 105 percent of the contrarian profits. These results indicate that most of the contrarian profits are due to overreaction to the firm-specific component of returns.

Table 4
Decomposition of contrarian profits when factor sensitivities are time varying

	Size-sorted subsamples	α_0 $\times 10^3$	α_1 $\times 10^3$	γ $\times 10^3$	$\alpha_1\sigma^2_{VWI}$ $\times 10^3$	$\gamma\left(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1}\right)$ $\times 10^3$
Small	1	0.0785	70.4662	96.7322	0.0324	0.5046
		(2.74)	(8.55)	(20.11)	[0.052]	[0.820]
	2	−0.0553	10.6151	113.0776	0.0049	0.3753
		(−2.41)	(1.65)	(18.42)	[0.015]	[1.156]
Medium	3	-0.1283	14.5168	137.5992	0.0067	0.3480
		(−6.19)	(2.54)	(18.45)	[0.030]	[1.539]
	4	−0.0876	0.8329	126.4785	0.0004	0.2349
		(- 5.34)	(0.18)	(15.50)	[0.003]	[1.593]
Large	5	-0.0073	2.0219	73.2897	0.0009	0.0903
		(-0.67)	(0.68)	(9.15)	[0.011]	[1.076]
	All	-0.0227	22.1252	99.1765	0.0102	0.2746
		(−1.18)	(4.48)	(15.59)	[0.039]	[1.048]

This table presents a decomposition of the contrarian profits based on the following regression:

$$\pi_t = \alpha_0 + \alpha_1(r_{VWI,t-1} - \overline{r}_{VWI})^2 + \gamma\theta_{t-1} + u_t,$$

where

$$\theta_t = \frac{1}{N_t}\sum_{i=1}^{N_t} e^2_{i,t}.$$

π_t is the contrarian profit, $r_{VWI,t}$ is the return on the value-weighted index, and $e_{i,t}$ is the firm-specific component of return in week t. The estimates of the firm-specific component of returns are obtained from the regression in Table 3. The estimates of contrarian profits due to delayed reactions to the common factor and overreaction to firm-specific information are given by $\alpha_1\sigma^2_{VWI}$ and $\gamma(\frac{1}{T}\sum_{t=1}^{T}\theta_{t-1})$, respectively. The numbers in square brackets are the ratios of each of these components relative to the average contrarian profit (π) presented in Table 1. These ratios do not add up to one due to estimation errors. The results are presented for the full sample as well as for five size-sorted subsamples. The sample period is 1963 to 1990.

3.3 Possible association between factor realization and factor sensitivities

Our assumption that the factor sensitivities $b_{0,i}$ and $b_{1,i}$ are uncorrelated with factor realizations enabled us to obtain a linear relation between the conditional expectation of contrarian profits and squared lagged factor realizations. In a more general setting one may expect the timeliness of stock price reactions to depend on the magnitude of factor realizations. For instance, it is possible that delayed reactions of lagging stocks may be more pronounced following large factor realizations than following small factor realizations. In general, if the timeliness of stock price reactions is correlated with the magnitude of factor realizations then our estimate of the contribution of the lead-lag effect to contrarian profits will be biased.

To examine whether the contribution of the lead-lag effect to contrarian profits depends on the magnitude of lagged factor realizations we divided the observation into two subsamples based on the lagged values of $(r_{VWI} - \bar{r}_{VWI})^2$. Equation (17) was fitted separately within these two subsamples. The contribution of the lead-lag effect to contrarian profits for the low and high lagged factor realization subsamples were 4.6 percent and 4.5 percent, respectively.[8] These results reinforce our conclusion that the relative contribution of the lead-lag effect to contrarian profits is small.

3.4 Nonsynchronous trading and the bid-ask spread

The estimates of the contribution of delayed reactions and overreaction to contrarian profits can be biased due to nonsynchronous trading and bid-ask bounce. To see the effect of nonsynchronous trading, consider the case when stock A generally trades closer to the end of the return measurement interval than stock B. In this case, the measured return for stock B at time t will reflect part of the information in time $t - 1$ return of stock A. Therefore, even if prices reflect all available information at the time stocks are traded, observed returns of A will tend to lead that of B and it may appear that stock B reacts to common factors with a delay. The bid-ask bounce induces negative serial covariance in the firm-specific component of returns and hence will contribute to the overreaction component.

