Essays in Empirical Financial Economics

by

Terence M. Lim

B.S.E., University of Pennsylvania (1988)
B.S., University of Pennsylvania (1988)

Submitted to the Sloan School of Management
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 1998
[June 1998]

Author ....
Sloan School of Management
April 30, 1998

Certified by ....
Andrew W. Lo
Harris and Harris Group Professor
Thesis Supervisor

Accepted by ....
Birger Wernerfelt
Chair, Doctoral Program

Essays in Empirical Financial Economics

by

Terence M. Lim

Submitted to the Sloan School of Management
on April 30, 1998, in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Abstract

This thesis comprises three essays in empirical financial economics.

In chapter one, we test a theory based on gradual information diffusion to explain medium-term momentum in stock returns and establish three key results. First, once one moves past the very smallest stocks the profitability of momentum strategies declines sharply with firm size. Second, holding size fixed, momentum strategies work particularly well among stocks which have low analyst coverage. Finally, the effect of analyst coverage is much more pronounced for stocks that are past losers than for stocks that are past winners.

A central assumption in market microstructure theory is that informed investors attempt to disguise their trades, taking account of the effect of their trades on prices. In chapter two, we examine transactions data for a sample of NYSE tender-offer target firms during the pre-announcement period to test this assumption empirically. We find that the decrease in the adverse selection component of spreads accompanying increased share volume is asymmetric: the declines are smaller for large buyer-initiated trades. Furthermore, buyer-initiated trades are more frequent in small and medium trade sizes, and tend to occur in sequences. Overall, small and medium-sized trades and trade sequences contribute more to overall stock price changes.

In chapter three, we investigate why analysts' forecasts of corporate earnings are optimistically biased. Using a large sample of individual analysts' estimates, we find that the positive bias is robust across time and industries. This bias remains after adjusting for specific factors such as large discretionary accounting charges, stale forecasts, investment banking relationships and newly-initiated forecasts. Empirically, most of the positive forecast bias is associated with earnings estimates of small and volatile companies, or companies who recently experienced negative earnings surprises or stock price returns. Smaller brokerage firms tend to issue more optimistically biased forecasts. These results are consistent with the hypothesis that analysts rationally report biased forecasts to improve management access and forecast precision.

Thesis Supervisor: Andrew W. Lo
Title: Harris and Harris Group Professor

Chapter 1

Introduction

Several recent papers have documented that, at medium-term horizons ranging from three to twelve months, stock returns exhibit momentum--i.e., past winners continue to perform well, and past losers continue to perform poorly. For example, Jegadeesh and Titman (1993), using a U.S. sample of NYSE/AMEX stocks over the period 1965-1989, find that a strategy that buys past six-month winners (stocks in the top performance decile) and shorts past six-month losers (stocks in the bottom performance decile) earns approximately one percent per month over the subsequent six months. Not only is this an economically interesting magnitude, but the result also appears to be robust: Rouwenhorst (1997a) obtains very similar numbers in a sample of 12 European countries over the period 1980-1995.[1]

While the existence of a momentum effect in stock returns does not seem to be too controversial, it is much less clear what might be driving it. Some have suggested a risk-based

[1]Rouwenhorst (1997b) finds that momentum strategies also earn significant profits on average in a sample of 20 emerging markets. See also Haugen and Baker (1996) for confirmatory evidence from the U.S. and several European countries.

interpretation of momentum.[2] This is certainly a logical possibility, although there is little evidence that cuts clearly in favor of a risk story. In this vein, Fama and French (1996) note that momentum effects are not subsumed by their three-factor model.

Turning to "behavioral" (i.e., non-risk-based) explanations, there are a number of theories that can give rise to positive medium-term return autocorrelations. In some of these, prices initially overreact to news about fundamentals, then continue to overreact further for a period of time. The positive-feedback-trader model of DeLong et al (1990) fits in this camp, as does the overconfidence model of Daniel, Hirshleifer and Subrahmanyam (1997). In other models, momentum is a symptom of underreaction--prices adjust too slowly to news.

The set of underreaction theories can be further subdivided according the exact mechanism that is at work. In Barberis, Shleifer and Vishny (1997), there is a representative investor who suffers from a conservatism bias (Edwards 1968), and who does not update his beliefs sufficiently when he observes new public information. In Hong and Stein (1997) the emphasis is instead on heterogeneities across investors, who observe different pieces of private information at different points in time. Hong and Stein make two key assumptions: 1) firm-specific information diffuses gradually across the investing public; and 2) investors are unable to perform the rational-expectations-equilibrium (REE) trick of extracting this information from prices.[3] Taken together, these two assumptions are sufficient to generate underreaction and

[2]Conrad and Kaul (1997) argue that momentum effects simply reflect cross-sectional differences in long-run mean returns. If this is true, it could fit with a risk-based story.

[3]In other words, the focus is on a Walrasian equilibrium with private valuations, not a fully or partially revealing REE as in Grossman (1976) or Grossman and Stiglitz (1980).

positive return autocorrelations.

Our goal in this paper is to test the Hong-Stein version of the underreaction hypothesis. In other words, we look for evidence that momentum reflects the gradual diffusion of firm-specific information.[4] To do so, we begin by sorting stocks into different classes, for which information is a priori more or less likely to spread gradually. The central prediction is then that stocks with slower information diffusion should exhibit more pronounced momentum.[5]

One natural sorting variable--which forms the basis for our first set of tests--is firm size. It seems plausible that information about small firms gets out more slowly; this would happen if, e.g., investors face fixed costs of information acquisition, and hence choose in the aggregate to devote more effort to learning about those stocks in which they can take large positions.

Unfortunately, even if firm size is in fact a useful measure of the rate of information diffusion, it is likely to capture other things as well, potentially confounding our inferences. For example, it is probably also the case that market-making or arbitrage capacity is less in small-cap stocks.[6] On the one hand, if there are supply shocks, this could lead to a greater tendency

[4]A recent paper that can be thought of in a similar spirit is Chan, Jegadeesh and Lakonishok (1996). They show that momentum strategies are profitable even after controlling for post-earnings-announcement drift (Bernard and Thomas 1989, 1990, Bernard 1992). This suggests that momentum at least in part reflects the adjustment of stock prices to the sort of information that (unlike earnings news) is not made publicly available to all investors simultaneously.

[5]To obtain this prediction, we are assuming that smart-money arbitrage does not completely eliminate differences in momentum across stocks. This property holds in a wide range of settings. For example, if there is a pool of arbitrageurs that operate across all stocks, it suffices to assume that they are risk-averse and hence prefer to hold diversified portfolios.

[6]See, e.g., Merton (1987) and Grossman and Miller (1988) for theories in which investor participation or market-making capacity can vary across stocks.

towards reversals (i.e., negatively correlated returns) in small stocks, which would obscure the gradual-information-flow effect we are interested in. On the other hand, one might argue that whatever behavioral phenomenon is driving positive serial correlation in returns, less arbitrage means that it will have a bigger impact in small stocks, leading us to overstate the importance of gradual information flow as the specific mechanism at work. The bottom line is that while it is certainly interesting to see how momentum profits vary with firm size, this probably does not by itself constitute a clean test of our central hypothesis.

As an alternative proxy for the rate of information flow, we consider analyst coverage. The idea here is that stocks with lower analyst coverage should, all else equal, be ones where firm-specific information moves more slowly across the investing public. Thus our second set of tests boils down to checking whether momentum strategies work better in low-analyst-coverage stocks. The one important caveat is that analyst coverage is very strongly correlated with firm size (Bhushan 1989). So in this second set of tests, we control for the influence of size on analyst coverage, by sorting stocks into groups according to their residual analyst coverage, where the residual comes from a regression of coverage on firm size.[7]

To preview, we obtain the predicted results for both firm size and residual analyst coverage. First, with respect to size, once one moves past the very smallest-capitalization stocks

---

[7]Our use of residual analyst coverage as a forecaster of stock returns links us to work by Brennan, Jegadeesh and Swaminathan (1993). They are interested in understanding a higher-frequency phenomenon--the fact that at daily and weekly horizons, small stocks seem to lag large stocks (Lo and MacKinlay 1990). They show that holding fixed size, low-coverage stocks also tend to lag high-coverage stocks, which they interpret as evidence that analysts are important in helping stocks adjust to common information. Note that this is quite different than our story, which focuses on the role of analysts in propagating firm-specific information.

(where thin market-making capacity does indeed appear to be an issue) the profitability of momentum strategies declines sharply with market capitalization. Second, holding size fixed, momentum strategies work particularly well among stocks which have low analyst coverage.

In addition to these two basic findings, we also uncover a third interesting regularity. There is a strong asymmetry, in that the effect of analyst coverage is much more pronounced for stocks that are past losers than for stocks that are past winners. In other words, low-coverage stocks seem to react more sluggishly to bad news than to good news. This makes intuitive sense in the context of a theory based on the flow of firm-specific information. Think of a firm which has no analyst coverage, but which is sitting on good news. To the extent that its managers prefer higher to lower stock prices, they will push the news out the door themselves, via increased disclosures, etc. On the other hand, if the same firm is sitting on bad news, its managers will have much less incentive to bring investors up to date quickly. Thus the marginal contribution of outside analysts in getting the news out is likely to be greater when the news is bad. Our evidence fits very well with this informal story.[8]

The remainder of the paper is organized as follows. In Section 2 we describe our data, and analyze in detail the cross-sectional determinants of analyst coverage. Section 3 contains our main results on momentum strategies sorted by firm size and residual coverage. In Section 4 we present complementary results based on an alternative, much more parametrically structured regression approach. Section 5 concludes.

---

[8]Short-sales constraints may also be part of the explanation for why bad news gets incorporated slowly into prices, though they alone would not seem to explain why this effect is more pronounced when there are fewer analysts.

2. Cross-Sectional Determinants of Analyst Coverage

Our data come from two primary sources. The stock return data is from the CRSP Monthly Stocks Combined File, which includes NYSE, AMEX, and NASDAQ stocks. Throughout, we exclude ADRs, REITs, closed-end funds, and primes and scores.[9] The data on analyst coverage is from the I/B/E/S Historical Summary File, and is available on a monthly basis beginning in 1976. For each stock on CRSP, we set the coverage in any given month equal to the number of I/B/E/S analysts who provide Fiscal Year 1 earnings estimates that month. If no I/B/E/S value is available (i.e., the CRSP cusip is not matched in the I/B/E/S database), we set the coverage equal to zero.

Table 1 provides an overview of the extent of analyst coverage on a year-by-year basis, for both our entire sample (Panel A), as well as for five size-based subsamples. (Panels B-F). The first striking thing that emerges from Panel A is how many firms show up as having zero analysts. This is especially true in the first few years of the sample period, 1976-1978. For example, in 1976, 77.3% of all firms appear as having zero analysts. There is a marked deepening of coverage around 1979, with the fraction of uncovered firms dropping to 57%. After that, things change much more smoothly, with the fraction of uncovered firms declining gradually to 36.9% in 1996.

While the numbers no doubt largely reflect the reality that many firms are simply not covered by analysts, we worry that they may also be somewhat contaminated by measurement

[9]Specifically, we exclude stocks that do not have a CRSP share type code of 10 or 11.

error. It is possible that the I/B/E/S data set is missing information on some firms' analysts. Alternatively, it is possible that I/B/E/S has the data, but has assigned a different cusip number to a firm than CRSP. In this case, we would mistakenly code the CRSP firm as having no analysts. In principle, such measurement error should make our tests err on the side of conservatism--it will be harder to discern significant differences across stocks that we classify as low-coverage vs. high-coverage.[10] Because of this concern, and because the number of zeros is so much higher in the first few years, all the tests that we present below use a sample period that runs from 1980-1996.[11] However, it should be noted that none of our results are materially altered if we instead begin in 1976.

A second key fact that comes out of Table 1 is that for the smallest firms, there is simply no variation in coverage. In particular, Panel B focuses on those firms that are smaller than the 20th percentile NYSE/AMEX firm. As can be seen, almost all of these firms have zero analysts--for example, 82% are uncovered in 1988, which is roughly the midpoint of the sample period we will be using. Consequently, we simply cannot use this part of the population to test any hypotheses having to do with analyst coverage. Hence all our coverage-related tests begin with a subsample that excludes those firms that are below the 20th percentile NYSE/AMEX breakpoint

---

[10]The only way we could go wrong would be if the propensity to mismeasure analyst coverage was somehow related to a stock's intrinsic autocorrelation characteristics, holding fixed its size. It is hard to imagine how this could happen.

[11]For reasons that we explain below, we will typically measure analyst coverage six months before we actually begin to implement our momentum strategies. Since our sample period for measuring returns begins in 1980, we will be using analyst data as far back as 1979.

in any given month.[12] Note that there is much more variation in analyst coverage in the next size class, which runs from the 20th to the 40th percentile of NYSE/AMEX–in 1988, only 41.7% of the firms in this class are uncovered, and a substantial fraction have as many as three or four analysts.

In Table 2, we examine the cross-sectional determinants of analyst coverage. When we actually implement our trading strategies in the next section, we run a separate regression every month to create our measure of residual coverage. Because the regressions look so similar month to month, we only present one set in Table 2 for illustrative purposes, corresponding to December of 1988, which is around the midpoint of our sample period. Again, note that in each case, the regression is only run on those stocks which are larger than the 20th percentile NYSE/AMEX breakpoint in the given month.

The first point to note is that unlike some previous researchers who have run similar regressions (e.g., Bhushan 1989 and Brennan and Hughes 1991) we use as our left-hand side variable log(1+ANALYSTS), rather than the raw number of analysts. We do this because it is crucial for our tests in Section 3 that the residuals from our regressions bear no relationship to firm size. Were we to use the raw number of analysts as the dependent variable instead, there would be a strong tendency for smaller firms to have lower absolute values of the residual.[13]

[12]The cutoff point is around $30 million in market cap as of the midpoint of the sample period, and rises to almost $60 million by 1996.

[13]To see this, suppose that a small firm is only ever likely to have zero, one or two analysts. Thus it is hard to get a residual bigger than two if the regression is run with the raw number of analysts. In contrast, a large firm may have anywhere from, say, 10 to 20 analysts, so the scope for large residuals is much greater.

Even with the log(1+ANALYSTS) specification, of course, we will have to check carefully that our regressions produce residuals with the desired properties, as the underlying relationship may not be a perfectly linear one.

In Model 1, we use OLS, and the only two right-hand side variables are log(SIZE), where SIZE is current market capitalization, and a NASDAQ dummy variable.[14] The size variable is clearly enormously important, generating an R^2 of .61. In Model 2, we add 15 industry dummies to the regression.[15] This has a small effect, raising the R^2 to .63.

In Models 3 and 4, we try adding the firm's book-to-market ratio. We do this because book-to-market is well known to forecast returns (Fama and French 1992, Lakonishok, Shleifer and Vishny 1994) and we want to make sure that any return-predicting power we get out of analyst coverage is not simply capturing a book-to-market effect. As it turns out, the coefficient on book-to-market is positive and significant, but it adds nothing at all to the R^2. Thus it is unlikely that any of the results we report below are driven by anything to do with book-to-market.[16] In Models 5 and 6, we undertake a similar experiment with beta.[17] The coefficient on

[14]The NASDAQ dummy is the only variable whose behavior changes much over the sample period. In earlier years, it is strongly negative, which is why we include it in our baseline model. However, by the late 1980's, it is typically positive, though not always significantly so.

[15]The dummies correspond to the following grouping of two-digit SIC codes: 1) SIC 01-09; 2) SIC 10-14; 3) SIC 15-19; 4) SIC 20-21; 5) SIC 22-23; 6) SIC 24-27; 7) SIC 28-32; 8) SIC 33-34; 9) SIC 35-39; 10) SIC 40-48; 11) SIC 49; 12) SIC 50-52; 13) SIC 53-59; 14) SIC 60-69; and 15) SIC 70-79.

[16]Even if high-coverage stocks do have higher mean returns because they have a higher loading on book-to-market, this cannot explain our central result, namely that high-coverage stocks exhibit less momentum.

[17]Throughout, we calculate beta with the Scholes-Williams (1977) method, using daily returns

beta is positive and strongly significant, and in this case, the R^2 is raised a bit, going from .61 to .63 when we do not use industry dummies.

In Model 7, we add to the industry-dummy specification of Model 2 a number of variables that are considered in Brennan and Hughes (1991): 1/P, where P is the price of a share; the variance of daily returns; and five years' worth of annual lagged returns. Although many of the coefficients are individually significant, the overall impression is that these extra variables are not very important in explaining the variation in coverage–jointly they raise the R^2 from .63 to .65.[18]

Finally, in Model 8, we take the baseline specification of Model 1 and add a turnover measure, defined as the number of shares traded over the prior six months divided by total shares outstanding. (Because turnover numbers may not have the same interpretation in a dealer market, we allow the coefficient on turnover to be different for NASDAQ firms.) Turnover is significantly positively correlated with coverage on all exchanges, and it raises the R^2 somewhat, from .61 to .64. However, with this regression, one needs to be especially careful in attaching any causal interpretation. On the one hand, it is possible that turnover causes coverage: analysts

---

and the value-weighted CRSP index in the prior calendar year. We require that 50% of single-day trade-only returns (computed using closing prices, not bid/ask averages) be available. This is the same approach used by CRSP in its NYSE/AMEX Excess Returns File.

[18]Interestingly, our results call into question the conclusions of Brennan and Hughes (1991), who obtain significant positive coefficients on 1/P. In our regressions, we tend to get the opposite sign. We conjecture that this arises because we are using log(1+ANALYSTS) on the left-hand side, rather than the raw number of analysts. Because 1/P is correlated with firm size, and because firm size is of such dominant importance, any differences in how one models the analyst-size relationship is likely to have a strong influence on the 1/P coefficient.

may be more inclined to follow naturally high-turnover stocks if this makes it easier to generate brokerage commissions for their employers. On the other hand, Brennan and Subrahmanyam (1995) find evidence that some causality runs in the other direction: more analysts reduce the adverse-selection costs of trading, and thereby attract a greater volume of trade.[19] As we argue in Section 3.D below, depending on which story one believes, it may or may not make sense to control for turnover in generating our measure of residual analyst coverage.

Overall, the results in Table 2 make it clear that while a number of other variables are significantly related to analyst coverage, firm size is far and away the dominant factor. Thus in addition to worrying about the influence of these other variables, it is also important to think about potential non-linearities in the relationship between log(1+ANALYSTS) and log(SIZE). In this spirit, we proceed as follows. We start in Section 3.B by using the simple size-based regression in Model 1 as our baseline method of generating residual analyst coverage. Next, in Section 3.C, we rerun all of our tests separately for each of the size classes (except the very smallest) in Table 1. In this case, we will each month be running a separate cross-sectional analyst regression for: firms in the 20th-40th NYSE/AMEX percentiles; firms in the 40th-60th percentiles, etc. Among other things, this approach allows the relationship between log(1+ANALYSTS) and log(SIZE) to take on a piecewise linear form, hopefully correcting any deficiencies that arise from imposing an overly simple linear structure on the entire sample.

In addition, in Section 3.D, we also do sensitivities that take into account the potential for analyst coverage to be correlated with some of the other more significant-looking variables

[19]See also Hayes (1996).

considered in Table 2. For example, we use alternative definitions of residual coverage based on both Model 2, which adds the industry dummies, and Model 8, which adds turnover. And we redo all our tests in terms of beta-adjusted returns, just in case the pronounced relationship between beta and analyst coverage might somehow be affecting the results.

3. Momentum Strategies, Cut Different Ways

3.A Cuts on Raw Size

We begin our analysis of momentum strategies in Table 3. In this table, unlike in any of those that come later, we look at the entire universe of stocks, without dropping those below the 20th NYSE/AMEX percentile. In so doing, we follow the methodology of Jegadeesh and Titman (1993) closely in many respects. In particular, we focus on their preferred six-month/six-month strategy, we couch everything in terms of raw returns, and we equal-weight these returns. But there are also three noteworthy differences. First, our sample period of 1980-1996 is more recent. Second, we do not exclude NASDAQ stocks. And third, our measure of momentum differs from theirs. They sort stocks into ten deciles according to past performance, and then measure the return differential of the most extreme deciles--which they denote by P10-P1. In contrast, we place less emphasis on the tails of the performance distribution. We sort our sample into only three parts based on past performance: P1, which includes the worst-performing 30%; P2 which includes the middle 40%; and P3, which includes the best-performing 30%. Our basic measure of momentum is then P3-P1.[20]

---

[20]This is similar to the measure used by Moskowitz (1997) and Rouwenhorst (1997b).

We use this alternative, broader-based measure of momentum in order to generate better signal-to-noise properties for our key tests. Unlike Jegadeesh and Titman (1993), we are not so much interested in establishing the existence of momentum per se, but in comparing momentum effects across subsamples of stocks. In some cases, we will be looking at as many as 12 subsamples, when we sort by size and residual analyst coverage simultaneously. (See Table 5 below.) If we also were to use ten performance deciles, we would end up chopping the universe of stocks into 120 portfolios, and we would reach a point where some of the individual portfolios are quite undiversified, thereby creating larger standard errors in our test statistics.[21] The first column in Table 3 confirms that there is significant momentum in the full sample: the baseline strategy that buys top-30% (P3) winners and shorts bottom-30% (P1) losers generates 0.53% per month (t-stat = 2.61).[22] The next columns break the momentum effect down by size (measured six months before the start of the ranking period). We use an independent sort to generate ten subsamples, with the breakpoints determined by NYSE/AMEX deciles. Figure 1

[21]In fact, we have redone all our key tests, using the Jegadeesh-Titman P10-P1 momentum measure in place of our P3-P1 measure. As might be expected, the point estimates of interest --i.e., the differences in momentum between low- and high-coverage firms--are typically larger in absolute value. However, the standard errors are also larger, so in many cases the t-statistics turn out to be smaller. This confirms the notion that our P3-P1 measure has better signal-to-noise properties for the particular type of tests we focus on.

[22]This is lower than the Jegadeesh-Titman figure of 0.95% per month. The difference arises for two distinct reasons noted above. First, our strategy invests in stocks with less extreme past performance. And second, it turns out that including the smaller NASDAQ firms substantially damps the results, since as can be seen from Table 3, the momentum measure is actually negative for the very smallest firms. The different sample period is not responsible for the difference in results--when we use an NYSE/AMEX sample and a P10-P1 momentum measure over our sample period, we obtain numbers almost identical to Jegadeesh and Titman.

illustrates the results, plotting the relationship between size and the magnitude of the momentum effect. As can be seen, there is a pronounced, inverted U-shape. In the very smallest stocks (which are tiny, with a mean market capitalization of $7 million) momentum is actually negative. By the second size decile, momentum profits are significantly positive, and they reach a peak in the third size decile, where market capitalization averages about $45 million and where the profits are a striking 1.43% per month (t-stat = 6.66), which is almost three times the value for the sample as a whole. After the third size decile, momentum profits decline monotonically, to the point where they are essentially zero in the largest stocks.[23]

The non-monotonic effect of raw size can be easily understood in the context of the informal theory sketched in the Introduction: smaller firms may have slower information diffusion, which would lead to greater momentum, but they probably also have more limited investor participation (i.e., thinner market-making capacity) which can lead to more pronounced supply-shock-induced reversals.[24] Under this interpretation, the sharp decline in momentum profits that occurs between the third and the tenth size classes is testament to the economic importance of gradual information diffusion in mid-cap stocks.

Another interesting pattern that emerges in Table 3 is that the bulk of the momentum

---

[23]Jegadeesh and Titman also find that momentum profits follow a hump shape with respect to size. (See their Table III, p. 78). But their results are less dramatic, with only small differences across subsamples. This is because they only use three size classes, and exclude NASDAQ firms; much of the interesting variation in size is either blurred or omitted.

[24]Alternatively, it may be that many of the tiniest stocks trade at very low dollar prices, so we are picking up some discreteness-induced negative correlation. Since we do not pay any further attention to this class of stocks in what follows, we do not pursue this possibility.

effect seems to come from losers, as opposed to winners. Consider for example, the column corresponding to the third size class, where as we noted above, the P3-P1 winners-minus-losers measure is 1.43% per month. Of that, 1.05%, or about three-quarters of the total, comes from the difference between average performers and losers, i.e., from P2-P1. As can be seen from the table, this general tendency holds--with remarkable consistency--in every one of the size classes (i.e., deciles two through eight) where there are positive momentum profits to begin with. It suggests that to the extent that stock prices do underreact, they are more prone to underreact to bad news than to good news. We will return to this theme in greater detail below.

3.B Cuts on Residual Analyst Coverage

Next we turn to the cuts based on residual analyst coverage. Here, and in everything else that follows, we exclude all stocks that are below the 20th percentile NYSE/AMEX breakpoint. Again, this is because the vast majority of these small stocks simply never have any analysts, so there is no variation to work with. Within this truncated universe, we create three subsamples based on residual analyst coverage, with the residuals coming from month-by-month cross-sectional regressions of log(1+ANALYSTS) on log(SIZE) and a NASDAQ dummy, just as in Model 1 of Table 2.

In implementing this technique, we choose to measure residual coverage six months before we start our preformation ranking period.[25] We use slightly "stale" data on analyst

[25]Concretely, our first month's worth of observations has the following timing: 1) we measure residual coverage based on a regression using data as of January 1979; 2) in an independent sort, we rank stocks on their performance in the six months from June 30, 1979 to December 31, 1979

coverage in order to address a possible endogeneity concern. McNichols and O'Brien (1996) find that analysts are more likely to begin covering firms when they are optimistic about their near-term prospects. When one combines this finding with Womack's (1996) evidence that there is stock price drift for up to six months in response to analyst recommendations, it raises the possibility that recent innovations in analyst coverage may be informative about future returns. Although we have no reason to expect that this form of endogeneity would bias any of our key tests one way or another, we adopt the stale data approach as a simple precaution. Intuitively, any patterns that we now find will be driven by the permanent component of coverage, and not by recent (and possibly return-predicting) innovations in coverage.[26]

Table 4 presents the results of this approach. Before getting to the returns for the three subsamples, it is important to check that they have the desired characteristics with respect to size and coverage. Ideally, the subsamples will contain stocks of the same size, yet will display a healthy spread in coverage. As can be seen from the table, the variation in coverage is certainly there. The low-coverage subsample, which we denote by SUB1, has median coverage of 0.1 (mean of 1.5) and the high-coverage subsample SUB3 has median coverage of 7.6 (mean of 9.7).[27] We do a little less well in terms of size matching. SUB1 has a somewhat larger mean size than SUB3 ($962 million vs. $455 million) and at the same time a smaller median size ($103

---

and assign them to either P1, P2 or P3; and 3) we then calculate the realized returns for the coverage/past-performance portfolios over the next six months, which run until June 30, 1980.

[26]These caveats notwithstanding, our results seem very insensitive to exactly when we measure analyst coverage. We have experimented with measuring it zero, twelve and eighteen months prior to our ranking period, and in each case we obtain very similar results.

million vs. $180 million). Evidently, due to non-linearities in the analyst-size relationship, the simple linear regression technique is giving us residuals that do not have exactly the same size distribution across the three subsamples.[28] We will attempt to remedy this deficiency shortly, in Table 5. For the moment, it suffices to say that the imperfect size matching in Table 4 does not color any of the conclusions.

Turning to the returns numbers, two patterns emerge that hold up throughout our subsequent analysis. First, as predicted by the theory, there is more momentum in stocks with low residual coverage. The P3-P1 momentum measure is 1.13% per month in the low-residual-coverage subsample SUB1, and only 0.72% per month in the high-residual-coverage subsample SUB3.[29] The difference of 0.42% between SUB1 and SUB3 in this regard is highly statistically significant, with a t-stat of 3.50. Moreover, the economic magnitude is clearly important--momentum profits are roughly 60% higher in SUB1 than in SUB3.

The second key finding is that the effect of residual coverage on the P3-P1 momentum measure is entirely driven by what happens in the loser stocks in P1.[30] P1/SUB1 stocks

---

[27]The "medians" are not integers because they are time-series means of monthly medians.

[28]What seems to be going on is this: after a point, the number of analysts simply maxes out, and no longer increases with size. Thus with a linear model, the very largest firms--the Intel's and GM's of the world--tend to show up as having abnormally low coverage relative to their size, thereby landing in SUB1. This pushes the mean size in SUB1 up relative to that in SUB3.

[29]For the full sample in Table 4, the P3-P1 value is 0.94% per month. This is higher than in Table 3 because we have now dropped the smallest firms, which as seen above, have negative momentum.

[30]Indeed, the numbers in P3 go slightly the "wrong way"--low-coverage winners show a bit <u>worse</u> continuing performance than high-coverage winners. Although this difference between P3/SUB1 and P3/SUB3 is statistically significant in Table 4, it, much more so than our other

underperform P1/SUB3 stocks by 0.70% per month. This difference is also highly significant, with a t-stat of 5.16. In other words, one attractive strategy, which we call the "loser-analyst-spread trade", or "LAST" strategy, is simply to buy the stocks in P1/SUB3 and short those in P1/SUB1, without ever dealing with any of the winner stocks in P3. This strategy is not only size-neutral, it is also (unlike the Jegadeesh-Titman strategy) momentum-neutral. So to the extent that anybody ever makes an argument that momentum returns are proxying for a risk factor, our LAST strategy earns 0.70% per month with no loading on that risk factor.[31]

Taken together, these two patterns suggest that analyst coverage is especially important in propagating bad news. This ties together nicely with our earlier finding that the bulk of momentum profits seem to come from loser stocks. And as we noted in the Introduction, it also makes intuitive economic sense. When firms are sitting on good news, managers probably have every incentive to push this news out to investors as fast as possible, which makes analysts less important. In contrast, when there is bad news, managers are likely to be less forthcoming, so outside analysts have a more crucial role to play.

3.C Two-Way Cuts on Size and Residual Coverage

In Table 5, we disaggregate the analysis of Table 4 by size. The methodology is exactly

---

results, appears to be fragile. For example, it totally disappears when we work with beta-adjusted returns in Table 6 below. To the extent that there is a premium for beta our sample period, this should not be surprising, since as we saw in Table 2, low coverage is associated with lower values of beta. In fact, the median beta in SUB1 is .75, vs. .95 in SUB3.

[31]See below for a discussion of whether the LAST strategy is significantly exposed to other risk factors, such as beta, industry factors, or book-to-market.

the same except we look at four separate subsamples. The first includes all stocks between the 20th and 40th NYSE/AMEX percentiles, the second includes those between the 40th and 60th percentiles, and so forth. We have two motivations for doing this disaggregation. First, as a matter of economics, it seems reasonable to conjecture that the marginal importance of coverage will be greater in the smaller stocks, which have fewer analysts on average, and are probably less well-researched in other ways. Second, as a matter of methodology, this approach should give us better size matches across residual coverage classes, since we now will be running the analyst coverage regressions separately for each size-based subsample. Compared to our earlier approach, this is like allowing the analyst-size relationship to be piecewise linear.

As can be seen from the table, the size matching is now almost flawless, except for in the largest class of stocks. Consider first the results for the smallest size class, that corresponding to the 20th-40th percentile range. The mean size is $63 million in SUB1, vs. $64 million in SUB3. (The medians are $59 and $61 million respectively.) Yet we still have a good spread in coverage, with a mean of 0.0 analysts in SUB1 and 3.7 analysts in SUB3. And the basic results from Table 4 carry over. The P3-P1 momentum measure is 1.51% per month in SUB1, and 1.15% per month in SUB3. The difference of 0.36% is statistically significant, (t-stat of 2.13) even though the standard errors are quite a bit higher with the smaller sample.

As we move to progressively larger size classes, two things happen. First, the overall momentum effect shrinks, just as in Table 3. Second, the differential in momentum between SUB1 and SUB3 shrinks also, consistent with the hypothesis that the marginal importance of analysts should decline with size. In the next size class, covering the 40th-60th percentile range

--in which stocks average around \$200 million in market capitalization--the SUB3-SUB1 momentum differential is not much smaller, at 0.33% (t = 1.95). But by the time we get to the 60th-80th percentile range--with mean size of close to \$700 million--the differential is down to 0.18% (t = 1.18). And it is essentially zero for the largest size class.

Overall, the size disaggregation effort in Table 5 lends further credence to our interpretation of the evidence. It makes it clear that the earlier numbers in Table 4 are not an artifact of imperfect size matching in the full sample. And it is comforting to know that analyst coverage has more of an impact on momentum in precisely those parts of the size distribution where one a priori suspects that gradual information diffusion is likely to be important and where momentum effects are most pronounced to begin with.

Table 5 also helps put into perspective the extent to which firm size and residual coverage might each be capturing something related to the phenomenon of gradual information flow. On the one hand, it is natural to focus most of the attention on residual coverage as a proxy for this phenomenon--it makes for a cleaner test of our hypothesis because it is less likely than size to be bringing in other confounding factors. But in gauging the quantitative significance of the results, it is important to recognize that, if we hold size fixed, we cannot hope to capture the full magnitude of any gradual-information-flow effect.

To be specific, return to the results for the smallest set of firms in Table 5--those in the 20th-40th percentile range. Among these firms, those with the fewest analysts have momentum of 1.51% per month; those with the most analysts have momentum of 1.15% per month. While the difference of 0.36% is good-sized, it is still just a fraction of the total momentum effect. One reading of this might be that gradual information diffusion can only "explain" a fraction of the overall momentum in stock returns. However, such an inference is at best superficial. Recall that even the most heavily-covered stocks in this class have only three or four analysts, and only average $60 million in market cap. Thus they might naturally be expected to have slower information diffusion than, say, a $10 billion company with 25 analysts. The bottom line is that residual analyst coverage, viewed in isolation, is unlikely to provide a full picture of the importance of gradual information flow. This is where the cuts on raw size in Tables 3 and 5 add potentially useful evidence.

3.D Sensitivities

In Tables 6-9, we redo the analysis of Table 4, using a variety of alternative specifications. First, in Table 6, we depart from Jegadeesh and Titman's (1993) focus on raw returns. Given that our economic story is all about firm-specific information, it seems sensible to focus on returns adjusted for any market-wide factors. In Table 6 all the returns--both in the pre-formation and post-formation periods--are market-model adjusted, using individual stock betas.[32] As can be seen, the use of this beta adjustment does not significantly alter our central results. The P3-P1 momentum measure for the entire sample actually rises somewhat, to 1.20% per month (it was 0.94% in Table 4), and the difference between the low-coverage SUB1 and the high-coverage SUB3 also goes up a bit, to 0.49%, with a t-stat of 4.04 (it was 0.42% in Table

[32]This is also a useful precaution since, as was seen in Table 2, analyst coverage is correlated with beta.

4). Finally, the LAST strategy, which is long P1/SUB3 and short P1/SUB1, continues to do well–though not quite as well as before–generating an average beta-adjusted return of 0.50% per month (t-stat = 3.64).

In Table 7, we go back to using raw returns, but we now generate the coverage residuals from Model 2 of Table 2, which includes the 15 industry dummies. As can be seen, the results are not much changed. The difference in P3-P1 momentum between SUB1 and SUB3 falls slightly, to 0.33% per month, but is still strongly significant, with a t-stat of 3.06. As for our LAST strategy which operates only in P1, it now generates a monthly return of 0.60% (t-stat = 5.03). Note that given the combined results in Tables 6 and 7, it appears that one can design a profitable LAST strategy that is not only size-neutral and momentum-neutral, but beta-neutral as well as neutral to any industry factors. This makes it all the more improbable that one can explain the substantial returns to this strategy based on any kind of risk story.[33]

However, a final caveat on this point is that we have not checked whether the profits to the LAST strategy continue to be large after controlling for book-to-market effects. One might think that this correction would be relevant in light of the evidence in Table 2 that analyst coverage is positively correlated with book-to-market. As it turns out, though, the differences in book-to-market across SUB1 and SUB3 are too small to matter much. Using our Model 1 residuals, the median value of book-to-market is .57 in SUB1 and .69 in SUB3 (the means are .67 and .78 respectively). Based on the evidence in Fama and French (1992), this book-to-

[33]Moskowitz (1997) argues that momentum effects are in part explained by industry factors. Whether or not this is correct <u>on average</u>, Table 7 suggests that our results about <u>cross-sectional differences</u> in the power of momentum strategies are not driven by industry factors.

market spread corresponds to a return differential of roughly 0.10% per month, only a small fraction of the profits to our LAST strategy.[34]

In Table 8, we again use raw returns, and this time generate the coverage residuals from Model 8 of Table 2, which includes the turnover variables. But before turning to the numbers, we should point out that it is far from clear that it makes economic sense to control for turnover in this way. As noted above, it may well be that the positive correlation of coverage and turnover reflects causality running from the former to the latter: high-coverage stocks have lower adverse-selection costs of trading, and hence attract more trading volume (Brennan and Subrahmanyam 1995). To the extent that this story is true, we should not use Model 8 to generate our residuals--we will just be reducing the exogenous variation in coverage by regressing it on a noisy proxy for itself, thereby weakening the power of our tests.

On the other hand, there are other stories, according to which it is more sensible to use Model 8. To take a simple example, one might argue that our basic measure of firm size is misleading, because for some stocks, the "float" (i.e., those shares that trade on a regular basis in the public market) is much smaller than the market cap. And it is possible that both analyst coverage, as well as costs of arbitrage, are driven primarily by float, rather than by market cap. In this setting, a turnover control--presumably a good proxy for float--would be warranted.

Overall, this discussion suggests that by using a turnover control as in Table 8, we are

---

[34]See their Table IV (pp. 442-443), which covers the period 1963-1990. Our SUB1 and SUB3 median values of book-to-market correspond roughly to the fourth and fifth deciles of their book-to-market distribution, respectively. On average, for each decile one moves between the second and the ninth, there is a 0.10% per month return increment.

erring on the side of being too conservative--the control may or may not make economic sense, and it potentially wastes some statistical power. We also end up sacrificing further power because of two data limitations: 1) we can only run the turnover-adjusted tests for the shorter sample period 1984-1996, due to a lack of earlier turnover data on NASDAQ; and 2) we also lose roughly 12% of the firms--typically among the smaller ones--from our Table 4 sample because of the requirement that turnover numbers be available for six months prior to the measurement of analyst coverage. With all these flags in mind, the results in Table 8 are surprisingly strong. The difference in P3-P1 momentum between SUB1 and SUB3 falls slightly relative to Table 4, to 0.31% per month, but even with the shorter sample it is still significant, with a t-stat of 2.23. The return to the LAST strategy is now 0.56% per month, with a t-stat of 3.58. The bottom line is that our results appear to be robust, even to this (possibly ill-conceived) control for the correlation between turnover and analyst coverage.

In Table 9, we do everything else the same as in Table 4, except that we skip a month between the six-month ranking period and the six-month investment holding period. Jegadeesh and Titman (1993) suggest this approach as a way to check that neither bid-ask bounce nor any other high-frequency phenomenon is coloring any of the results. As it turns out, nothing changes--the numbers are almost identical to those in Table 4.

Finally, in Table 10, we break our sample into three subperiods: 1980-1984; 1985-1990; and 1991-1996. We then exactly repeat our baseline analysis from Table 4 for each subperiod. Our principal results hold up well to this time disaggregation. The P3-P1 momentum measure is meaningfully larger for the low-coverage SUB1 in each of the three subperiods: the difference between SUB1 and SUB3 bounces around from 0.65% to 0.31%. Even more impressively, the LAST strategy earns positive and statistically significant returns in each of the three subperiods.

In fact, the only surprise in Table 10 is that there appears to be little momentum on average in the last subperiod, which runs from 1991-1996. The overall point estimate for P3-P1 over this period is only 0.33%, compared to values of 1.14% and 1.38% for the first two subperiods respectively. It is hard to say whether this reflects just noise in a short sample, or the fact that more arbitrageurs have caught on to momentum effects and are beginning to drive them out of existence.[35] In any case, what is noteworthy from our perspective is that while the average degree of momentum may be declining over time, there is not yet any evidence that the cross-sectional differences in momentum that we are emphasizing have begun to disappear.

3.E Cumulative Returns in Event Time

We have focused throughout on the six-month/six-month strategy, because it has become a standard benchmark for evaluating momentum strategies. But of course this is somewhat arbitrary. To provide more information, Figure 2 plots cumulative returns in event time. In so doing, we use the methodology of Table 6--we assign stocks to performance categories based on six months' prior beta-adjusted returns, and do an independent sort based on the analyst-coverage residuals from Model 1. We then track cumulative beta-adjusted returns on a month-by-month basis, out to 36 months.

[35]Alternatively--and in the spirit of our basic story--one might speculate that increased analyst coverage in the latter part of the sample is partially responsible for the decline in momentum.

In Panel A, we plot the cumulative returns to the P3-P1 momentum strategy separately for the low-coverage subsample SUB1 and the high-coverage subsample SUB3. There appear to be two distinct things going on. First, up to about the ten-month mark, we see roughly a linear extrapolation of our earlier results: momentum strategies continue to earn incremental monthly profits in both SUB3 and SUB1, but the effect is stronger in SUB1, so that the cumulative differential keeps on widening. After this point, something else quite interesting happens. The cumulative performance of the high-coverage subsample SUB3 flattens out--in other words, there is no more momentum left after ten months for the high-coverage stocks.[36] But the low-coverage subsample SUB1 continues to display some momentum out to about the two-year mark. Consequently, the cumulative differential between SUB1 and SUB3 keeps on growing until this point. Twenty-four months after portfolio formation, the total P3-P1 profit for SUB1 is 19.63%, vs. 8.90% for SUB3, a difference of 10.73%.

This dynamic pattern is, of course, completely consistent with the theory of gradual information diffusion that we have been emphasizing. In the context of this theory one would interpret Figure 1A as follows: high-coverage SUB3 firms underreact by roughly 9% to the information contained in lagged six-month returns, and it takes them a little less than a year to fully catch up. In contrast, low-coverage SUB1 firms underreact by more, on the order of 20%. Their adjustment to long-run equilibrium not only involves more movement in the first year, but also requires a longer period of time to fully play itself out.

---

[36]This is similar to Jegadeesh and Titman's finding that momentum effects die out after about twelve months.

In Panel B, we explore the dynamics of our LAST strategy. Focusing only on the past-loser stocks in P1, we plot the cumulative returns for P1/SUB1, P1/SUB3, and the LAST portfolio that is short the former and long the latter. The time profile that emerges is almost identical to that in Panel A, and is consistent with our earlier conclusion that virtually all of the SUB1 vs. SUB3 action is coming from the losers in P1. In particular, the high-coverage P1/SUB3 stocks continue to perform poorly for about ten months, and then flatten out. The low-coverage P1/SUB1 stocks not only perform worse over the first ten months, but continue to do poorly until about two years out. Consequently, the LAST strategy keeps on earning incremental profits up to the two-year mark, with the cumulated profit amounting to 9.32%.