To examine whether our assessment of the importance of delayed reaction and overreaction of stock prices are affected by nonsynchronous trading and the bid-ask bounce, we examined a contrarian strategy where we skip a day between the portfolio formation date and the holding period. Specifically, the portfolio weights are assigned on the basis of Tuesday through Monday returns and the portfolio is held from the following Wednesday through Tuesday.[9] The average contrarian profit of this strategy is also reliably different from zero at $.2045 \times 10^{-3}$ (1.04 percent per dollar long.). The contributions of the lead-lag structure and overreactions to firm-specific information estimated based on Equation (17) are 4 percent and 125 percent, respectively. These results are consistent with the results documented earlier that it is the overreaction to firm-specific information that is

[8] We also estimated the contribution of the lead-lag effect within five subsamples formed based on lagged values of $(r_{VWI} - \bar{r}_{VWI})^2$. The estimates of the contribution of the lead-lag effect varied from −14.74 percent to 5.9 percent within these subsamples. The standard errors of the subsample estimates of α_1 in Equation (17) were, however, large relative to that for the full sample estimates because of the smaller dispersion of $(r_{VWI} - \bar{r}_{VWI})^2$ within each subsample.

[9] Lo and MacKinlay (1990) consider a simple model of nonsynchronous trading and find that in their model unrealistically high levels of nontrading is required to match the observed lead-lag relation. Boudoukh, Richardson, and Whitelaw (1994), however, argue that this model probably underestimates the effect of nonsynchronous trading. The advantage with our approach is that it circumvents potential biases due to nontrading (and also due to bid-ask bounce) without relying on any specific model.

exploited by contrarian strategies and not the delayed reactions to common factors.

An alternate approach to circumvent potential biases in measured contrarian profits due to bid-ask bounce is to compute returns using bid prices rather than transaction prices. The bid prices, unfortunately, are not available in machine-readable form for stocks traded on the NYSE and AMEX, but they are available for stocks traded on the NASDAQ. To examine whether our inference above is sensitive to the method used for circumventing the potential bias due to bid-ask bounce, we examined the profitability of the contrarian strategy implemented with stocks traded on the NASDAQ using returns computed based on bid prices.

The bid price data are obtained from the CRSP NMS database. The bid price data are available on this database from March 1983. The contrarian profits using bid-to-bid returns of NASDAQ stocks is $.422 \times 10^{-3}$ (1.86 percent per dollar long). The average sensitivities to contemporaneous and lagged factor realizations estimated using Equation (14) are .774 and .232, respectively. These estimates indicate that NASDAQ stocks also, on average, react with a delay to the common factor. However, for the NASDAQ stocks $\hat{\delta}$ is .0076, which is of the opposite sign compared with what we obtained for NYSE-AMEX stocks. This indicates that stocks with higher-than-average contemporaneous betas also tend to have higher-than-average lagged betas. Therefore, the delayed reaction to the common factor hurts contrarian profits. The contribution of the delayed reaction to contrarian profits, given by $-\hat{\delta}\sigma^2_{VWI}$, is -1.3 percent. The average serial covariance of the residuals from Equation (14) is $-.423 \times 10^{-3}$, which indicates that virtually all the contrarian profits are attributable to overreaction to the firm-specific component of returns.

3.5 Contrarian profits due to additional factors

Our results so far indicate that the contribution of the lead-lag effects due to delayed reactions to the first factor contributes at most about 4 percent of the contrarian profits. As we showed earlier [see Equation (12)], the contribution of delayed reactions to the remaining $K-1$ common factors to contrarian profits is

$$-\sum_{k=2}^{K} \delta_k \sigma^2_{f_k} = -\frac{1}{N}\sum_{k=2}^{K} \mathrm{E}\left(\sum_{i=1}^{N} b^t_{0,i,k} b^t_{1,i,k}\right)\sigma^2_{f_k} + \sum_{k=2}^{K} \mathrm{E}(\overline{b}^t_{0,k}\overline{b}^t_{1,k})\sigma^2_{f_k}. \tag{18}$$

From Equation (11), the average cross-serial covariance due to delayed reactions to the additional common factors is

$$C_{2,K} = \sum_{k=2}^{K} \mathrm{E}(\overline{b}_{0,k}^{t}\overline{b}_{1,k}^{t})\sigma_{f_k}^2 - \frac{1}{N^2}\sum_{k=2}^{K} \mathrm{E}\left(\sum_{i=1}^{N} b_{0,i,k}^{t} b_{1,i,k}^{t}\right)\sigma_{f_k}^2. \quad (19)$$