4. An Alternative, More Tightly Structured Regression Approach

In this section, we take a somewhat different approach to measuring the same basic phenomenon. In the most general terms, our central hypothesis is that stocks which are small and which have low residual analyst coverage should display more positively autocorrelated returns at medium horizons. A simple (perhaps naive) way to test this would be to estimate a serial correlation coefficient for each stock, and then regress this serial correlation coefficient on measures of the stock's analyst coverage and size.

This is what we attempt to do now. More precisely, at the beginning of each year t, we collect all stocks which have a market capitalization greater than the 20th percentile NYSE/AMEX breakpoint, and for which we have complete return data through year t+5. We then estimate for each stock i the serial correlation of its six-month excess returns (relative to Tbills), using 49 overlapping observations over the five-year period from t to t+5, and call this variable RHO_{it}.[37] Next, we perform a cross-sectional regression, running RHO_{it} against $\log(1+ANALYSTS_{it})$ and $\log(SIZE_{it})$, as well as a NASDAQ dummy variable.[38]

We should note one caveat associated with this method. For any stock i, our measure of serial correlation RHO_{it} is affected not only by the correlation of its firm-specific information, but also by its loading on any common factors. To see this, suppose the returns on stock i, r_{it}, are given by a one-factor model (suppressing constants):

$$r_{it} = b_i m_t + e_{it} \qquad (1)$$

where m_t is the common factor, b_i is the loading on this factor, and e_{it} represents firm-specific information. Even if we assume for simplicity that the common factor is serially uncorrelated, ($\text{cov}(m_t, m_{t-1}) = 0$) a regression of r_{it} on r_{it-1} produces the following theoretical coefficient ρ_i^*:

$$\rho_i^* = \text{cov}(e_{it}, e_{it-1})/(b_i^2 \text{var}(m_t) + \text{var}(e_{it})) \qquad (2)$$

---

[37]It is well known that in a small sample, one obtains downward-biased measures of serial correlation. Kendall (1954) shows that the bias is given by $-(1+3\rho)/T$, where ρ is the true value and T is the number of independent observations. This does not affect the conclusions from our cross-sectional regressions, however. We could easily rescale all our estimates of RHO_{it} to de-bias them, and none of our regression t-statistics would change.

[38]All the right-hand-side variables are measured at the start of year t, so one can think of this regression as an attempt to forecast stock i's serial correlation over the next five years.

This suggests that, all else equal, our constructed left-hand side variable RHO_{it} will be lower for stocks with higher factor loadings--i.e., higher betas. This is potentially a matter of concern because as we have seen in Table 2, there is a positive cross-sectional correlation between beta and analyst coverage. Thus one might mistakenly conclude that high coverage is reducing RHO_{it} by reducing the serial correlation of firm-specific information, when in fact it is proxying for a beta effect. In order to address this issue, we have rerun the regressions that we present below, adding firm betas to the right-hand side. As it turns out, none of our results is materially altered.[39]

Before turning to these results, it is useful to discuss how this general approach compares to what we have done above. The main difference is that it imposes more parametric structure, some of which may be unwarranted. For example, the regression approach we are now proposing does not allow for asymmetries across winners and losers; yet we have seen that such asymmetries are pronounced in the data. In addition, the regression approach only makes sense if residual analyst coverage is a firm-level attribute that is "quasi-fixed"--i.e., that does not vary much over five-year periods of time. If there is significant high-frequency variation in residual coverage, this is again something that the less structured method of the previous section will be better equipped to handle.

The offsetting advantage is that if the parametric structure we impose with the regression is not too inappropriate, our statistical power along certain dimensions should be enhanced. In

---

[39]For example, when we add beta to the regression, the coefficient on the coverage term reported in Panel A of Table 10 below does indeed drop in absolute magnitude, as predicted, but only by about 12% of its value--an economically and statistically insignificant change.

particular, if we are interested in doing the analysis over very short intervals of time--e.g., to check the stability of our estimates--the regression approach may be especially useful.

Table 11 summarizes the results. In Panel A, we present the coefficients on the coverage and size variables from cross-sectional regressions run each year over the 14 years 1979-1992.[40] We also aggregate the annual information in two different ways. First, we calculate Fama-MacBeth (1973) time-series averages of the coefficients. Second, we run a giant pooled regression with year dummies. Not surprisingly, this latter approach tends to produce point estimates almost identical to the Fama-MacBeth method, but higher t-statistics.

All the evidence in Panel A points to a consistent negative effect of analyst coverage on a stock's serial correlation. Of the yearly coefficients, 13 out 14 are negative, the majority significantly so. The Fama-MacBeth and pooled estimates are strongly significant. The point estimates for size are also negative, but statistically insignificant.

In Panel B, we modify the specification by adding an interaction term, given by log(1+ANALYSTS)*log(SIZE). This is motivated by our evidence in Table 5 that the importance of analyst coverage is decreasing in firm size. The cross-sectional regressions bear out this finding. The coverage and size terms increase in magnitude relative to Panel A (the size term is now statistically significant) and the interaction term is positive, as expected, implying that the negative influence of coverage on serial correlation becomes weaker for larger firms.

It is interesting to compare the economic magnitudes implied by Table 11 to those in our

[40]We have to stop in 1992 because we need to go five years forward from that point to calculate RHO_{it}.

earlier tables. Think of two equal-sized firms, one with the SUB1 median coverage of 0.1 (from Table 4), the other with the SUB3 median coverage of 7.6. According to the Fama-MacBeth coverage-term estimate of -0.0125 in Panel A of Table 11, the SUB1 firm should have a serial correlation coefficient that is .026 higher than that of the SUB3 firm. (.0125x(log(8.6)-log(1.1)) = .026) When one combines this with the observation that the past return differential between P1 and P3 stocks is approximately 60%, this implies that a P3-P1 momentum strategy should be expected to return 1.56% more over six months for the SUB1 firm, (.026x60% = 1.56%), or about 0.25% per month extra. This is very much in the same ballpark as--albeit a bit smaller than--the SUB1/SUB3 differential of 0.42% per month reported in Table 4.

A similar calculation based on the interactive specification in Panel B can be used to back out the implied momentum differentials for firms in varying size classes. For example, consider the smallest class of firms (those between the 20th and 40th NYSE/AMEX percentiles) in the first column of Table 5, which have a mean market cap of around $60 million. Comparing a SUB1 firm in this class with median coverage of 0.0 to a SUB3 firm with median coverage of 3.1, the Fama-MacBeth coefficients in Panel B imply that a momentum strategy will return 3.91% more over six months for the SUB1 firm, or roughly 0.60% per month extra. This is again roughly in line with--although in this case somewhat larger than--the analogous number of 0.36% reported in Table 5.

Overall then, Table 11 provides further comfort as to the robustness of our central results. Even with a very different measurement approach, we get not only the same qualitative outcome--higher six-month return autocorrelations among lower-coverage stocks--but remarkably comparable economic magnitudes.

5. Conclusions

Recently, a number of researchers--e.g., Barberis, Shleifer and Vishny (1997), Daniel, Hirshleifer and Subrahmanyam (1997), and Hong and Stein (1997)--have begun to develop behavioral models that aim to unify a range of previously documented "anomalies" in asset returns. In a critique of this work, Fama (1997) argues that one should not be too impressed if these models simply rationalize those existing patterns that they were specifically designed to capture. Rather, the acid test should be the "out-of-sample" one: the ability to generate new hypotheses that are ultimately borne out in future empirical work: "The over-riding question should always be: does the new model produce coherent rejectable predictions..." (p. 10)

We agree wholeheartedly with this sentiment, and this paper represents an attempt to take one step in the indicated direction.[41] The gradual-information-diffusion model of Hong and Stein (1997) was built for the express purpose of delivering both medium-term momentum and long-term reversals in stock returns; in the spirit of Fama (1997), then, it should be evaluated more on the basis of other, previously untested auxilliary predictions. Here we have focused on one relatively simple and clear-cut such hypothesis, namely: if momentum comes from gradual information flow, then there should be more momentum in those stocks for which information gets out more slowly.

[41] A recent paper with a similar motivation is Klibanoff, Lamont and Wizman (1997). They test the behavioral hypothesis that investors react more strongly to news that is "salient"--in this case, news about countries that appears on the front page of The New York Times.

Rather than restating all our findings, at this point it suffices to say that they are strongly consistent with the above hypothesis. This is not to claim that alternative interpretations of some or all of the evidence cannot be put forth. If concrete alternatives are in fact offered, it will be necessary to do more refined testing to sort things out. But in any case, we hope that this effort has demonstrated at least one point: non-classical models of asset pricing can do more than just provide ex-post rationalizations of existing anomalies; they can--and should--be subject to the same standards of out-of-sample empirical testing as more traditional theories.

References

Barberis, Nicholas, Andrei Shleifer and Robert Vishny 1997. "A Model of Investor Sentiment," University of Chicago working paper, forthcoming in Journal of Financial Economics.

Bernard, Victor L. 1992. "Stock Price Reactions to Earnings Announcements," in R. Thaler ed., Advances in Behavioral Finance, Russell Sage Foundation, New York.

Bernard, Victor L. and J. Thomas 1989. "Post-Earnings Announcement Drift: Delayed Price Response or Risk Premium?" Journal of Accounting Research, Supplement 27: 1-48.

Bernard, Victor L. and J. Thomas 1990. "Evidence that Stock Prices do not Fully Reflect the Implications of Current Earnings for Future Earnings," Journal of Accounting and Economics 13: 305-340.

Bhushan, Ravi 1989. "Firm Characteristics and Analyst Following," Journal of Accounting and Economics 11: 255-274.

Brennan, Michael J. and Patricia Hughes 1991. "Stock Prices and the Supply of Information," Journal of Finance 46: 1655-1691.

Brennan, Michael J., Narasimhan Jegadeesh and Bhaskaran Swaminathan 1993. "Investment Analysis and the Adjustment of Stock Prices to Common Information," Review of Financial Studies 6: 799-824.

Brennan, Michael J. and Avanidhar Subrahmanyam 1995. "Investment Analysis and Price Formation in Securities Markets," Journal of Financial Economics 38: 361-381.

Chan, Louis K.C., Narasimhan Jegadeesh and Josef Lakonishok 1996. "Momentum Strategies," Journal of Finance 51: 1681-1713.

Conrad, Jennifer and Gautam Kaul 1997. "An Anatomy of Trading Strategies," University of Michigan working paper.

Daniel, Kent D., David Hirshleifer and Avanidhar Subrahmanyam 1997. "A Theory of Overconfidence, Self-Attribution, and Security Market Under- and Over-reactions," Northwestern University working paper, forthcoming in Journal of Finance.

DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers and Robert Waldmann

1990. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation," Journal of Finance 45: 379-395.

Edwards, W. 1968. "Conservatism in Human Information Processing," in B. Kleinmutz ed., Formal Representation of Human Judgment, New York, John Wiley and Sons.

Fama, Eugene F. 1997. "Market Efficiency, Long-Term Returns, and Behavioral Finance," CRSP working paper #448, University of Chicago.

Fama, Eugene F. and Kenneth R. French 1992. "The Cross-Section of Expected Stock Returns," Journal of Finance 47: 427-465.

Fama, Eugene F. and Kenneth R. French 1996. "Multifactor Explanations of Asset Pricing Anomalies," Journal of Finance 51: 55-84.

Fama, Eugene F. and James D. MacBeth 1973. "Risk, Return and Equilibrium: Empirical Tests," Journal of Political Economy 81: 607-636.

Grossman, Sanford J. 1976. "On the Efficiency of Competitive Stock Markets Where Traders Have Diverse Information," Journal of Finance 31: 573-585.

Grossman, Sanford J. and Merton H. Miller 1988. "Liquidity and Market Structure," Journal of Finance 43: 617-633.

Grossman, Sanford J. and Joseph Stiglitz 1980. "On the Impossibility of Informationally Efficient Markets," American Economic Review 70: 393-408.

Haugen, Robert A. and Nardin L. Baker 1996. "Commonality in the Determinants of Expected Stock Returns," Journal of Financial Economics 41: 401-439.

Hayes, Rachel M. 1996. "The Impact of Trading Commission Incentives on Stock Coverage and Earnings Forecast Decisions by Security Analysts," Stanford GSB thesis.

Hong, Harrison and Jeremy C. Stein 1997. "A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets," NBER working paper 6324.

Jegadeesh, Narasimhan and Sheridan Titman 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," Journal of Finance 48: 65-91.

Kendall, M.C. 1954. "Note on Bias in the Estimation of Autocorrelation," Biometrika 41: 403-404.

Table 1: Descriptive Statistics for Analyst Coverage, 1976-1996

Panel A: All Stocks

				# of Analysts at Coverage Percentiles									
YEAR	No. of Firms	Mean Size (Millions)	Median Size (Millions)	10	20	30	40	50	60	70	80	90	% of firms un-covered
76	4402	183.6	18.7	0	0	0	0	0	0	0	1	4	77.3%
77	4259	199.7	22.3	0	0	0	0	0	0	0	1	4	75.8%
78	4472	176.4	22.7	0	0	0	0	0	0	0	2	5	71.5%
79	4350	208.0	28.2	0	0	0	0	0	1	2	4	8	57.0%
80	4329	248.9	34.6	0	0	0	0	0	1	2	4	9	58.2%
81	4375	286.0	38.1	0	0	0	0	0	1	2	5	10	58.1%
82	4754	249.3	30.3	0	0	0	0	0	1	2	5	11	59.3%
83	4757	304.4	38.5	0	0	0	0	0	1	2	5	12	55.9%
84	5049	332.3	44.4	0	0	0	0	0	1	3	6	12	50.8%
85	5462	330.5	37.1	0	0	0	0	0	1	3	6	12	50.5%
86	5364	387.4	42.5	0	0	0	0	0	1	3	6	14	50.5%
87	5496	475.0	45.9	0	0	0	0	1	2	3	6	14	48.3%
88	5932	402.2	32.6	0	0	0	0	0	1	3	5	12	50.1%
89	5765	457.5	36.0	0	0	0	0	1	1	3	6	13	48.4%
90	5567	500.7	34.5	0	0	0	0	1	2	3	7	13	45.4%
91	5521	520.2	28.2	0	0	0	0	1	2	3	6	13	46.8%
92	5438	672.8	49.8	0	0	0	0	1	2	3	6	13	48.7%
93	5558	741.4	66.8	0	0	0	0	1	2	4	7	13	42.0%
94	5890	802.9	81.1	0	0	0	0	1	3	4	7	13	40.0%
95	6358	735.9	71.2	0	0	0	1	1	2	4	7	12	38.2%
96	6460	978.1	90.8	0	0	0	1	2	3	4	7	12	36.9%

Table 1 (Continued): Descriptive Statistics for Analyst Coverage, 1976-1996

Panel B: Stocks Below 20th Percentile, NYSE/AMEX Breakpoints

				# of Analysts at Coverage Percentiles									
YEAR	No. of Firms	Mean Size (Millions)	Median Size (Millions)	10	20	30	40	50	60	70	80	90	% of firms un-covered
76	1525	4.3	4.1	0	0	0	0	0	0	0	0	0	99.3%
77	1696	6.0	5.3	0	0	0	0	0	0	0	0	0	98.7%
78	1565	5.1	4.8	0	0	0	0	0	0	0	0	0	98.4%
79	1498	6.2	5.6	0	0	0	0	0	0	0	0	0	94.1%
80	1556	7.9	7.0	0	0	0	0	0	0	0	0	0	94.5%
81	1595	8.8	8.0	0	0	0	0	0	0	0	0	0	93.0%
82	1977	8.1	7.2	0	0	0	0	0	0	0	0	0	93.2%
83	1968	9.8	8.6	0	0	0	0	0	0	0	0	0	92.3%
84	2201	12.9	11.0	0	0	0	0	0	0	0	0	1	86.2%
85	2467	10.9	9.0	0	0	0	0	0	0	0	0	1	84.3%
86	2318	11.3	9.2	0	0	0	0	0	0	0	0	1	85.0%
87	2389	12.6	10.5	0	0	0	0	0	0	0	0	1	81.5%
88	2597	9.6	8.3	0	0	0	0	0	0	0	0	1	82.0%
89	2537	10.3	8.7	0	0	0	0	0	0	0	0	1	81.1%
90	2506	9.7	7.9	0	0	0	0	0	0	0	1	2	76.6%
91	2425	7.3	5.8	0	0	0	0	0	0	0	0	1	80.8%
92	2232	11.3	9.3	0	0	0	0	0	0	0	0	1	83.6%
93	2148	15.3	13.3	0	0	0	0	0	0	0	1	1	79.8%
94	2311	20.3	17.3	0	0	0	0	0	0	0	1	2	75.9%
95	2651	19.7	17.7	0	0	0	0	0	0	0	1	2	71.4%
96	2647	23.6	20.4	0	0	0	0	0	0	1	1	2	69.5%

Table 1 (Continued): Descriptive Statistics for Analyst Coverage, 1976-1996

Panel C: Stocks Between 20th and 40th Percentile, NYSE/AMEX Breakpoints

				# of Analysts at Coverage Percentiles									
YEAR	No. of Firms	Mean Size (Millions)	Median Size (Millions)	10	20	30	40	50	60	70	80	90	% of firms un-covered
76	954	15.8	15.0	0	0	0	0	0	0	0	0	0	92.2%
77	882	23.4	22.4	0	0	0	0	0	0	0	0	0	90.6%
78	1013	20.0	19.1	0	0	0	0	0	0	0	0	1	89.8%
79	995	24.5	23.6	0	0	0	0	0	0	1	1	2	66.6%
80	992	32.4	30.5	0	0	0	0	0	0	1	1	2	65.9%
81	1035	37.5	35.3	0	0	0	0	0	0	1	1	3	65.3%
82	1012	35.7	33.9	0	0	0	0	0	0	1	2	3	63.2%
83	1024	45.5	43.2	0	0	0	0	0	1	1	2	3	56.2%
84	1082	57.3	54.8	0	0	0	0	1	1	2	2	4	44.2%
85	1192	54.3	50.9	0	0	0	0	1	1	2	3	4	41.9%
86	1182	56.9	53.4	0	0	0	0	1	1	2	3	4	43.8%
87	1267	63.2	59.5	0	0	0	0	1	2	2	3	5	40.0%
88	1363	45.1	42.5	0	0	0	0	1	1	2	3	4	41.7%
89	1351	52.3	48.3	0	0	0	1	1	1	2	3	5	38.9%
90	1273	52.0	47.6	0	0	0	1	1	2	3	4	6	33.9%
91	1259	43.0	38.8	0	0	0	1	1	2	2	3	5	36.2%
92	1290	65.4	59.7	0	0	0	1	1	2	2	3	4	37.8%
93	1441	79.0	72.6	0	0	0	1	1	2	2	3	4	33.4%
94	1587	101.1	92.8	0	0	1	1	2	2	3	4	5	29.4%
95	1680	98.3	89.6	0	0	1	1	2	2	3	4	5	23.9%
96	1692	121.1	111.6	0	0	1	1	2	3	3	4	5	24.1%

Table 1 (Continued): Descriptive Statistics for Analyst Coverage, 1976-1996

Panel D: Stocks Between 40th and 60th Percentile, NYSE/AMEX Breakpoints

				# of Analysts at Coverage Percentiles									
YEAR	No. of Firms	Mean Size (Millions)	Median Size (Millions)	10	20	30	40	50	60	70	80	90	% of firms un-covered
76	802	42.8	40.6	0	0	0	0	0	0	0	1	2	77.2%
77	704	63.6	60.4	0	0	0	0	0	0	1	1	2	69.3%
78	787	53.7	51.1	0	0	0	0	0	0	1	1	2	62.8%
79	799	67.7	63.1	0	0	0	1	1	2	2	3	4	32.3%
80	763	88.9	82.9	0	0	0	1	2	2	3	4	6	32.5%
81	767	108.8	102.5	0	0	0	1	2	3	4	5	7	33.5%
82	756	99.8	90.9	0	0	0	1	2	3	4	5	7	30.6%
83	787	129.7	123.4	0	0	1	2	3	3	4	5	7	23.6%
84	787	159.2	151.3	0	1	2	2	3	4	5	7	8	15.8%
85	800	158.7	146.3	0	1	2	3	3	4	5	7	9	13.9%
86	842	168.9	159.0	0	1	2	3	4	5	6	8	11	17.6%
87	841	196.5	181.6	0	1	2	3	4	5	6	8	11	15.8%
88	937	147.1	133.3	0	0	1	2	3	4	5	7	9	21.5%
89	892	180.4	164.3	0	1	2	3	4	5	8	8	10	16.4%
90	843	183.2	168.7	0	1	2	3	5	5	7	8	11	14.2%
91	871	165.1	153.2	0	1	2	3	4	5	6	7	9	13.7%
92	913	234.5	215.5	0	1	2	3	4	5	6	7	9	14.9%
93	922	270.0	249.9	1	2	3	4	4	5	6	8	10	9.1%
94	931	341.3	320.6	1	2	3	4	5	6	7	8	11	9.5%
95	922	319.0	293.2	1	2	3	4	5	5	7	8	10	9.4%
96	973	391.8	367.4	1	2	3	4	5	5	6	8	10	8.9%

Table 1 (Continued): Descriptive Statistics for Analyst Coverage, 1976-1996

Panel E: Stocks Between 60th and 80th Percentile, NYSE/AMEX Breakpoints

				# of Analysts at Coverage Percentiles									
YEAR	No. of Firms	Mean Size (Millions)	Median Size (Millions)	10	20	30	40	50	60	70	80	90	% of firms un-covered
76	618	135.8	120.2	0	0	0	0	1	1	2	3	4	48.9%
77	538	191.9	169.8	0	0	0	1	1	2	3	4	6	38.8%
78	618	161.1	149.8	0	0	0	1	2	2	3	4	6	31.1%
79	588	201.9	186.8	0	1	2	3	4	5	6	8	10	16.3%
80	554	263.4	246.4	0	1	3	4	5	6	7	9	11	16.1%
81	533	317.5	293.3	0	2	4	5	7	8	9	10	13	15.2%
82	567	295.7	270.3	0	3	4	6	7	9	10	11	14	12.0%
83	541	388.0	350.1	1	4	5	7	8	9	11	13	15	9.2%
84	550	454.0	430.8	1.5	4	6	7	9	10	11	13	16	7.6%
85	578	484.3	442.3	2	4	6	7	8	10	11	14	16	6.6%
86	608	546.6	490.4	1	4	6	7	9	11	13	15	19	7.7%
87	584	662.7	594.8	2	4	6	8	9	11	13	15	20	7.0%
88	607	554.0	495.8	1	4	6	7	8	10	12	14	17	7.7%
89	573	657.7	596.6	2	5	7	8	10	11	13	15	19	6.1%
90	546	688.2	625.9	2	6	7	9	10	12	14	16	19	6.6%
91	550	647.9	588.1	3	5	7	8	10	11	13	15	18	5.8%
92	570	849.5	771.6	2.5	5	7	8	9	11	13	15	17.5	5.1%
93	596	939.0	877.8	3	5	7	8	9	11	12	14	17	5.4%
94	596	1089.4	997.8	4	6	7	9	10	12	13	15	18	4.4%
95	630	1012.5	938.8	3	6	7	8	9	11	13	14	17	4.3%
96	645	1234.7	1149.6	3	5	7	8	9	11	12	14	17	4.0%

Table 1 (Continued): Descriptive Statistics for Analyst Coverage, 1976-1996

Panel F: Stocks above 80th Percentile, NYSE/AMEX Breakpoints

				# of Analysts at Coverage Percentiles									
YEAR	No. of Firms	Mean Size (Millions)	Median Size (Millions)	10	20	30	40	50	60	70	80	90	% of firms un-covered
76	506	1321.4	640.0	0	1	3	5	6	8	10	12	15	18.2%
77	442	1520.0	746.8	0	2	4	5	7	9	12	14	17	13.8%
78	492	1257.3	642.2	0	3	5	7	8	11	13	16	19	13.0%
79	473	1476.7	757.9	0	6	8	10	11	14	16	18	21	11.0%
80	464	1766.3	952.3	0	6	8	10	12	14	15	17	20	12.3%
81	448	2110.9	1159.8	0	7	10	12	14	15	17	19	21	10.0%
82	445	2000.8	1117.4	3	9	12	14	16	17	19	21	23	8.5%
83	437	2448.8	1322.4	6	10	13	15	17	18	20	23	25	6.9%
84	432	2807.1	1521.7	7	12	14	16	18	20	22	24	27	6.3%
85	428	3053.7	1751.9	7	12	14	16	18	20	21	24	30	6.5%
86	417	3622.5	2156.2	8	13	16	19	21	23	25	27	34	7.0%
87	418	4661.2	2806.8	7	13	17	19	21	23	26	28	32	6.5%
88	431	4235.7	2390.7	8	13	16	19	21	23	26	28	30	5.6%
89	415	4827.4	2682.4	8	14	17	21	23	25	27	29	32	6.5%
90	402	5390.6	2901.4	10	15	18	21	23	25	27	30	33	5.5%
91	419	5490.7	2845.7	9	14	16	19	21	24	25	28	32	4.8%
92	436	6540.4	3326.8	8	13	16	18	21	22	24	27	31	4.8%
93	454	6973.3	3786.7	9	14	16	18	20	23	25	28	31	4.8%
94	468	7596.9	4167.5	10	13	16	18	21	23	26	28	32	5.1%
95	476	7413.7	3851.2	9	13	15	17	20	22	25	27	31	4.4%
96	506	9633.9	4770.9	9	12	15	17	19	22	24	27	31	4.2%

Table 2: Determinants of Analyst Coverage, 12/1988

Dependent variable is log (1+analyst coverage). Log Size is the log of a firm's year-end market value. NASD is a NASDAQ dummy. Book/Mkt is the ratio of a firm's year-end book to market value. Beta is a firm's market beta. P is a firm's share price. Var is the variance of a firm's return using last 200 observations from year-end. R_k is the rate of return of a firm lagged k years for k=0,1,2,3,4. Turnover is a firm's turnover defined as prior six months' trading volume divided by shares outstanding. NASD*Turnover is the NASDAQ dummy times firm turnover. INDS is a set of CRSP industry dummies. There are 2012 observations. T-stats are in parentheses.

Model #	Log Size	NASD	Book/ Mkt	Beta	1/P	Var	R_0	R_1	R_2	R_3	R_4	Turn-Over	NASD* Turnover	INDS	R
1	.54	.03												NO	.6
	(52.67)	(0.99)													
2	.56	.04												YES	.6
	(52.90)	(1.21)													
3	.55	.05	.12											NO	.6
	(53.03)	(1.50)	(3.15)												
4	.57	.07	.17											YES	.6
	(52.22)	(2.00)	(4.30)												
5	.50	.07		.38										NO	.6
	(48.41)	(2.28)		(11.54)											
6	.51	.09		.40										YES	.6
	(46.11)	(2.62)		(10.94)											
7	.57	.09			-.52	-1.27	-.50	-.28	-.28	-.04	-.16			YES	.6
	(49.87)	(2.59)			(-3.12)	(-3.23)	(-9.46)	(-6.06)	(-6.00)	(-0.85)	(-3.46)				
8	.52	-.02										3.82	-.53	NO	.6
	(51.46)	(-.54)										(8.18)	(-.93)		

Table 3: Momentum Strategies, 1/1980-12/1996: Using Raw Returns and Sorting by Size

This table includes all stocks. The relative momentum portfolios are formed based on 6-month lagged raw returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. Portfolio P1 is an equally weighted portfolio of stocks in the worst performing 30%, portfolio P2 includes the middle 40%, and portfolio P3 includes the best performing 30%. This table reports the average monthly returns of these portfolios and portfolios formed using size-based subsamples of stocks. Using NYSE/AMEX decile breakpoints, the smallest firms are in size class 1, the next in 2, and largest in 10. Mean (median) size is in millions. T-stats are in parentheses.

		Size Class (NYSE/AMEX Decile Breakpoints)									
PAST	All Stocks	1	2	3	4	5	6	7	8	9	10
P1	0.01043	0.02106	0.00653	0.00231	0.00194	0.00469	0.00573	0.00606	0.01010	0.00922	0.01258
	(2.44)	(4.44)	(1.37)	(0.52)	(0.43)	(1.05)	(1.32)	(1.43)	(2.51)	(2.25)	(3.37)
P2	0.01378	0.01662	0.01290	0.01280	0.01244	0.01395	0.01374	0.01375	0.01393	0.01401	0.01355
	(4.48)	(4.97)	(3.84)	(3.88)	(3.75)	(4.18)	(4.14)	(4.27)	(4.40)	(4.43)	(4.50)
P3	0.01570	0.01733	0.01507	0.01664	0.01570	0.01655	0.01608	0.01491	0.01436	0.01363	0.01278
	(4.35)	(4.40)	(3.89)	(4.35)	(4.05)	(4.26)	(4.26)	(4.13)	(4.04)	(3.96)	(3.84)
P3-1	0.00527	-0.00374	0.00854	0.01433	0.01376	0.01187	0.01035	0.00885	0.00425	0.00441	0.00021
	(2.61)	(-1.77)	(3.60)	(6.66)	(6.10)	(5.32)	(4.80)	(3.72)	(1.90)	(1.73)	(0.08)
$\frac{P2-P1}{P3-P1}$		----	0.746	0.732	0.763	0.780	0.774	0.869	0.901	1.086	----
Mean Size		7	21	44	79	138	242	437	806	1658	7290
Median Size		7	21	43	78	136	237	430	786	1612	4504
Mean Analyst		0.1	0.5	1.1	2.0	3.2	5.0	7.3	10.6	15.3	21.4
Median Analyst		0.0	0.0	0.7	1.3	2.5	4.4	6.9	10.5	15.7	22.4

Table 4: Momentum Strategies, 1/1980-12/1996: Using Raw Returns and Sorting by Model 1 Residuals

This table includes only stocks above the NYSE/AMEX 20^{th} percentile. The relative momentum portfolios are formed based on 6-month lagged raw returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. Portfolio P1 is an equally weighted portfolio of stocks in the worst performing 30%, portfolio P2 includes the middle 40%, and portfolio P3 includes the best performing 30%. This table reports the average monthly returns of these portfolios and portfolios formed using an independent sort on Model 1 analyst coverage residuals of log size and a NASDAQ dummy. The least covered firms are in Sub1, the medium covered firms in Sub2, the most covered firms in Sub3. Mean (median) size is in millions. T-stats are in parentheses.

		Residual Coverage Class			
PAST	**ALL STOCKS**	**Low:SUB1**	**Medium:SUB2**	**High:SUB3**	**SUB1-SUB3**
P1	0.00622	0.00271	0.00669	0.00974	-0.00703
	(1.54)	(0.66)	(1.70)	(2.31)	(-5.16)
P2	0.01367	0.01257	0.01397	0.01439	-0.00182
	(4.40)	(4.20)	(4.58)	(4.29)	(-2.11)
P3	0.01562	0.01402	0.01583	0.01690	-0.00288
	(4.35)	(3.95)	(4.52)	(4.45)	(-2.80)
P3-1	0.00940	0.01131	0.00915	0.00716	0.00415
	(4.89)	(5.46)	(4.64)	(3.74)	(3.50)
Mean Size		962	986	455	
Median Size		103	200	180	
Mean Analyst		1.5	6.7	9.7	
Median Analyst		0.1	3.5	7.6	

Table 5: Momentum Strategies, 1/1980-12/1996: Using Raw Returns and Sorting by Size and Model 1 Residuals

This table includes only stocks above the NYSE/AMEX 20th percentile. The relative momentum portfolios are formed based on 6-month lagged raw returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. Portfolio P1 is an equally weighted portfolio of stocks in the worst performing 30%, portfolio P2 includes the middle 40%, and portfolio P3 includes the best performing 30%. This table reports the average monthly returns to portfolios formed by sorts on size and Model 1 analyst coverage residuals of log size and a NASDAQ dummy. Size is sorted using NYSE/AMEX breakpoints. The least covered firms are in Sub1, the medium covered firms in Sub2, the most covered firms in Sub3. Mean (median) size is in millions. T-stats are in parentheses.

Residual Coverage Class	Size Class: 1: 20^{th}-40^{th} Percentile	2: 40^{th}-60^{th} Percentile	3: 60^{th}-80^{th} Percentile	4: 80^{th}-100^{th} Percentile
Low:Sub1	P3-P1=.01511 (6.46) Mean Size=63 Median Size=59 Median Coverage=0.0	P3-P1=.01057 (4.49) Mean Size=199 Median Size=183 Median Coverage=0.6	P3-P1=.00605 (3.11) Mean Size=653 Median Size=592 Median Coverage=3.7	P3-P1=.00092 (0.49) Mean Size=5056 Median Size=2363 Median Coverage=11.1
Medium:Sub2	P3-P1=0.01369 (5.48) Mean Size=61 Median Size=56 Median Coverage=0.9	P3-P1=0.00975 (4.95) Mean Size=207 Median Size=193 Median Coverage=3.6	P3-P1=0.00316 (1.62) Mean Size=678 Median Size=629 Median Coverage=9.0	P3-P1=0.00009 (0.05) Mean Size=5163 Median Size=2853 Median Coverage=18.8
High:Sub3	P3-P1=0.01147 (5.10) Mean Size=64 Median Size=61 Median Coverage=3.1	P3-P1=0.00730 (3.60) Mean Size=202 Median Size=188 Median Coverage=7.6	P3-P1=0.00424 (2.02) Mean Size=663 Median Size=615 Median Coverage=14.7	P3-P1=0.00070 (0.33) Mean Size=3650 Median Size=2511 Median Coverage=24.9
Sub1-Sub3	P3-P1=0.00364 (2.13)	P3-P1=0.00327 (1.95)	P3-P1=0.00180 (1.18)	P3-P1=0.00023 (.14)

Table 6: Momentum Strategies, 1/1980-12/1996: Using Beta-Adjusted Returns and Sorting by Model 1 Residuals

This table includes only stocks above the NYSE/AMEX 20th percentile. The relative momentum portfolios are formed based on 6-month lagged beta-adjusted returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. Portfolio P1 is an equally weighted portfolio of stocks in the worst performing 30%, portfolio P2 includes the middle 40%, and portfolio P3 includes the best performing 30%. This table reports the average monthly beta-adjusted returns of these portfolios and portfolios formed using an independent sort on Model 1 analyst coverage residuals of log size and a NASDAQ dummy. The least covered firms are in Sub1, the medium covered firms in Sub2, the most covered firms in Sub3. Mean (median) size is in millions. T-stats are in parentheses.

		Residual Coverage Class			
PAST	ALL STOCKS	Low:SUB1	Medium:SUB2	High:SUB3	SUB1-SUB3
P1	-0.00753	-0.01007	-0.00712	-0.00511	-0.00497
	(-3.29)	(-3.97)	(-3.30)	(-2.13)	(-3.64)
P2	0.00280	0.00313	0.00299	0.00231	0.00081
	(2.44)	(2.48)	(2.92)	(1.73)	(1.06)
P3	0.00444	0.00423	0.00454	0.00430	-0.00006
	(3.17)	(2.76)	(3.50)	(2.74)	(-0.06)
P3-1	0.01197	0.01431	0.01167	0.00940	0.00491
	(5.99)	(6.79)	(5.76)	(4.62)	(4.04)
Mean Size		1070	998	434	
Median Size		106	221	186	
Mean Analyst		1.8	7.1	9.9	
Median Analyst		0.2	4.0	7.9	

Table 7: Momentum Strategies, 1/1980-12/1996: Using Raw Returns and Sorting By Model 2 Residuals

This table includes only stocks above the NYSE/AMEX 20^{th} percentile. The relative momentum portfolios are formed based on 6-month lagged raw returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. Portfolio P1 is an equally weighted portfolio of stocks in the worst performing 30%, portfolio P2 includes the middle 40%, and portfolio P3 includes the best performing 30%. This table reports the average monthly returns of these portfolios and portfolios formed using an independent sort on Model 2 analyst coverage residuals of log size, a NASDAQ dummy and industry dummies. The least covered firms are in Sub1, the medium covered firms in Sub2, the most covered firms in Sub3. Mean (median) size is in millions. T-stats are in parentheses.

		Residual Coverage Class			
PAST	ALL STOCKS	Low:SUB1	Medium:SUB2	High:SUB3	SUB1-SUB3
P1	0.00622	0.00328	0.00633	0.00929	-0.00602
	(1.54)	(0.79)	(1.60)	(2.23)	(-5.03)
P2	0.01367	0.01270	0.01392	0.01435	-0.00165
	(4.40)	(4.20)	(4.54)	(4.36)	(-2.21)
P3	0.01562	0.01427	0.01560	0.01692	-0.00264
	(4.35)	(3.98)	(4.46)	(4.51)	(-2.95)
P3-1	0.00940	0.01100	0.00927	0.00762	0.00337
	(4.89)	(5.46)	(4.68)	(3.87)	(3.06)
Mean Size		940	987	476	
Median Size		103	195	182	
Mean Analyst		1.6	6.7	9.6	
Median Analyst		0.1	3.5	7.5	

Table 8: Momentum Strategies, 1/1984-12/1996: Using Raw Returns and Sorting by Model 8 Residuals

This table includes only stocks above the NYSE/AMEX 20th percentile. The relative momentum portfolios are formed based on 6-month lagged raw returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. Portfolio P1 is an equally weighted portfolio of stocks in the worst performing 30%, portfolio P2 includes the middle 40%, and portfolio P3 includes the best performing 30%. This table reports the average monthly returns of these portfolios and portfolios formed using an independent sort on Model 8 analyst coverage residuals of log size, a NASDAQ dummy, firm turnover and NASDAQ dummy times firm turnover. The least covered firms are in Sub1, the medium covered firms in Sub2, the most covered firms in Sub3. Mean (median) size is in millions. T-stats are in parentheses.

		Residual Coverage Class			
PAST	ALL STOCKS	Low:SUB1	Medium:SUB2	High:SUB3	SUB1-SUB3
P1	0.00498	0.00190	0.00553	0.00747	-0.00557
	(1.11)	(0.42)	(1.26)	(1.56)	(-3.58)
P2	0.01209	0.01126	0.01273	0.01229	-0.00103
	(3.44)	(3.44)	(3.67)	(3.16)	(-1.00)
P3	0.01351	0.01210	0.01377	0.01458	-0.00248
	(3.38)	(3.20)	(3.54)	(3.31)	(-2.11)
P3-1	0.00853	0.01020	0.00824	0.00711	0.00309
	(4.22)	(4.67)	(3.92)	(3.46)	(2.23)
Mean Size		1412	1078	442	
Median Size		124	282	180	
Mean Analyst		2.9	8.3	10.0	
Median Analyst		0.4	4.9	7.7	

Table 9: Momentum Strategies, 1/1980-12/1996: Using Raw Returns and Sorting by Model 1 Residuals (Skip One Month Between Ranking and Portfolio Formation)

This table includes only stocks above the NYSE/AMEX 20th percentile. The relative momentum portfolios are formed based on 6-month lagged raw returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. Portfolio P1 is an equally weighted portfolio of stocks in the worst performing 30%, portfolio P2 includes the middle 40%, and portfolio P3 includes the best performing 30%. This table reports the average monthly returns of these portfolios and portfolios formed using an independent sort on Model 1 analyst coverage residuals of log size and a NASDAQ dummy, after skipping one month between the ranking and portfolio formation period. The least covered firms are in Sub1, the medium covered firms in Sub2, the most covered firms in Sub3. Mean (median) size is in millions. T-stats are in parentheses.

		Residual Coverage Class			
PAST	ALL STOCKS	Low:SUB1	Medium:SUB2	High:SUB3	SUB1-SUB3
P1	0.00577	0.00232	0.00622	0.00927	-0.00695
	(1.44)	(0.57)	(1.59)	(2.23)	(-5.15)
P2	0.01389	0.01288	0.01420	0.01450	-0.00162
	(4.45)	(4.26)	(4.63)	(4.33)	(-1.94)
P3	0.01630	0.01481	0.01647	0.01743	-0.00262
	(4.49)	(4.12)	(4.64)	(4.55)	(-2.55)
P3-1	0.01053	0.01249	0.01025	0.00816	0.00433
	(5.56)	(6.12)	(5.28)	(4.35)	(3.70)
Mean Size		962	986	455	
Median Size		103	200	180	
Mean Analyst		1.5	6.7	9.7	
Median Analyst		0.1	3.5	7.6	

Table 10: Momentum Strategies for Sub-Periods, 1/1980-12/1996: Using Raw Returns and Sorting by Model 1 Residuals

This table includes only stocks above the NYSE/AMEX 20th percentile. The relative momentum portfolios are formed based on 6-month lagged raw returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. Portfolio P1 is an equally weighted portfolio of stocks in the worst performing 30%, portfolio P2 includes the middle 40%, and portfolio P3 includes the best performing 30%. This table reports the average monthly returns of these portfolios and portfolios formed using an independent sort on Model 1 analyst coverage residuals of log size and a NASDAQ dummy. The least covered firms are in Sub1, the medium covered firms in Sub2, the most covered firms in Sub3. Mean (median) size is in millions. T-stats are in parentheses.