The terms in the second summation in Equation (19) become arbitrarily small as the number of assets in the cross-section becomes large. Since we have 1987 firms, on average, in our cross-section, we will ignore this term in the following analysis. We can then substitute $C_{2,K}$ into Equation (18) to yield

$$-\sum_{k=2}^{K} \delta_k \sigma_{f_k}^2 = -\frac{1}{N}\sum_{k=2}^{K} \mathrm{E}\left(\sum_{i=1}^{N} b_{0,i,k}^{t} b_{1,i,k}^{t}\right)\sigma_{f_k}^2 + C_{2,K}. \quad (20)$$

In the case where stocks react either contemporaneously to these $K-1$ common factors with no lagged reaction (i.e., $b_{0,i,k} \neq 0$ and $b_{1,i,k} = 0$) or they fail to react contemporaneously but react fully with a one-period lag (i.e., $b_{0,i,k} = 0$ and $b_{1,i,k} \neq 0$), the first term in the expression above equals zero. Equation (20) thus implies that in this special case the contrarian profits due to the delayed reactions to the last $K-1$ factors is given by $C_{2,K}$, the average cross-serial covariances of the residuals after extracting the first factor. On the other hand, if stocks react partially contemporaneously to the common factors and partially with a delay (i.e., $b_{0,i,k} > 0$ and $b_{1,i,k} > 0$), then as we discussed earlier, the contribution of delayed reaction to contrarian profits will be less than the average cross-serial covariance after extracting the first factor, that is, $-\sum_{k=2}^{K} \delta_k \sigma_{f_k}^2 < C_{2,K}$.

The average cross-serial covariance of the residuals from Equation (17) is .000024. In comparison, the average cross-serial covariance of raw returns is .00011. These estimates indicate that we have removed about 80 percent of the cross-serial covariances by removing the first factor. As discussed above, if stocks do not react partially to any of the common factors except the first, then the cross-serial covariances of the residuals of Equation (17) give an estimate of the contrarian profits due to delayed reactions to these additional factors.

The total contrarian profits is .000262 (see Table 1), which indicates that the upper boundary on contrarian profits due to delayed reaction to the additional factors is $\frac{.000024}{.000262} = 9.16$ percent. This provides an upper boundary on the contrarian profits due to delayed reactions to additional factors. When we add this contribution to the 3.96 percent contribution that is attributable to delayed reaction to the first factor (see Table 4), we get the upper boundary on the contribution of the lead-lag relation as 13.12 percent.

Note, however, that in the likely event that there is partial reaction, the contrarian profit due to this delayed reaction will be significantly smaller. To put these numbers in perspective, note that while the average cross-serial covariance due to delayed reactions to the first factor was four times as large as the cross-serial covariance due to the remaining factors, it contributed only to 3.96 percent of the contrarian profits. Therefore, if the partial reactions to the last $K - 1$ factors are similar to the partial reactions to the first factor we can reasonably expect that these delayed reactions will contribute another 1 percent of the contrarian profits.

4. Conclusion

Recent findings that short-horizon contrarian strategies yield abnormal returns were initially interpreted as evidence of significant stock price overreactions to information [e.g., Jegadeesh (1990) and Lehmann (1990)]. Lo and MacKinlay (1990), however, question this inference and argue that the contrarian profits result mainly from some stocks reacting quicker to information than others. This article separately examines the nature of price reactions to common factors and firm-specific information. We find that stock prices react with a delay to common factors but overreact to firm-specific information. The delayed reactions to common factors give rise to the lead-lag effect in stock returns. While in principle both overreaction and delayed reaction could lead to the profitability of contrarian strategies, our results indicate that the delayed reactions cannot be exploited by contrarian trading strategies. We further show that the primary source of observed contrarian profits is the reversal of the firm-specific component of returns.

The reversal of the firm-specific component of returns has generally been interpreted as corrections of prior overreactions, but other interpretations are also possible. An alternate interpretation which we explore in detail in our companion article, Jegadeesh and Titman (1995), is that the return reversals are caused by price pressure generated by liquidity motivated trades. Under this interpretation, the magnitude of return reversals, and hence the profitability of contrarian strategies, may be expected to decline over time as the liquidity of the market improves. Regardless of the interpretation, the results presented here indicate that return reversals are economically significant and warrant further attention.

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