Panel A: 1/1980-12/1994

		Residual Coverage Class			
PAST	ALL STOCKS	Low:SUB1	Medium:SUB2	High:SUB3	SUB1-SUB3
P1	0.00713	0.00282	0.00806	0.01215	-0.00933
	(0.94)	(0.35)	(1.09)	(1.63)	(-3.48)
P2	0.01598	0.01516	0.01580	0.01671	-0.00155
	(2.62)	(2.46)	(2.68)	(2.64)	(-1.05)
P3	0.01852	0.01706	0.01850	0.01991	-0.00286
	(2.62)	(2.30)	(2.69)	(2.79)	(-1.31)
P3-1	0.01139	0.01424	0.01044	0.00777	0.00647
	(3.27)	(3.61)	(2.88)	(2.52)	(2.90)
Mean Size		507	496	318	
Median Size		71	108	155	
Mean Analyst		0.9	4.7	8.5	
Median Analyst		0.0	2.3	6.9	

Table 10 (Continued): Momentum Strategies for Sub-Periods, 1/1980-12/1996: Using Raw Returns and Sorting by Model 1 Residuals

Panel B: 1/1985-12/1990

		Residual Coverage Class			
PAST	ALL STOCKS	Low:SUB1	Medium:SUB2	High:SUB3	SUB1-SUB3
P1	-0.00302	-0.00617	-0.00205	-0.00081	-0.00536
	(-0.41)	(-0.85)	(-0.28)	(-0.10)	(-2.21)
P2	0.00914	0.00734	0.01042	0.00957	-0.00223
	(1.44)	(1.23)	(1.67)	(1.38)	(-1.35)
P3	0.01079	0.00920	0.01164	0.01145	-0.00225
	(1.54)	(1.38)	(1.70)	(1.50)	(-1.29)
P3-1	0.01381	0.01538	0.01369	0.01227	0.00311
	(4.65)	(4.86)	(4.42)	(4.05)	(1.62)
Mean Size		744	972	412	
Median Size		85	199	162	
Mean Analyst		1.3	7.4	10.2	
Median Analyst		0.0	3.8	7.8	

Table 10: Momentum Strategies for Sub-Periods, 1/1980-12/1996: Using Raw Returns and Sorting by Model 1 Residuals

Panel C: 1/1991-12/1996

		Residual Coverage Class			
PAST	ALL STOCKS	Low:SUB1	Medium:SUB2	High:SUB3	SUB1-SUB3
P1	0.01472	0.01151	0.01428	0.01828	-0.00677
	(2.49)	(1.91)	(2.49)	(2.95)	(-3.34)
P2	0.01626	0.01563	0.01599	0.01726	-0.00162
	(4.70)	(4.88)	(4.63)	(4.44)	(-1.23)
P3	0.01805	0.01632	0.01781	0.01983	-0.00351
	(4.06)	(3.79)	(4.05)	(4.16)	(-2.36)
P3-1	0.00333	0.00481	0.00353	0.00155	0.00326
	(0.97)	(1.33)	(1.02)	(0.43)	(1.60)
Mean Size		1541	1403	608	
Median Size		144	275	216	
Mean Analyst		2.2	7.8	10.2	
Median Analyst		0.3	4.3	7.9	

Table 11: Cross-Sectional Momentum Regressions, 1979-1992

This table includes only stocks above the NYSE/AMEX 20th percentile. Dependent variable is RHO: regression coefficient of 6-month returns (net risk-free) on lagged 6-month returns. Panel A: Independent variables are log (1+analyst coverage), log size, and a NASDAQ dummy. Panel B: Independent variables are log (1+analyst coverage), log size, interaction of log (1+analyst coverage) and log size and a NASDAQ dummy. No[illegible] T-stats are adjusted for serial correlation.

Panel A

Year	Coverage	t-stats	Size	t-stats
79	-0.0015	-0.1800	-0.0097	-1.7530
80	-0.0014	-0.2040	-0.0188	-3.8600
81	-0.0039	-0.6090	-0.0061	-1.2800
82	0.0040	0.5500	-0.0259	-4.5520
83	-0.0136	-1.9020	0.0050	0.8900
84	-0.0280	-3.9300	0.0168	2.9200
85	-0.0166	-2.1330	0.0146	2.4060
86	-0.0357	-5.6310	0.0240	4.7650
87	-0.0111	-1.8160	0.0040	0.8480
88	-0.0163	-2.5820	-0.0108	-2.2560
89	-0.0141	-2.2900	-0.0071	-1.5550
90	-0.0208	-3.2060	-0.0004	-0.0860
91	-0.0126	-1.7100	0.0059	1.1680
92	-0.0031	-0.4720	0.0019	0.4070
Fama-MacBeth	-0.0125	-3.8023	-0.0005	-0.1265
Pooled w/ Year Dummies	-0.0127	-5.0898	-0.0004	-0.2832

Table 11 (Continued): Cross-Sectional Momentum Regressions, 1979-1992

Panel B

Year	Coverage	t-stats	Size	t-stats	Interaction: coverage*size	t-stats
79	0.0306	0.7260	-0.0060	-0.8320	-0.0027	-0.775
80	0.1000	2.5930	-0.0064	-0.9480	-0.0084	-2.674
81	0.0055	0.1430	-0.0049	-0.6980	-0.0008	-0.248
82	-0.0382	-0.8500	-0.0321	-3.7080	0.0035	0.951
83	-0.0053	-0.1270	0.0061	0.7730	-0.0007	-0.205
84	-0.1441	-3.3310	-0.0001	-0.0060	0.0095	2.721
85	-0.1618	-3.3860	-0.0092	-0.9330	0.0118	3.079
86	-0.0457	-1.1950	0.0224	2.8280	0.0008	0.265
87	-0.0664	-1.8020	-0.0051	-0.6720	0.0044	1.521
88	-0.1622	-4.2580	-0.0359	-4.4700	0.0118	3.884
89	-0.0837	-2.4370	-0.0189	-2.5800	0.0057	2.059
90	-0.1372	-3.6960	-0.0212	-2.6360	0.0094	3.184
91	-0.0898	-2.2350	-0.0084	-0.9450	0.0063	1.954
92	-0.0836	-2.3560	-0.0118	-1.5720	0.0065	2.308
Fama-MacBeth	-0.0630	-1.8920	-0.0094	-2.3701	0.0041	1.5423
Pooled w/ Year Dummies	-0.0648	-5.0533	-0.0087	-3.7494	0.0043	4.4487

Figure 1: Momentum Profits vs. Firm Size

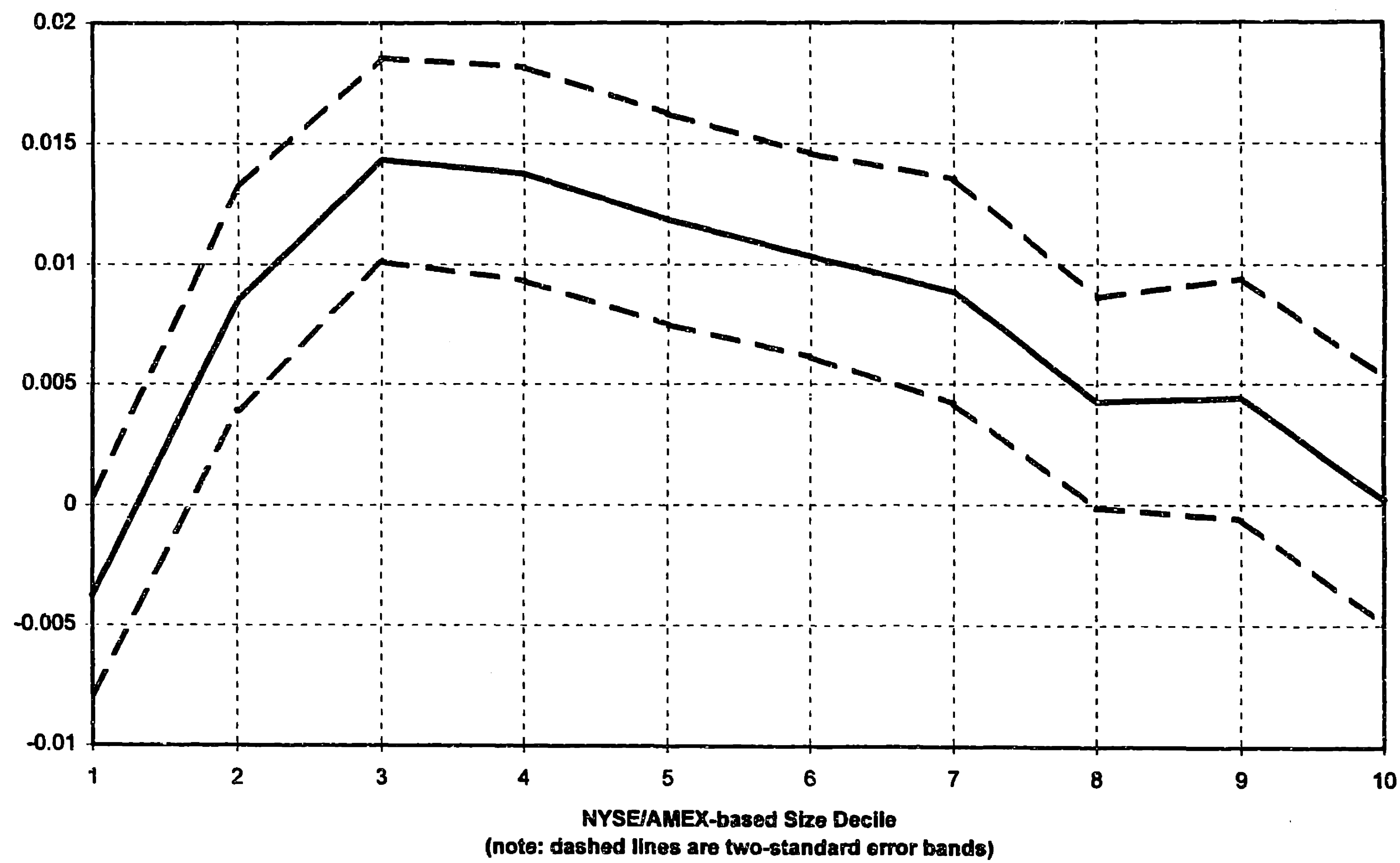


Figure 2: Cumulative Beta-Adjusted Returns in Event Time
Panel A: Momentum Profits for SUB1 and SUB3

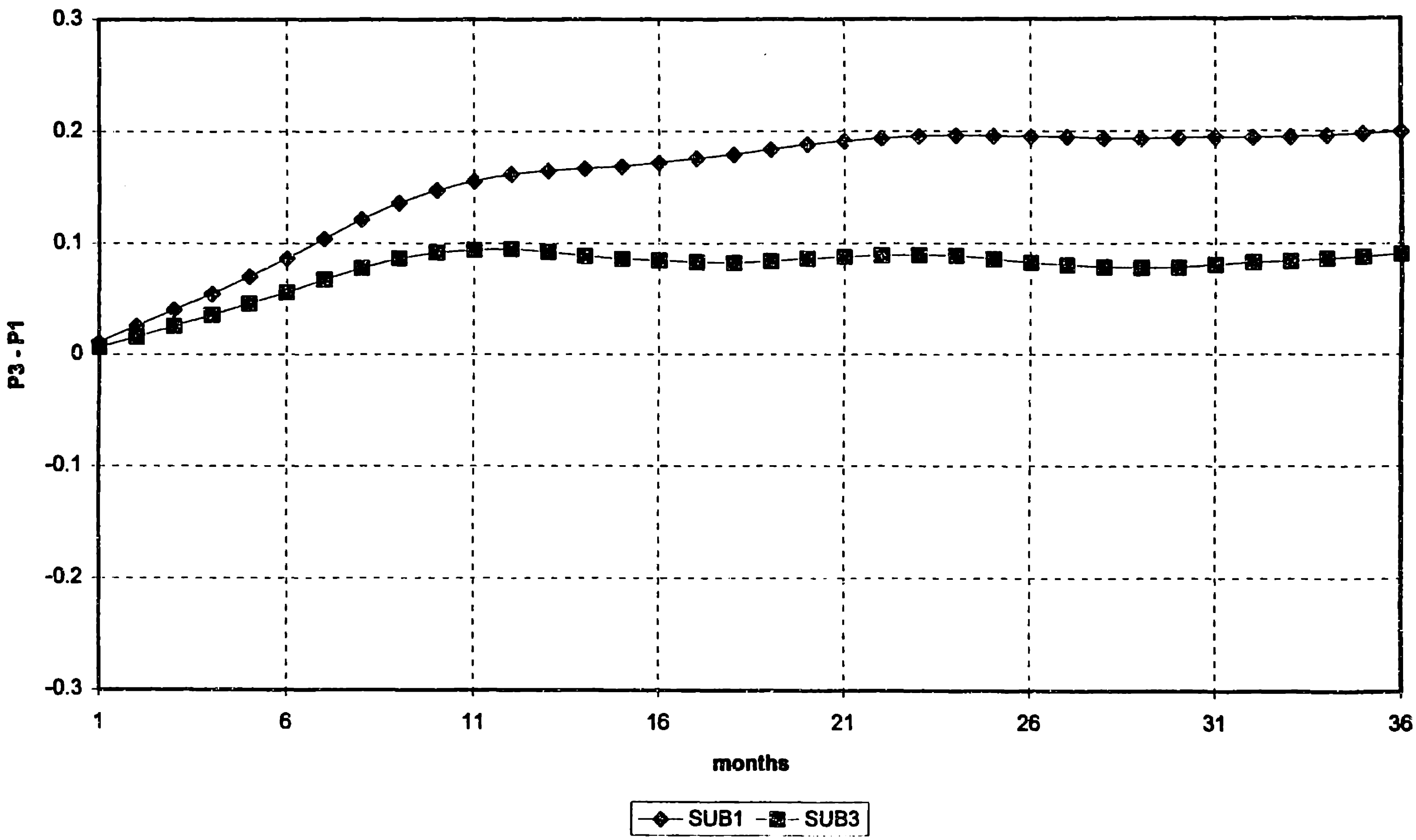
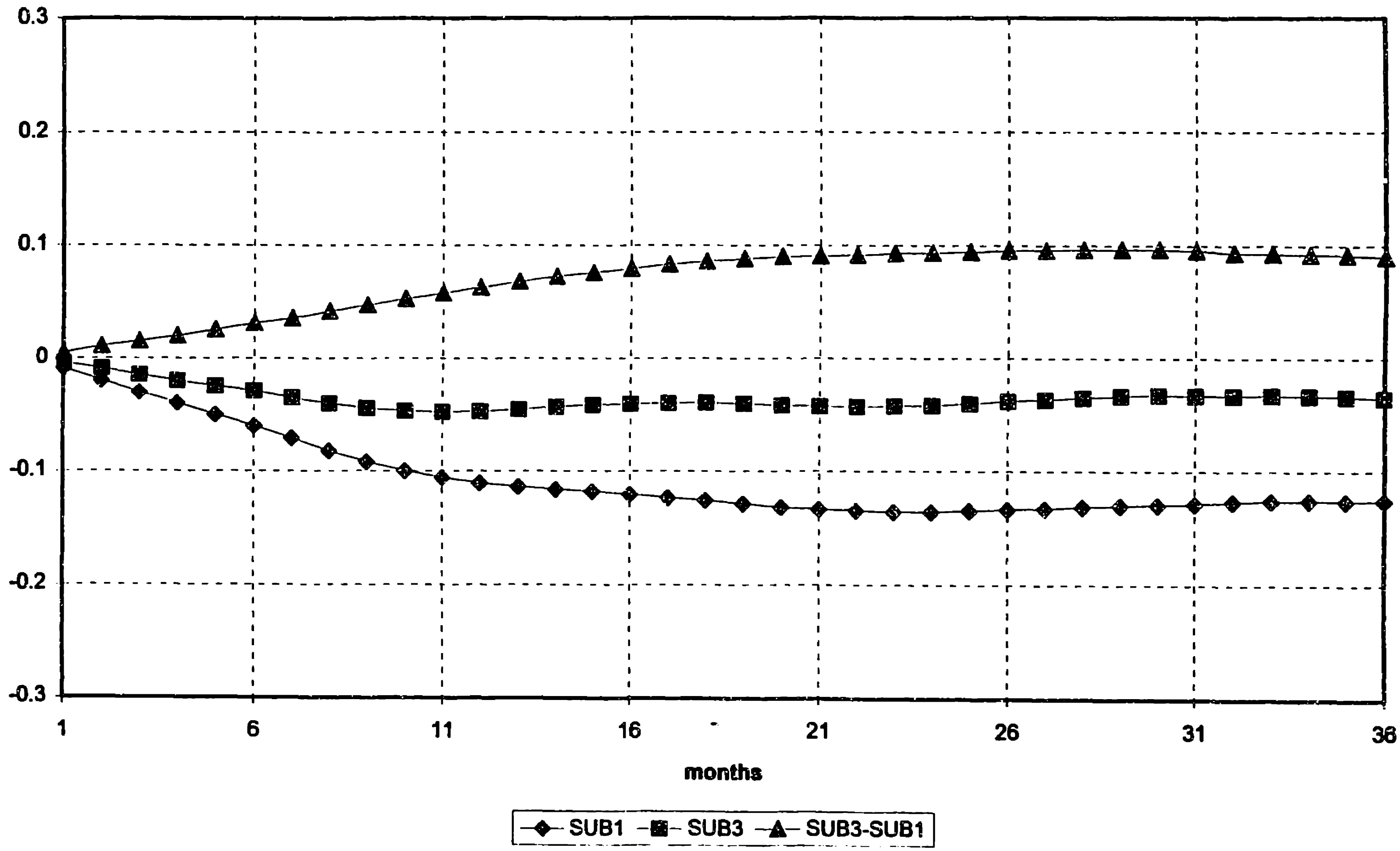


Figure 2: Cumulative Beta-Adjusted Returns in Event Time
Panel B: Profits to the LAST Strategy



Chapter 2

Introduction

A major development in market microstructure theory has been to relate the effect of information asymmetry between buyers and sellers on the order placement strategies of traders and the response of prices to order flow. This theory rests on the assumptions of rationality on the part of both uninformed market makers and informed traders. The first assumption implies that the market maker will take account of the information in order flow in setting prices. The second predicts that traders, in determining the size and order placement strategy for their trades, will take account of the effect of their trades on the prices at which they are executed.

The easier it is for the market maker to deduce the underlying information, the faster prices converge to their true value, and the smaller the opportunity of profits for informed traders. An investor with private information would like to trade in such a way as to disguise his identity to the market. The attempt of informed traders to hide among the trades of the uninformed is the motivation for the theoretical work of Admati and Pfleiderer (1988, 1989) and Foster and Viswanathan (1990, 1993). In these papers, the informed strategically select the size of their trades so that their orders are most difficult to detect. Kyle (1985) derived a sequential equilibrium in which informed traders make numerous smaller trades rather than one large trade to camouflage their trades. This behavior causes informed traders' information to be incorporated into prices gradually and weakens any relation between trade size and information effects. Easley and O'Hara (1987, 1992) developed models of competitive trading where a separating equilibrium can hold in which uninformed investors may trade in small or large quantities, while informed traders deal only in large quantities. However, if the threat of informed trading is too large, the market can be in a pooling equilibrium, where the informed essentially spread out across trade sizes. In this equilibrium, both large and small trades can be information-based and trade size effects are minimal. Barclay and Warner (1993) suggested that most informed trades will be undertaken through medium-sized trades. Small trades would take too much time and incur excessive execution costs. Large (block) trades are likely to become visible; the market for block trades (typically trades of over 10,000 shares) is characterized by a lack of anonymity and if the large-block trader cannot be certified to be a liquidity trader, he would have to incur a substantial price concession. Consequently, large orders based on private information are likely to be broken up into medium-sized trades. Barclay and Warner labeled this behavior "stealth trading".

Our goal in this paper is to test the implications of the strategic trading hypothesis on the properties of transactions stock prices during periods of increased information asymmetry. We first classify all trades into categories based on the characteristics of the trade. We group trades into three categories based on trade size. We also identify whether the trade was initiated by the buyer or seller (i.e. the "sign" of the trade). Finally, we classify a trade by its sequence, that is, whether it follows a trade of the same sign (a "continuation") or a trade of the opposite sign (a "reversal"). We postulate that these classifications provide important information about the order flow, on which our main empirical tests are based.

The pre-announcement period for tender-offer target firms provides a good testing ground for our analysis. First, the large announcement day price effects, reflecting the price premium that acquirers typically have to pay for shares in the target firm, give an incentive for insiders and other informed traders to trade before the public announcement day. Second, a large portion of the takeover-related price increases occurs well before the announcement day[1]. The pre-announcement price run-up indicates that some traders have private information prior to the official announcement. Third,

[1]See Asquith (1983), Keown and Pinkerton (1981) and others.

most prosecuted insider trading cases involve tender-offer or merger announcement trading, indicating that at least one class of informed trading (by corporate insiders) takes place during this period. In Meulbroek's (1992) study of 183 illegal insider trading episodes, 145 were takeover related. In her sample, insider trading occurred on average 13.2 trading days before the insider information was publicly announced. Almost half the pre-announcement run-up (defined as the cumulative return in event days -20 through -1 relative to the announcement day) occurred on the days with insider trading, suggesting that informed insider trading is an important contributor to the pre-announcement price run-up.

In our initial tests, we examine how the market maker sets prices in response to information in the order flow during a period of significant informed trading – the thirty trading days prior to the public announcement of a tender-offer. Specifically, we examine the effective spreads charged and revisions in quoted prices made by market makers in response to different type of trades, when classified by trade size, direction and sequences. By doing so, we can test how market liquidity differs for these different types of trades. Since private knowledge of an impending tender offer generally leads an informed investor to want to accumulate as much stock in the target firm as possible ahead of the public announcement, we would expect less market liquidity for large buy orders, assuming market makers hold rational expectations.

Next, we examine abnormal buyer- (or seller-) initiated trading activity during the pre-announcement period, relative to a normal non-event period, for different types of trades. If large trades are more expensive, and if the informed attempt to disguise their identities to the market, we would expect these informed traders to make numerous smaller trades rather one large buy to camouflage their information. A simple order-splitting strategy of breaking up a single large trade into a number of smaller trades of equal size[2] would suggest that these smaller buyer-initiated trades

[2]Lo and Bertsimas (1997) showed that this common approach to "working orders" is optimal, in the sense of minimizing execution costs, only in a special case: when price impact is linear in the trade size, permanent in its affect on future prices, and when prices follow an arithmetic random walk. With more realistic and general assumptions, the best-execution strategy under a dynamic programming solution may vary through time as a function of several state variables that measure market conditions and fill rates.

would be detected more in sequences of trades of the same direction.

Last, we compare how much of the overall excess stock returns, defined as the cumulative changes in midquotes (average of bid and ask quoted prices) in the pre-announcement period relative to the control period, can be attributed to trading in the different trade type categories. If informed traders choose small and medium-sized trades, and stock price movements are due mainly to private information revealed through trading, we would expect that the cumulative excess returns taking place on small and medium-sized trades to contribute most to the stock's overall excess return.

To preview our results, after controlling for the overall decline in effective spreads and adverse selection components of the spread in the pre-announcement period accompanying greater share volume, we find that market liquidity becomes relatively tighter for large buyer-initiated trades. We also find that buyer-initiated trades are more frequent in small and medium trade sizes, and also tend to occur in sequences. These results also hold when the data sample is restricted to the very largest firms, which are less subject to price pressure or supply shock effects and for which inventory risk on the part of market makers is likely to be less important. Similar results are also found for the subsample of firms with the largest price runups, in which informed trading is probably even more pronounced. Overall, small and medium trade size categories and trade continuations accounted for significantly more of cumulative stock price changes, even after accounting for differences in the volume of shares transacted in each category.

This research can be differentiated from prior empirical work which addressed the informativeness of trade size. Barclay and Warner (1993) compared the proportion of the cumulative stock-price change that occurs in different trade size categories, using trade price data only. However, as discussed in the next section, their measure can be biased by bid-ask bounce effects. Easley, Kiefer and O'Hara (1994) and Lee (1994) used trade process (i.e. the occurrences of buyer- or seller-initiated trades) data only. Our approach can be viewed as incorporating three related methodologies using transactions data on prices and trades as well as quotes. Brennan and Subrahmanyam (1998) found a negative cross-sectional relation across firms between average trade size and measures of market liquidity. Jones, Kaul and Lipson (1994b), using coarser daily data, found that the well-documented volume-volatility relationship in stock prices simply reflects the relationship between volatility and number of transactions, rather than trade size. However, neither of these papers test for any relationship between informed traders' choice of trade size and market liquidity.

The remainder of the paper is organized as follows. In Section 2, we describe the market microstructure methodologies used for our analysis. Section 3 describes our sample and data sources. We present our main empirical results in Section 4. Section 5 concludes.

2.1 Methodology

Our analysis begins by classifying trades into categories based on trade size, buyer- or seller-initiation, and sequence. We first assign trades for each company into one of three size categories – small, medium or large. The trade size category breakpoints were computed separately for each company based on trades in a 30-day non-event period beginning 249 trading days before the announcement date, when trading activity is assumed to be "normal". The smallest 75 percent of trades were defined to be small, the largest 5 percent were defined as large, and the remainder were classified as medium-sized. These percentiles were chosen to be similar to the overall distribution of trade sizes on the NYSE[3]. Hence the share size cutoffs corresponding to each category are determined based on each firm's normal trade size distributions. This procedure defines large and small trades for each firm relative to the order flow experience for the firm. Prior studies have used the raw numbers of shares traded for all firms uniformly to classify trade sizes. However, such a criterion treats trades in small or low-priced firms differently from large or high-priced firms; for example, a 10,000 share trade for a large firm in which such trades are more common may have a

[3]According to the NYSE 1995 Fact Book, five percent of all NYSE trades were larger than 10,000 shares – the traditional definition of a large "block" trade – and 78 percent of trades were smaller than 2099 shares – the largest size of public market orders that could be electronically routed through NYSE's electronic order system, SuperDot.

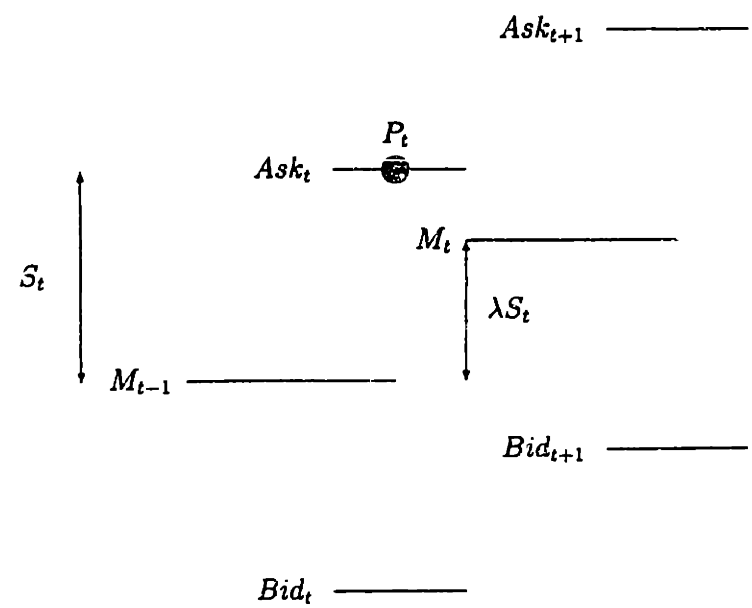
different impact than for a small firm with a smaller share base[4]. Other studies have used cutoffs based on dollar amounts, as this reflects better the wealth effects on the part of investors. A problem with dollar-based cutoffs is that simple price movements will cause similar round-lot trades to be classified into different size categories. For example, if a stock is trading at 25 dollars, a 10,000 dollar cutoff would classify all trades between 100 and 400 shares in the smallest trade size category. If the stock moved up by just one tick, suddenly only 100 to 300 share trades will be classified as small, although traders are not likely to immediately adjust the size of their trades due to such small price changes.

We also identify if a trade is buyer- or seller-initiated. Because tender offers are generally "good news" for the stock price of the majority of our firms, we expect that informed traders possessing private information about the impending announcement would tend to be initiators of buy transactions. The third and final trade characteristic with which we classify trades is based on whether the trade followed a prior one of the same sign. If a buyer-initiated (seller-initiated) trade followed a prior trade that was also buyer-initiated (seller-initiated), we classify the trade as a *continuation*. If a buyer-initiated (seller-initiated) trade followed a prior trade that was seller-initiated (buyer-initiated), we classify the trade as a *reversal*.

We next describe an empirical model of transactions price movements in the spirit of Kyle (1985) and Glosten and Harris(1988) to motivate the test methodologies we employ. The model can be interpreted as a simple specification of how private information becomes incorporated into prices through an imbalance of orders (by informed traders) on one side of the market and by the market maker uncovering information from trades. It incorporates standard market microstructure theories of market makers' quote-setting behavior, given adverse information risks and dealer gross profits. Figure 1 illustrates these effects.

[4]We have replicated our study using 2,100 and 10,000 share cutoffs uniformly across all firm, and our findings remain qualitatively unchanged.

Figure 1. Illustration of transactions price effects subsequent to a trade at the ask at time t.



At time t, the bid and ask prices, are assumed to bracket the unobserved fundamental stock price (which reflects all public information including the previous trade), M_{t-1}. The spread, S_t, is simply half the difference of the bid and ask prices. It has been observed that trades often take place inside the quoted bid and ask prices. An explanation is that quoted spreads are simply the starting point for negotiation: the actual execution price may depend on the size or form of the order, as well as possibly other factors[5]. The quoted spread reflects only disseminated quotes, but implicit quotes inside the disseminated quotes may exist on the exchange. If the trade occurs at a price other than the quotes, we use the trade price to measure the effective spread, i.e. $S_t = |P_t - Q_t|$, where P_t is the trade price and Q_t is the quote midpoint prevailing at the time of the trade[6].

The spread is assumed to comprise an adverse information and dealer gross profit

[5]For example, see Knez and Ready (1996), Petersen and Fialkowski (1994) and McInish and Wood (1992).

[6]All quotes and trade prices are expressed in logs.

component[7]. The dealer's gross profit represents compensation for inventory costs, order processing expenses and specialists' rents. The adverse information component, modeled in Glosten and Milgrom (1985) and Copeland and Galai (1983), represents the expected profit from trading with uninformed traders, which compensates for the expected loss to informed traders. According to Glosten (1987), the adverse information component can be described as the anticipated change in expected stock price that will occur in response to a buy or sell. The adverse information component is denoted by λ_t. For example, if a public buy occurs at the dealer's ask price, the revised expected stock value is $M_t = M_{t-1} + \lambda_t S_t$. If a public sell occurs at the dealer's bid price, the revised expected stock value is $M_t = M_{t-1} - \lambda_t S_t$. Let I_t be an indicator that takes on the value +1 if trade t is buyer-initiated and −1 if seller-initiated. This yields the following two equations:

$$M_t = M_{t-1} + \lambda_t S_t I_t \tag{2.1}$$

$$P_t = M_t + (1 - \lambda_t) S_t I_t \tag{2.2}$$

The three test statistics we employ are based on taking the expectations of Equation 2.1, conditional on trade t being of a particular trade category, and setting M_t equal to the (log) quote midpoint as in Glosten (1987).

$$E[M_t - M_{t-1} | C(t)] = E[\lambda_t S_t I_t | C(t)] \tag{2.3}$$

where $C(t)$ denotes the category of trade t, based on its size, sign and sequence.

Specifically, we compute the following test statistics using all trades t in the same category.

- λ, the adverse information component of the spread S, reflects the expected

[7]The model does not include an inventory component. Estimates by George, Kaul, and Nimalendran (1991), Hasbrouck (1988), Madhavan and Smidt (1993) and Hasbrouck and Sofianos (1993) suggest that inventory holding costs (the cost of holding inventory that may deviate from the desired level) appear to be relatively small. Hence adverse information and order costs appear to be the main components of spreads.

value of the private information conveyed by a public buyer or seller. It is an empirical estimate of the "Kyle lambda", or the (inverse) measure of market depth, for trades in each category. λ is computed as the coefficient from a pooled regression using Equation 2.1.

- $E[I_t]$, which reflects the proportion of buyer-initiated less buyer-initiated trades, is a measure of the order imbalance in each trade category. We expect the privately-informed to trade on one side of the market: if the stock is undervalued (overvalued), investors possessing this information will most likely initiate more buy (sell) transactions. Hence this measure can be used to test for increased adverse trading activity.

- $[\sum_{C(t)}[M_t - M_{t-1}|C(t)]/[\sum_t M_t - M_{t-1}]$, the proportion of the total stock midquote returns taking place on trades in a trade category. Intuitively, the trade category in which most informed traders trade should account for a relatively larger proportion of the cumulative price change.

Barclay and Warner (1993) first introduced a methodology of comparing the proportion of the cumulative stock price change that occurs in each (size) category to infer which group includes the higher fraction of informed traders. However, their analysis used trade price changes, which do not control for undesired bid-ask bounce effects. Recall that market makers' bid-ask spreads compensates specialists or other intermediaries for providing liquidity services. If buy orders go off at the ask price and sell orders at the bid price, then trades will have a temporary price component which is reflected in a price rebound in the next (or subsequent) transaction. These temporary price components average out to zero across all trades in a given size category only if the likelihood of sequences of buy or sell orders is the same across all types of trades. Compounding these temporary price effects, when the sequence of orders across trade categories do differ, could bias our estimates. Specifically, combining Equations 2.1 and 2.2 and solving for the price changes $P_t - P_{t-1}$ yields

$$P_t - P_{t-1} = M_t - M_{t-1} + (1 - \lambda)S(I_t - I_{t-1}) \tag{2.4}$$

The last term on the right hand side demonstrates that, because of the gross profits component of spreads $(1-\lambda)S$, price changes include movements from bid to ask prices due merely to the path of buy and sell transactions even in the absence of any changes in the expected value of the stock. Furthermore, cumulating stock price changes may not cancel out the bid-ask bounce effects, if the likelihood of trade *sequences* varies among different trade categories. This is because $E(I_t - I_{t-1})$, conditional on the classification of trade t, may not be equal to zero. As a simple numerical illustration, suppose that $E(I_t) = 0.1$ for a particular trade category, and such trades always follows a reversal. Then $E(I_{t-1}) = -0.1$, and the cumulative price change includes a non-information-based component equal to 0.2 of the gross profit portion of the spread. Such differences in the likelihood of trade sequences are an important consequence of informed trader's order placement strategies, as our empirical analysis later will show.

One possible criticism of our methodology is that it only uses a short window to measure price effects associated with a trade. Hasbrouck (1988, 1991a, 1991b) and Hausman, Lo and MacKinlay (1992) have used high-order vector autoregression and ordered probit specifications respectively to model protracted price effects. Nevertheless, our study does explicitly account for temporary price components caused by microstructure bid-ask bounce effects as well as sequences of past trades. To fully account for any protracted permanent information effects, we would like to measure price changes over several transactions surrounding the given trade. However, using longer measurement intervals incorrectly assigns part of a trade's price changes to the surrounding trades. Also, the empirical findings of Hasbrouck (1988) and Holthausen, Leftwich, and Mayers (1990) suggest that most of the price effects of a trade are reflected by the subsequent trade, which is captured by our use of midquote revisions.

2.2 Data

Transactions data were collected from the TAQ data set, provided by the New York Stock Exchange, for the years 1993 through 1995. The stocks were cross-matched with the 1995 CRSP Stocks file, from which information on share type, shares outstanding and distributions were obtained. We imposed error filters on the trades and quotes data to eliminate possible recording errors[8]. We excluded all trades that were not coded as "regular", or that were executed off the primary exchange[9]. We also excluded opening trades and trades reported after the close of trading at 4:00 pm. Similarly, we excluded all quotes that were not BBO (best bid or offer) eligible, or that originated off the primary exchange. We note that large trades sometimes have multiple participants on the other side of the trades. Reporting conventions may treat such a transaction as multiple trades, when we would want only one trade. To mitigate this problem, all trades occurring within five seconds of each other at the same price without an intervening quote revision are combined into one trade[10]. Transactions are recorded in the TAQ database, but their direction is not. As is standard in the literature, we use the "midpoint test" and "tick test" to classify trades as buyer-initiated or seller-initiated. Trades at prices above the midpoint of the bid-ask interval are classified as buys; trades below the midpoint are classified as sells. Trades exactly at the midpoint are classified depending on price movements. A midpoint price trade is a sell if the midpoint is lower than the midpoint of the bid-ask interval at the previous trades. If these midpoints are the same, we look further back until we find a price movement. If the midpoint had moved up, the midpoint trade is classified as buy. We identify the prevailing quotes for each transaction as the quotes that are in effect five seconds

[8]Any quote or price that was more than the greater of three and a half standard deviations or ten dollars from the day's mean was excluded. Quotes and prices more than 20 percent from the previous quote or trade price were also elimininated, as were any quotes implying non-positive spreads or spreads over five dollars.

[9]We do not wish to compound market microstructure effects which differ across trading mechanisms and exchanges; see Affleck-Graves, Hedge and Miller (1994) and Huang and Stoll (1995). Furthermore, there is evidence that non-NYSE trades and quotes contribute less to price discovery for NYSE-listed stocks. For example, Blume and Goldstein (1995) and Lee (1993) showed that non-NYSE markets obtain order flow for reasons other than posting the best prices.

[10]See Hasbrouck (1988) for a discussion of this timing problem.

earlier, because quotes are often recorded ahead of the trade that triggered them[11].

2.2.1 Tender Offer Target Firms

Our main tests focus on a sample of 102 NYSE firms that were tender offer targets in 1994 and 1995. Mergerstat Review was the source of tender offer announcements. We required our sample of target firms to be non-utility companies having common stock listed on the NYSE, and that the acquirer bid for at least 30 percent of the stock outstanding. The Wall Street Journal Index was searched to determine the day of the first announcement of the tender offer. We excluded stocks that split within one year prior to the announcement date, because our tests compares transactions from a non-event period beginning 249 trading days prior to the announcement, and we do not wish to compound liquidity effects due to stock splits. Table 1 lists the ticker symbols of the firms, as well as the announcement date, the size of the firm one year prior, and the size decile assigned by CRSP at that date. The sample has a large variation of firm sizes, from $11 million up to $18 billion market capitalization, and includes 29 decile 10 (i.e. largest decile) stocks.

Table 2 presents some summary cross-sectional statistics of the sample of target firms. Cumulative abnormal returns[12] averaged 19.2 percent, with a median of 18.1 percent. More importantly, large cumulative abnormal returns were also associated with the pre-announcement period, corresponding to trading days -31 through -2 relative to the Wall Street Journal announcement day. The average run-up was 7.0 percent, with a median of 3.3 percent. Trading volume, both in terms of the number of trades and share volume, increased in the pre-announcement period relative to the non-event period, which we defined to be days -249 through -220 relative to the tender-offer announcement. The daily number of trades averaged 63, with a median of 33, in the pre-announcement period, compared to an average of 46 and median of 29 in the non-event period. The average share volume increased to 172,527 in the pre-

[11]Lee and Ready (1991) showed that most of the mis-sequencing can be avoided by requiring a time separation of at least 5 seconds between quotes and trades.

[12]CRSP daily excess returns file was the source of beta-adjusted returns.

announcement period from 122,067 in the non-event period, while the median daily share volume rose to 73,637 from 60,043. Interestingly, the distribution of average trade sizes was remarkably similar in the pre-announcement and non-event periods. Hence volume increases appear to be due principally to an increase in the number of transactions: average order size does not change.

An increase in trading activity coincided with a decline in the level of the spread. Quoted bid-ask spreads were similar in the non-event period and pre-announcement periods. In the non-event period, the relative quoted spread (defined as half the bid-ask spread normalized by the midpoint of the quotes) averaged 0.68 percent, with a median of 0.59 percent. In the pre-announcement period, the relative half-spread had an average of 0.67 per cent and median of 0.51 percent. The average and median spreads dropped to 0.48 percent and 0.38 percent respectively on the announcement day. These effects were not due solely to the denominator (i.e. price) rising: quoted dollar spreads also showed a similar pattern. These results are consistent with prior studies that documented the relationship between spreads, volume and order size around tender offer announcements. For example, Conrad and Niden (1992) also found little evidence of increased adverse information effects (in the form of increased spread levels) prior to the announcement day for their sample of tender offer firms.

2.3 Empirical Results

2.3.1 Trade Size

We first examine trades categorized by size. Table 3 reports our results for our full sample of 102 NYSE tender offer target firms, for trades classified into small, medium and large size categories. The four panels correspond to estimates of the effective spread, the adverse selection component of spreads, the proportion of buyer- minus seller-initiated trades, and the proportion of cumulative midquote returns. Statistics for the non-event period are pooled estimates over all trades in the period. In the pre-announcement period, transactions for all securities in the same category are pooled, and reported numbers are time-series averages from daily (in event days relative to the announcement date) statistics: the time-series standard errors of the daily averages are used to perform t-tests for differences in means between the pre-announcement and non-event periods.

Panel A shows that effective spreads, in the non-event period, increase only slightly from small to large trade sizes. Since spreads contain non-informational components, reflecting order processing costs, market makers' rents and inventory costs, their magnitude in relation to trade size cannot be predicted purely by adverse information considerations. As fixed costs can be spread over more shares for large trades, the order cost component should decrease with trade size; however, large trades may also require increased effort and costs to be executed. Spread sizes uniformly declined for all trade size categories in the pre-announcement period, accompanying the 45 percent increase in the total shares volume. Transactions in all trade size categories rose by approximately the same proportion, as the distribution of trade sizes were similar in both periods. Figure 2 displays the daily average effective spreads during the pre-announcement period.

Panel B reports the estimates of the adverse selection component of spreads. This component is lowest for small trades, at 8.0 percent, and increases to 16.8 percent for medium-sized trades and 24.9 percent for large trades during the non-event period. Market makers infer more information from larger trades and provide less liquidity for large trades compared with small trades. The overall estimated adverse information components are slightly lower in the pre-announcement period, but this difference is not statistically significant. The daily adverse selection component estimates are plotted in Figure 3.

The increase in the proportion of buyer-initiated minus seller-initiated trades from 5.0 percent in the non-event period to 8.3 percent in the pre-announcement period is significant (t-stat=5.6), as shown in Panel C. The is consistent with a rise in adverse trading activity by informed investors in anticipation of stock prices increases when tender offers are announced. However, the increase is due mainly to small and medium trade sizes. The proportion of buyer-initiated minus seller-initiated trades *declined* in the large trade size category from 6.0 percent to 1.6 percent. This suggests that informed traders concentrated their increased buying activity in small and medium-sized trades. This data is graphed in Figure 4.

Panel D suggests that the decline in adverse trading activity in large trades led to a large trades contributing somewhat less to total stock price changes, in terms of cumulative midquote revisions, in the pre-announcement period (8.3 percent) compared to the non-event period (18.9 percent). However the changes in mean are not statistically significant. This could be because of the noise introduced by observations with small total price changes: recall that the total price change is the denominator for our measure of the proportion of cumulative returns attributed to each trade size category. We will attempt to account for this through a weighted least-squares regression analysis later in this section.

2.3.2 Buyer- versus Seller-initiated Trades

In the presence of increased adverse buyer-initiated trading activity, we might expect that market makers, holding rational expectations, would adjust their quotes asymmetrically for buyer- and seller-initiated trades, particularly for potentially more costly large trades. Table 4 reports estimates of effective spreads and the adverse information components of spreads for trades categorized by size as well as sign.

Panel A shows that the overall decline in spreads from the non-event period to the pre-announcement period is not symmetric for buyer- and seller-initiated trades. For large buys, the spreads decline by only 0.03 percent, compared with a decline of 0.07 percent for large sells – a difference with a t-stat of 3.9.

Panel B reports a similar pattern for estimates of the adverse information component of spreads. In the non-event period, the adverse information component is 39.5 percent for large sell trades, compared with only 21.3 percent for large buys. This suggests that sell trades are generally more informative than buys, possibly because of institutional constraints that make it more expensive to trade on negative news. However, in the pre-announcement period, this relationship reverses: large sells are associated with only a 21.4 percent adverse information component, compared with

30.8 percent for large buy trades. Figures 5 and 6 display the daily pooled estimates of the adverse selection components of spreads for buyer- and seller-initiated trades respectively.

2.3.3 Trade Sequences

The evidence thus far suggests that informed traders respond to the increased illiquidity in large buy orders by concentrating their transactions in small and medium-sized trades. If they used a simple order-splitting trading strategy of breaking up their desired trade into equal smaller orders, we could expect to see more adverse trading activity in sequences of trades. Table 5 reports the estimates of effective spreads, adverse information components of spreads, as well as the proportion of buyer- minus seller-initiated transactions for trades categorized by size as well as sequence.

The declines in spreads and adverse information components from the non-event to pre-announcement periods reported in Panels A and B do not show any significant difference in patterns between trade continuations (trades following a prior trade of the same sign) and reversals (trades following a prior trade of the opposite sign).

However, the proportion of buyer-initiated trades is greater for trade continuations than for trade reversals in the pre-announcement period, both in absolute proportions and relative to the non-event period, as shown in Panel C. The proportion of buyer- minus seller-initiated trades for continuations increased overall from 7.3 percent to 11.9 percent; most of this can be attributed to significant increases in small and medium-sized trade continuations (t-stat=7.0 and 2.4 respectively): large trade continuations actually showed a slight decline. The proportion of buyer- minus seller-initiated trades for reversals remained approximately unchanged at 0.1 percent in both periods. Hence the increase detected for trade continuations cannot be solely attributed to a general rise in the buyer-initiated trades: otherwise, we would expect to find an increase in the proportion of buyer-initiated trades following reversals as well. Large trade reversals also showed a decline in the proportion of buyer- minus seller-initiated trades, from 0.3 percent in the non-event period to -9.4 percent in the pre-announcement period (t-stat=-9.7). Figures 7 and 8 graph the daily proportions of buyer- minus seller-initiated trades for trade continuations and reversals respectively.

2.3.4 Large Firms

In Table 6 we repeat the analysis of Tables 3, 4 and 5 for a subsample of the 29 largest tender offer firms, classified by CRSP to be among the largest decile of stocks in their combined exchanges stock file. Large, liquid firms are less likely to be affected by price pressure or supply shock effects; hence the microstructure patterns we analyzed here should reflect the asymmetric information effects we want. The results remain qualititatively similar.

Panels A and B show that the levels of spreads and adverse components of the spread are much lower for this subsample of larger, more liquid firms compared to the full sample. Overall, effective spreads showed a significant decline of 0.27 percent (t-stat=-16.2) from the non-event period to the pre-announcement period. The overall decrease in the adverse selection component of 1.2 percent (t-stat=-4.2) is primarily due to seller-initiated trades, which declined by 2.7 percent (t-stat=-3.7). Large buy trades were actually associated with a slight increase in the estimated adverse information component of the spread.

Panel C also shows that while the proportion of buyer-initiated trades increased significantly, all of this effect is due to small and medium-sized trades: large trades showed a significant decrease (t-stat=-2.8) in buyer- minus seller-initiated trades from 6.7 percent to 1.5 percent in the non-event and pre-announcement period respectively. This panel also reports that buyer-initiated trades are more likely for trade continuations, and shows no changes for trade reversals, when comparing the pre-announcement to the non-event period. Again, all of the increase in the proportion of buyer- minus seller-initiated trades for continuations is due to small and medium-sized trades, which showed significant increases of 6.3 (t-stat=6.4) and 2.5 percent (t-stat=2.0) respectively.

2.3.5 Firms with Large Positive Price Runups

On average, our full sample of target firms were undervalued, and the pre-announcement runup is consistent with informed traders accumulating stock. However, 25 of the 102 firms experienced negative excess returns. These firms, as well as those with small cumulative returns, probably had little informed trading during the pre-announcement period, adding noise to our analysis in Tables 3, 4 and 5. We address this issue by examining the firms in the top half of the sample with the largest cumulative returns. Table 7 reports that our results are qualitatively similar for this subsample of firms also.

Effective spreads declined less for large buys (-0.06 percent) than for large sell trades (-0.12 percent) from the non-event period to the pre-announcement period, as shown in Panel A. Panel B reports that the adverse information component of spreads for large buy trades was approximately unchanged at 29 percent, whereas the adverse selection component for large sells declined from 51 percent to 22 percent (t-stat=-28.6). Panel C shows that, as before, the increase in the proportion of buyer-initiated trades can be attributed mainly to small and medium-sized trade continuations.

2.3.6 A Regression Analysis

In this subsection, we undertake an alternative regression approach to attributing overall transactions price movements to trade categories. Table 8 reports the weighted least-squares regression of the difference between the pre-announcement and non-event periods in cumulative midquote returns occurring in each trade size-sequence category on dummy variables for each category and the difference in volume of transactions in that category. The regression is pooled across all sample firms. The weights used equal the absolute difference in the total cumulative midquote returns for the firm between the pre-announcement and non-event periods: this assigns less weight to those observations with smaller total stock price changes and presumably less informed trading. Specifically, the following regression relation is estimated:

$$EXRET_{i,c} = \hat{\beta}_{small}D_{small} + \hat{\beta}_{medium}D_{medium} + \hat{\beta}_{large}D_{large} + \hat{\beta}_{seq}D_{seq} + \hat{\beta}_{v}Vol_{i,c}$$

The subscript c denotes one of six trade size/sequence categorics, generated by three size classifications (small, medium and large) and two trade sequence classifications (continuations or reversals). $EXRET_{i,c}$ denotes the cumulative midquote return over all trades for company i in trade category c during the pre-announcement period, minus the corresponding cumulative midquote returns from the non-event period. $Vol_{i,c}$ is the difference in in total share volume that occurred in trade category c for company i. All 102 sample firms are pooled in the regression, resulting in 612 observations.

Under a straightforward alternative hypothesis, stock price changes could be due simply to increases in the amount of trading. Hence any changes in stock returns is simply proportional to changes in the level of trading volume in each group of trades. The regression results do not support this alternate hypothesis: the volume coefficient is essentially flat. The dummy coefficients show more of the differences in cumulative returns occurred in small and medium trade size categories than differences in trading volume would predict. The small and insignificant dummy coefficient for large trades suggests that large trades in aggregate contribute less than small and medium-sized trades to differences in cumulative returns. Finally, trade continuations, as indicated by the positive coefficient (t-stat=2.9) estimated for the trade sequence dummy variable, move prices more than trade reversals.

The regression results provide some complementary confirmation of our earlier findings against a general alternative that stock price changes are related to variations in trading volume. The aggregate information incorporated into prices through trading is greater for small and medium-sized trades, and for trade continuations.

2.4 Conclusion

This study presents new empirical evidence for the strategic paradigm that has been widely applied in theories of price formation in securities markets. Transactions price effects in the pre-announcement period for tender-offer target firms, during which informed trading is more pronounced, suggest that market makers rationally respond to asymmetric information by making the market for potentially more costly trades less liquid. We found specifically that while overall effective spreads and the adverse information component of spreads decreased with the increased total share volume during the pre-announcement period, this pattern is asymmetric: the declines are significantly smaller for large buy orders. At the same time, increased adverse trading activity in small and medium-sized trades and in sequences of consecutive trades suggest that informed investors scale back their order sizes and break up large trades into smaller packages. This is consistent with the notion that informed traders take account of the effect of trade size on the price at which they are executed.

Neither average trade size or trading volume could explain variations in cumulative intraday stock returns. Rather, most of the difference in cumulative stock returns during the pre-announcement period appear to be concentrated in small or medium trade sizes, and in trade continuations. Informed trading may be found not only for initiators of large trades. More generally, informed agents may choose along several other dimensions in response to trading costs, such as different order types (e.g. market orders versus limit orders), more complex or dynamic order placement strategies, time of day, and routing of orders through other available market mechanisms (e.g. trading at the open and off-exchange or off-hours order matching). Our study has focused on the informed traders' choices of trade size and trade sequences, and provides new evidence to support the strategic paradigm.

References

Admati, A. and P. Pfleiderer, 1988, "A Theory of Intraday Patterns: Volume and Price Variability", *Review of Financial Studies* 1, 3-40.

Admati, A. and P. Pfleiderer, 1989, "Divide and Conquer: A Theory of Intraday and Day-of-the-Week Mean Effects", *Review of Financial Studies* 2, 189-223

Affleck-Graves, J., S. Hedge, and R. Miller, 1994, "Trading Mechanisms and the Components of the Bid-ask Spread", *Journal of Finance* 49, 1471-1488.

Asquith, P., 1983, "Merger Bids, Uncertainty, and Stockholder Returns", *Journal of Financial Economics*, 11, 51-83.

Asquith, P., R. Bruner, and D. Mullins, 1983, "The Gains to Bidding Firms from Mergers", *Journal of Financial Economics* 11, 121-139.

Barclay, M., and J. Warner, 1993, "Stealth trading and volatility", *Journal of Financial Economics*, 34, 281-305.

Bertsimas, D. and A. Lo, 1996, "Optimal Control of Execution Costs", working paper, MIT.

Blume, M., and M. Goldstein, 1995, "Quotes, Order Flow, and Price Discovery", working paper, Rodney L. White Center for Financial Research, Wharton School, University of Pennsylvania.

Bradford, C. and E. Sirri, 1992, "The Reaction of Investors and Stock Prices to Insider Trading", *Journal of Finance* 47, 1031-1059.

Brennan, M., and A. Subrahmanyam, 1995, "Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns", *Journal of Financial Economics* 41, 444-464.

Brennan, M., and A. Subrahmanyam, 1998, "The Determinants of Average Trade Size", *Journal of Business* 71, 1-25.

Conrad, J. and C. Niden, 1992, "Order, Flow, Trading Costs and Corporate Acquisition Announcements", *Financial Management*, 22-31.

Copeland. T. and D. Galai, 1983. "Information Effects on the Bid-Ask Spread," *Journal of Finance* 38, 1457-1469.

Easley, D., and M. O'Hara, 1987, "Price, Trade Size, and Information in Securities Markets", *Journal of Financial Economics* 19, 113-138.

Easley, D., and M. O'Hara, 1992, "Adverse Selection and Large Trade Volume: the Implications for Market Efficiency", *Journal of Financial and Quantitative Analysis* 27, 185-208.

Easley, D., N. Kiefer and M. O'Hara, 1994, "The Information Content of the Trading Process", working paper, Cornell University.

Easley, D., N. Kiefer, M. O'Hara, and J. Paperman, 1996, "Liquidity, Information, and Infrequently Traded Stocks, *Journal of Finance* 51, 1405-1436.

Elliot, J., D. Morse and G. Richardson, 1984, "The Association between Insider Trading and Information Announcements", *Rand Journal of Economics,* 15, 521-536.

Foster, D., and S. Viswanathan, 1990, "A Theory of the Interday Variations in Volume, Variance, and Trading Costs in Securities Markets", *Review of Financial Studies* 3, 593-624.

Foster, D., and S. Viswanathan, 1993, "Variation in Trading Volume, Return Volatility and Trading Costs: Evidence on Recent Price Formation Models", *Journal of Finance* 48, 187-211.

George, T., G. Kaul, and M. Nimalendran, 1991, "Estimation of the Bid-Ask Spread and Its Components: A New Approach", *Review of Financial Studies* 4, 623-656.

Givoly, D. and D. Palmon, 1985, "Insider Trading and the Exploitation of Inside Information: Some Empirical Evidence", *Journal of Business* 58, 69-87.

Glosten, L., 1987, "Components of the Bid-Ask Spread and the Statistical Properties of Transaction Prices", *Journal of Finance* 42, 1293-142.

Glosten, L., 1989, "Insider Trading, Liquidity and the Role of the Monopolistic Specialist", *Journal of Business* 62, 211-235.

Glosten L., and L. Harris 1988, "Estimating the Components of the Bid-Ask Spread", *Journal of Financial Economics,* 21, 123-142.

Glosten, L., and P. Milgrom, 1985, "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders", *Journal of Financial Economics* 14, 71-100.

Harris, L., 1991, "Stock Price Clustering and Discreteness", *Review of Financial Studies* 4, 389-415.

Hasbrouck, J., 1988, "Trades, Quotes, Inventories, and Information", *Journal of Financial Economics* 22, 229-252.

Hasbrouck, J., 1991a, "Measuring the Information Content of Stock Trades"

Journal of Finance 46, 179-208.

Hasbrouck, J., 1991b, "The Summary Informativeness of Stock Trades: An Econometric Analysis", *Review of Financial Studies* 4, 571-595.

Hasbrouck, J., and T. Ho, 1987, "Order Arrival, Quote Behavior, and the Return-Generating Process," *Journal of Finance*, 42, 1035-1048.

Hasbrouck, J., and G. Sofianos, 1993, "The Trades of Market Makers: An Empirical Analysis of NYSE Specialists", *Journal of Finance* 48, 1565-1593.

Hausman, J., A. Lo, and C. MacKinlay, 1992, "An Ordered Probit Analysis of Transaction Stock Prices", *Journal of Financial Economics* 31, 319-379.

Holthausen, R., R. Leftwich, and D. Mayers, 1990, "Large-block transactions, the speed of response, and temporary and permanent stock-price effects", *Journal of Financial Economics*, 26, 71-95.

Huang R., and H. Stoll, 1994, "Market Microstructure and Stock Return Predictions", *Review of Financial Studies* 7, 179-213.

Huang, R., and H. Stoll, 1995, "Dealer versus Auction Markets: a Paired Comparison of Execution Costs on NASDAQ and the NYSE", working paper, Vanderbilt University.

Jarrell, G. and A. Poulsen, 1989, "Stock Trading before the Announcement of Tender Offers: Insider Trading or Market Anticipation?", *Journal of Law, Economics and Organizations* 5, 225-248.

Jones, C., G. Kaul and M. Lipson, 1994a, "Information, Trading, and Volatility", *Journal of Financial Economics* 36, 127-154.

Jones, C., G. Kaul and M. Lipson, 1994b, "Transactions, Volume and Volatility", *Review of Financial Studies* 7, 631-651.

Jones, C. and M. Lipson, 1995, "Continuations, Reversals and Adverse Selection on the Nasdaq and NYSE/AMEX", working paper, Princeton University.

Kaul, G., and M., Nimalendran, 1990, "Price Reversals: Bid-Ask Spread Errors or Market Overreaction?" *Journal of Financial Economics* 28, 67-93.

Keim, D., and A. Madhavan, 1995, "Anatomy of the Trading Process: Empirical Evidence on the Behavior of Institutional Traders", working paper, Wharton School, University of Pennsylvania.

Keown, A., and J. Pinkerton, 1981, "Merger Announcements and Insider Trading Activity: An Empirical Investigation", *Journal of Finance* 36, 855-869.

Kim, O., and R. Verrechia, 1991, "Trading Volume and Price Reaction to Public Announcements", *Journal of Accounting Research* 29, 302-321.

Knez, P., and M. Ready, 1996, "Estimating the Profits from Trading Strategies", *Review of Financial Studies* 9, 1121-1164.

Kyle, A., 1985, "Continuous Auctions and Insider Trading", *Econometrica* 53, 1315-1335.

Lee, C., 1993, "Market Integration and Price Execution for NYSE-listed Securities", *Journal of Finance* 48, 1009-1038.

Lee, C., and M. Ready, 1991, "Inferring Trade Direction from Intraday Data", *Journal of Finance* 46, 1009-1038.

Lee, C., B. Mucklow and M. Ready, 1993, "Spreads, Depths and the Impact of Earnings Information: An Intraday Analysis", *Review of Financial Studies* 6, 345-374.

Linn, J., G. Sanger, and G. Booth, 1995 "Trade Size and Components of the Bid-Ask Spread", *Review of Financial Studies* 8, 1153-1184.

Madhavan, A., and S. Smidt, 1993, "An Analysis of Changes in Specialist Inventories and Quotations", *Journal of Finance* 48, 1595-1628.

McInish, T. and R. Wood, 1991, "Hourly returns, volume, trade size and number of trades", *Journal of Financial Research* 14, 303-315.

McInish, T., and R. Wood, 1992, "An Analysis of Intraday Patterns in Bid-Ask Spreads for NYSE stocks", *Journal of Finance* 47, 753-764.

Muelbroek, L., 1992, "An Empirical Analysis of Illegal Insider Trading", *Journal of Finance* 47, 1661-1699.

Petersen, M., and Fialkowski D., 1994, "Posted versus effective spreads: Good prices or bad quotes?", *Journal of Financial Economics* 35, 269-292.

Sanders, R., and J. Zdanowicz, 1992, "Target Firm Abnormal Returns and Trading Volume around the Initiation of Change in Control Transactions", *Journal of Financial and Quantitative Analysis* 27, 109-129.

Seppi, D., 1992, "Block Trading and Information Revelation Around Quarterly Earnings Announcements", *Review of Financial Studies* 5, 281-305.

Stoll, H., 1989, "Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests", *Journal of Finance* 44, 115-134.

Table 1. Sample of 102 NYSE tender-offer target companies, 1994-1995

Ticker	Date	Size ($Mil)	Decile	Ticker	Date	Size ($Mil)	Decile
ACY	940803	4666	10	HIL	950127	419	9
AIH	940916	428	9	HLO	950602	146	6
AMI	941012	1220	10	HSX	940405	189	8
AOG	940325	284	8	HTI	941005	1886	10
ASZ	951219	267	8	I	951019	6303	10
ATM	940922	416	9	ICN	940803	152	6
BBB	940322	115	6	JOY	940819	263	9
BFL	940118	43	4	KEM	940315	2043	10
BKB	950724	2688	10	KNO	940816	50	5
BLH	950228	1152	10	KSU	940720	1623	10
BN	940913	2549	10	MAI	950313	190	8
BV	940107	3566	10	MAY	951211	234	9
C	950413	17995	10	MCH	950525	54	5
CAW	941220	1292	9	MCK	940712	1794	10
CBK	940128	1287	10	MCU	951201	718	9
CBS	950802	4833	10	MFC	940705	449	9
CCB	950801	11841	10	MPX	940105	168	7
CCP	950228	682	9	MRC	950405	180	8
CDS	951201	153	8	MRG	940513	224	8
CGY	950821	142	7	MRX	940524	581	9
CIC	941207	1599	10	MXS	950301	620	9
CKL	950329	1029	9	NBB	940510	236	8
CMB	950829	6953	10	NGA	941011	505	9
CNM	950403	398	8	NM	940114	118	7
CNR	950921	539	9	NSB	940614	29	4
CNW	950313	1148	10	OPI	940606	761	9
CNX	950921	206	7	PDS	941228	73	7
CRX	950517	140	7	PLP	950504	211	8
DAN	950309	138	7	PST	940824	1175	10
DPS	950123	1426	10	PT	950110	1835	10
DUF	950126	340	8	RB	950301	340	9
DXK	950328	423	9	REC	950522	138	8
E	941213	585	9	REE	940831	836	9
EBP	950516	123	5	RMO	940216	161	8
ECA	940804	427	9	RVW	950510	940	10
EFG	950811	485	8	RXR	951130	1470	9
EHI	950504	127	6	SCA	951011	751	9
EN	950627	345	8	SCZ	950228	67	4
ESY	950403	1477	10	SEC	950901	81	5
FBO	951107	1156	9	SNB	940802	660	9
FFB	950619	3695	10	SNC	950222	1976	10
FFM	950614	3531	10	SPP	950717	3979	10
FGI	950516	211	8	UI	940114	11	1
GEB	940524	2123	10	USC	940913	193	8
GEC	950828	3487	10	USR	950306	675	9
GHX	941215	66	6	VGR	951114	560	9
GII	951205	56	5	WCS	950731	721	9
GLE	940818	65	6	WLP	950327	638	9
GQ	940311	1109	9	WSN	940914	286	6
GRO	950508	255	8	WW	951220	209	7
HAY	950928	428	9	ZE	950718	362	8

Sample: 102 NYSE tender offer target companies in 1994 and 1995. Date is of the first tender-offer announcement in the Wall Street Journal. Size is the target firm's market capitalization one year prior to the announcement date. Decile is the size ranking in CRSP's combined exchanges file (10 is the largest size decile), based on market capitalization in the prior calendar year-end.

Table 2. Summary statistics of tender-offer target companies

	Event Days	-249 to -220	-31 to -2	-1 to 0	+1 to +10
Cumulative excess returns	Mean	-0.4	7.0	19.2	-0.4
	Median	-1.4	3.3	18.1	-1.3
	Max	33.5	80.9	59.4	22.9
	75th %	6.5	13.9	30.9	3.9
	25th %	-7.1	-1.2	6.4	-4.1
	Min	-31.2	-15.4	-16.9	-25.2
# Trades per day	Mean	46	63	257	93
	Median	29	33	197	56
	Max	572	481	1610	765
	75th %	55	72	345	112
	25th %	13	15	93	26
	Min	4	4	7	7
Share volume per day	Mean	122067	172527	1458108	403953
	Median	60043	73637	838700	218750
	Max	1947693	2310847	15638650	3926030
	75th %	117040	213610	1726050	473160
	25th %	22177	25843	368650	72100
	Min	2827	5052	5750	7560
Average trade size	Mean	2265	2371	5216	4302
	Median	2185	1925	4307	3423
	Max	5832	18286	18343	26328
	75th %	2991	2934	6331	4932
	25th %	1372	1408	3254	2423
	Min	572	571	746	574
Average Half-Spread ($)	Mean	0.11	0.10	0.09	0.09
	Median	0.10	0.10	0.08	0.08
	Max	0.50	0.19	0.16	0.20
	75th %	0.12	0.11	0.10	0.09
	25th %	0.09	0.08	0.08	0.07
	Min	0.07	0.07	0.06	0.06
Average Half-Spread (percent of price)	Mean	0.68	0.67	0.48	0.45
	Median	0.59	0.51	0.38	0.35
	Max	2.56	4.41	2.81	3.26
	75th %	0.87	0.92	0.65	0.59
	25th %	0.39	0.33	0.25	0.22
	Min	0.14	0.11	0.09	0.08

Sample: 102 NYSE tender offer target companies in 1994 and 1995. Table display cross-sectional descriptive statistics for each of four time periods relative to date of the first tender offer announcement in the Wall Street Journal (event date 0). Cumulative excess returns are computed from beta-adjusted returns in the CRSP Excess Returns File. Trades, share volume and trade size were computed from regular trades on the NYSE, excluding opening trades and transactions executed off the primary exchange or after market close. Spreads are computed from bid and offer quotes on the NYSE, and exclude quotes that are non-BBO-eligible or have a non-positive spread.

Table 3. Estimates of spreads, adverse selection components, proportions of buyer-initiated trades, and proportions of total returns, by trade size

Panel A. Effective spreads (percent of price)

Trade Size	Non-event period Mean	Avg Trds	[% Trds]	Pre-announcement period Mean	Avg Trds	[% Trds]	Difference Mean	(t-stat)
All	0.43	4495	[100.0%]	0.37	6239	[100.0%]	-0.06	(-12.6)
Small	0.42	3333	[74.2%]	0.37	4456	[71.4%]	-0.05	(-14.9)
Medium	0.43	929	[20.7%]	0.37	1412	[22.6%]	-0.06	(-9.1)
Large	0.44	233	[5.2%]	0.39	372	[6.0%]	-0.05	(-5.1)

Panel B. Adverse selection component of spreads (percent of spread)

Trade Size	Non-event period Mean	Avg Trds	[% Trds]	Pre-announcement period Mean	Avg Trds	[% Trds]	Difference Mean	(t-stat)
All	10.87	4495	[100.0%]	10.16	6239	[100.0%]	-0.72	(-1.2)
Small	8.04	3333	[74.2%]	7.34	4456	[71.4%]	-0.70	(-1.5)
Medium	16.80	929	[20.7%]	15.70	1412	[22.6%]	-1.10	(-0.9)
Large	24.93	233	[5.2%]	22.13	372	[6.0%]	-2.80	(-1.4)

Panel C. Proportion of buyer-initiated minus seller-initiated trades (percent of trades)

Trade Size	Non-event period Mean	Avg Trds	[% Trds]	Pre-announcement period Mean	Avg Trds	[% Trds]	Difference Mean	(t-stat)
All	5.02	4495	[100.0%]	8.29	6239	[100.0%]	3.26	(5.6)
Small	4.70	3333	[74.2%]	8.65	4456	[71.4%]	3.95	(6.8)
Medium	5.94	929	[20.7%]	8.83	1412	[22.6%]	2.89	(3.6)
Large	6.00	233	[5.2%]	1.59	372	[6.0%]	-4.41	(-3.3)

Panel D. Proportion of Total Returns (percent of total return)

Trade Size	Non-event period Mean	Avg Trds	[% Trds]	Pre-announcement period Mean	Avg Trds	[% Trds]	Difference Mean	(t-stat)
All	100.00	4495	[100.0%]	100.00	6239	[100.0%]	-0.00	(-0.0)
Small	0.55	3333	[74.2%]	65.83	4456	[71.4%]	65.28	(0.4)
Medium	80.55	929	[20.7%]	25.89	1412	[22.6%]	-54.65	(-0.6)
Large	18.91	233	[5.2%]	8.28	372	[6.0%]	-10.62	(-0.4)

Sample: 102 NYSE tender offer target companies in 1994 and 1995. Non-event period is days -249 to -220 relative to date of the first tender offer announcement in the Wall Street Journal; pre-announcement period is days -31 to -2. The table reports estimates of effective spreads (calculated as the absolute difference between trade price and prevailing midquote as a percentage of midquote price), adverse selection component of the spread (as a percentage of effective spread), proportion of buyer-initiated minus seller-initiated trades (as a percentage of total trades), and proportion of total midquote returns classified by trade size. In the pre-announcement period, transactions for all securities are pooled, and reported numbers are time-series averages and t-statistics from daily statistics. Small, medium and large trade categories are based on the 75th and 95th percentiles of trade sizes for each company in the 30-day non-event period. Only regular trades (excluding opening and after market close) and BBO-eligible quotes with positive spreads originating on the NYSE were used.

Table 4. Estimates of spreads and adverse selection components, by buyer- or seller-initiation

Panel A. Effective spreads (percent of price)

Trade Size	Non-event period Mean	Avg Trds	[% Trds]	Pre-announcement period Mean	Avg Trds	[% Trds]	Difference Mean	(t-stat)
Buyer-initiated								
All	0.42	2351	[100.0%]	0.37	3378	[100.0%]	-0.05	(-8.6)
Small	0.42	1738	[73.9%]	0.36	2418	[71.6%]	-0.05	(-9.2)
Medium	0.43	490	[20.9%]	0.37	770	[22.8%]	-0.06	(-7.4)
Large	0.43	123	[5.2%]	0.40	189	[5.6%]	-0.03	(-2.9)
Seller-initiated								
All	0.43	2125	[100.0%]	0.37	2840	[100.0%]	-0.06	(-20.5)
Small	0.43	1581	[74.4%]	0.37	2021	[71.2%]	-0.05	(-27.8)
Medium	0.44	435	[20.5%]	0.37	638	[22.5%]	-0.07	(-10.4)
Large	0.46	109	[5.1%]	0.38	181	[6.4%]	-0.07	(-7.1)
Buys minus Sells								
All	-0.01	4476	[100.0%]	-0.01	6218	[100.0%]	0.01	(1.2)
Small	-0.01	3319	[74.2%]	-0.01	4440	[71.4%]	-0.00	(-0.1)
Medium	-0.01	926	[20.7%]	-0.00	1408	[22.6%]	0.01	(2.4)
Large	-0.03	231	[5.2%]	0.01	370	[6.0%]	0.04	(3.9)

Panel B. Adverse selection component of spreads (percent of spread)

Trade Size	Non-event period Mean	Avg Trds	[% Trds]	Pre-announcement period Mean	Avg Trds	[% Trds]	Difference Mean	(t-stat)
Buyer-initiated								
All	11.33	2351	[100.0%]	12.06	3378	[100.0%]	0.73	(0.6)
Small	8.77	1738	[73.9%]	8.37	2418	[71.6%]	-0.40	(-0.4)
Medium	17.21	490	[20.9%]	18.30	770	[22.8%]	1.10	(0.4)
Large	21.27	123	[5.2%]	30.83	189	[5.6%]	9.56	(2.6)
Seller-initiated								
All	12.32	2125	[100.0%]	10.83	2840	[100.0%]	-1.49	(-1.4)
Small	8.06	1581	[74.4%]	7.35	2021	[71.2%]	-0.71	(-0.7)
Medium	18.69	435	[20.5%]	17.91	638	[22.5%]	-0.78	(-0.3)
Large	39.48	109	[5.1%]	21.35	181	[6.4%]	-18.14	(-4.6)
Buys minus Sells								
All	-0.99	4476	[100.0%]	1.22	6218	[100.0%]	2.22	(2.0)
Small	0.71	3319	[74.2%]	1.02	4440	[71.4%]	0.31	(0.2)
Medium	-1.48	926	[20.7%]	0.39	1408	[22.6%]	1.88	(0.6)
Large	-18.21	231	[5.2%]	9.48	370	[6.0%]	27.69	(5.5)

Sample: 102 NYSE tender offer target companies in 1994 and 1995. Non-event period is days -249 to -220 relative to date of the first tender offer announcement in the Wall Street Journal; pre-announcement period is days -31 to -2. The table reports estimates of effective spreads (calculated as the absolute difference between trade price and prevailing midquote as a percentage of midquote price) and adverse selection component of the spread (as a percentage of effective spread) classified by trade size and whether buyer- or seller-initiated. In the pre-announcement period, transactions for all securities are pooled, and reported numbers are time-series averages and t-statistics from daily statistics. Small, medium and large trade categories are based on the 75th and 95th percentiles of trade sizes for each company in the 30-day non-event period. Only regular trades (excluding opening and after market close) and BBO-eligible quotes with positive spreads originating on the NYSE were used.

Table 5. Estimates of spreads, adverse selection components and proportions of buyer-initiated trades, by trade sequence

Panel A. Effective spreads (percent of price)

Trade Size	Non-event period			Pre-announcement period			Difference	
	Mean	Avg Trds	[% Trds]	Mean	Avg Trds	[% Trds]	Mean	(t-stat)
Continuations								
All	0.43	3096	[100.0%]	0.37	4318	[100.0%]	-0.05	(-11.4)
Small	0.42	2288	[73.9%]	0.37	3068	[71.1%]	-0.05	(-13.8)
Medium	0.43	653	[21.1%]	0.37	1000	[23.2%]	-0.06	(-7.8)
Large	0.45	155	[5.0%]	0.40	250	[5.8%]	-0.05	(-4.3)
Reversals								
All	0.43	1400	[100.0%]	0.37	1921	[100.0%]	-0.06	(-14.5)
Small	0.42	1045	[74.7%]	0.37	1388	[72.2%]	-0.05	(-15.3)
Medium	0.44	277	[19.8%]	0.37	412	[21.4%]	-0.07	(-12.0)
Large	0.43	77	[5.5%]	0.37	122	[6.3%]	-0.05	(-5.7)

Panel B. Adverse selection component of spreads (percent of spread)

Trade Size	Non-event period			Pre-announcement period			Difference	
	Mean	Avg Trds	[% Trds]	Mean	Avg Trds	[% Trds]	Mean	(t-stat)
Continuations								
All	12.39	3096	[100.0%]	11.51	4318	[100.0%]	-0.88	(-1.5)
Small	9.74	2288	[73.9%]	8.84	3068	[71.1%]	-0.91	(-1.7)
Medium	17.92	653	[21.1%]	16.35	1000	[23.2%]	-1.57	(-1.3)
Large	25.43	155	[5.0%]	23.72	250	[5.[illegible]]	-1.71	(-0.9)
Reversals								
All	7.53	1400	[100.0%]	7.20	1921	[100.0%]	-0.33	(-0.3)
Small	4.28	1045	[74.7%]	4.04	1388	[72.2%]	-0.24	(-0.3)
Medium	14.30	277	[19.8%]	14.37	412	[21.4%]	0.07	(0.0)
Large	23.88	77	[5.5%]	18.11	122	[6.3%]	-5.76	(-1.9)

Panel C. Proportion of buyer-initiated minus seller-initiated trades (percent of trades)

Trade Size	Non-event period Mean	Avg Trds	[% Trds]	Pre-announcement period Mean	Avg Trds	[% Trds]	Difference Mean	(t-stat)
Continuations								
All	7.26	3096	[100.0%]	11.90	4318	[100.0%]	4.64	(5.7)
Small	6.47	2288	[73.9%]	12.08	3068	[71.1%]	5.61	(7.0)
Medium	9.66	653	[21.1%]	12.56	1000	[23.2%]	2.90	(2.4)
Large	8.83	155	[5.0%]	6.77	250	[5.8%]	-2.06	(-1.1)
Reversals								
All	0.07	1400	[100.0%]	0.10	1921	[100.0%]	0.03	(0.4)
Small	0.82	1045	[74.7%]	1.03	1388	[72.2%]	0.21	(0.8)
Medium	-2.83	277	[19.8%]	-0.30	412	[21.4%]	2.53	(2.5)
Large	0.34	77	[5.5%]	-9.35	122	[6.3%]	-9.70	(-5.2)

Sample: 102 NYSE tender offer target companies in 1994 and 1995. Non-event period is days -249 to -220 relative to date of the first tender offer announcement in the Wall Street Journal; pre-announcement period is days -31 to -2. The table reports estimates of effective spreads (calculated as the absolute difference between trade price and prevailing midquote as a percentage of midquote price) and adverse selection component of the spread (as a percentage of effective spread) classified by trade size and sequence. In the pre-announcement period, transactions for all securities are pooled, and reported numbers are time-series averages and t-statistics from daily statistics. Small, medium and large trade categories are based on the 75th and 95th percentiles of trade sizes for each company in the 30-day non-event period. A continuation is a trade following a prior same-day trade of the same sign (both trades initiated by buyers or both by sellers). A reversal is a trade following a prior same-day trade of a different sign (one trade initiated by a buyer and the other by a seller). Only regular trades (excluding opening and after market close) and BBO-eligible quotes with positive spreads originating on the NYSE were used.

Table 6. Estimates of spreads, adverse selection components, and proportions of buyer-initiated trades, by trade size, sequence and buyer- or seller-initiation, for 29 largest tender-offer target companies

Panel A. Effective spreads (percent of price)

Trade Size	Non-event period			Pre-announcement period			Difference	
	Mean	Avg Trds	[% Trds]	Mean	Avg Trds	[% Trds]	Mean	(tstat)
All	0.27	2621	[100.0%]	0.24	3956	[100.0%]	-0.03	(-16.2)
Small	0.27	1957	[74.7%]	0.24	2838	[71.7%]	-0.03	(-17.9)
Medium	0.28	530	[20.2%]	0.25	893	[22.6%]	-0.03	(-10.1)
Large	0.28	133	[5.1%]	0.24	225	[5.7%]	-0.04	(-8.9)
Buyer-initiated								
All	0.27	1382	[100.0%]	0.24	2163	[100.0%]	-0.03	(-17.2)
Small	0.27	1032	[74.7%]	0.24	1565	[72.4%]	-0.03	(-18.6)
Medium	0.27	279	[20.2%]	0.24	484	[22.4%]	-0.03	(-9.9)
Large	0.28	71	[5.1%]	0.25	114	[5.3%]	-0.03	(-5.9)
Seller-initiated								
All	0.28	1230	[100.0%]	0.25	1784	[100.0%]	-0.03	(-11.0)
Small	0.27	919	[74.7%]	0.25	1266	[71.0%]	-0.02	(-10.0)
Medium	0.28	248	[20.2%]	0.25	407	[22.8%]	-0.03	(-8.4)
Large	0.28	62	[5.0%]	0.24	110	[6.2%]	-0.05	(-8.8)

Panel B. Adverse selection component of spreads (percent of spread)

Trade Size	Non-event period			Pre-announcement period			Difference	
	Mean	Avg Trds	[% Trds]	Mean	Avg Trds	[% Trds]	Mean	(tstat)
All	5.24	2621	[100.0%]	4.04	3956	[100.0%]	-1.21	(-4.2)
Small	4.05	1957	[74.7%]	2.79	2838	[71.7%]	-1.26	(-3.7)
Medium	7.86	530	[20.2%]	6.62	893	[22.6%]	-1.24	(-2.1)
Large	10.91	133	[5.1%]	9.33	225	[5.7%]	-1.58	(-1.4)
Buyer-initiated								
All	5.41	1382	[100.0%]	4.57	2163	[100.0%]	-0.83	(-1.2)
Small	3.88	1032	[74.7%]	2.29	1565	[72.4%]	-1.59	(-1.9)
Medium	8.11	279	[20.2%]	7.52	484	[22.4%]	-0.59	(-0.5)
Large	11 73	71	[5.1%]	15.80	114	[5.3%]	4.07	(1.6)
Seller-initiated								
All	4.92	1230	[100.0%]	2.23	1784	[100.0%]	-2.69	(-3.0)
Small	3.69	919	[74.7%]	0.86	1266	[71.0%]	-2.83	(-3.1)
Medium	7.30	248	[20.2%]	5.58	407	[22.8%]	-1.72	(-1.0)
Large	10.48	62	[5.0%]	8.64	110	[6.2%]	-1.84	(-0.4)

Panel C. Proportion of buyer-initiated minus seller-initiated trades (percent of trades)

Trade Size	Non-event period Mean	Avg Trds	[% Trds]	Pre-announcement period Mean	Avg Trds	[% Trds]	Difference Mean	(tstat)
All	5.80	2621	[100.0%]	9.35	3956	[100.0%]	3.55	(5.4)
Small	5.75	1957	[74.7%]	10.29	2838	[71.7%]	4.54	(6.3)
Medium	5.76	530	[20.2%]	8.28	893	[22.6%]	2.52	(2.9)
Large	6.67	133	[5.1%]	1.49	225	[5.7%]	-5.18	(-2.8)
Continuations								
All	8.31	1812	[100.0%]	13.43	2747	[100.0%]	5.12	(5.5)
Small	7.79	1345	[74.2%]	14.11	1957	[71.3%]	6.32	(6.4)
Medium	9.81	379	[20.9%]	12.32	640	[23.3%]	2.51	(2.0)
Large	9.80	88	[4.8%]	8.69	150	[5.5%]	-1.11	(-0.4)
Reversals								
All	0.18	809	[100.0%]	0.05	1209	[100.0%]	-0.13	(-2.0)
Small	1.27	613	[75.7%]	1.79	881	[72.8%]	0.51	(1.6)
Medium	-4.42	151	[18.6%]	-1.96	254	[21.0%]	2.45	(2.3)
Large	0.66	46	[5.7%]	-13.59	75	[6.2%]	-14.25	(-7.1)

Sample: 29 NYSE tender offer target companies in 1994 and 1995 in CRSP decile ten (largest size class). Non-event period is days -249 to -220 relative to date of the first tender offer announcement in the Wall Street Journal; pre-announcement period is days -31 to -2. The table reports estimates of effective spreads (calculated as the absolute difference between trade price and prevailing midquote as a percentage of midquote price), adverse selection component of the spread (as a percentage of effective spread), proportion of buyer-initiated minus seller-initiated trades (as a percentage of total trades), and proportion of total midquote returns classified by trade size, sequence and whether buyer- or seller-initiated. In the pre-announcement period, transactions for all securities are pooled, and reported numbers are time-series averages and t-statistics from daily statistics. Small, medium and large trade categories are based on the 75th and 95th percentiles of trade sizes for each company in the 30-day non-event period. A continuation is a trade following a prior same-day trade of the same sign (both trades initiated by buyers or both by sellers). A reversal is a trade following a prior same-day trade of a different sign (one trade initiated by a buyer and the other by a seller). Only regular trades (excluding opening and after market close) and BBO-eligible quotes with positive spreads originating on the NYSE were used.

Table 7. Estimates of spreads, adverse selection components, and proportions of buyer-initiated trades, by trade size, sequence and buyer/seller-initiation, for 51 tender-offer target companies with largest price run-ups

Panel A. Effective spreads (percent of price)

Trade Size	Non-event period			Pre-announcement period			Difference	
	Mean	Avg Trds	[% Trds]	Mean	Avg Trds	[% Trds]	Mean	(t-stat)
All	0.47	1826	[100.0%]	0.39	3026	[100.0%]	-0.08	(-19.6)
Small	0.47	1351	[74.0%]	0.39	2081	[68.8%]	-0.08	(-20.1)
Medium	0.48	378	[20.7%]	0.38	742	[24.5%]	-0.10	(-16.5)
Large	0.49	98	[5.3%]	0.40	203	[6.7%]	-0.09	(-9.4)
Buyer-initiated								
All	0.48	930	[100.0%]	0.39	1660	[100.0%]	-0.09	(-17.2)
Small	0.48	681	[73.2%]	0.39	1132	[68.2%]	-0.09	(-16.3)
Medium	0.48	197	[21.2%]	0.38	422	[25.4%]	-0.10	(-16.6)
Large	0.46	52	[5.6%]	0.40	106	[6.4%]	-0.06	(-5.5)
Seller-initiated								
All	0.46	888	[100.0%]	0.39	1356	[100.0%]	-0.07	(-16.9)
Small	0.45	664	[74.8%]	0.39	942	[69.5%]	-0.06	(-17.1)
Medium	0.48	179	[20.1%]	0.39	318	[23.5%]	-0.09	(-12.3)
Large	0.52	45	[5.1%]	0.39	96	[7.1%]	-0.12	(-11.4)

Panel B. Adverse selection component of spreads (percent of spread)

Trade Size	Non-event period			Pre-announcement period			Difference	
	Mean	Avg Trds	[% Trds]	Mean	Avg Trds	[% Trds]	Mean	(t-stat)
All	13.00	1826	[100.0%]	12.67	3026	[100.0%]	-0.33	(-0.3)
Small	9.51	1351	[74.0%]	9.30	2081	[68.8%]	-0.21	(-0.3)
Medium	20.10	378	[20.7%]	20.30	742	[24.5%]	0.20	(0.1)
Large	31.21	98	[5.3%]	21.90	203	[6.7%]	-9.32	(-3.4)
Buyer-initiated								
All	12.74	930	[100.0%]	17.63	1660	[100.0%]	4.89	(2.3)
Small	9.48	681	[73.2%]	12.95	1132	[68.2%]	3.47	(1.7)
Medium	21.38	197	[21.2%]	27.94	422	[25.4%]	6.56	(1.5)
Large	29.09	52	[5.6%]	28.52	106	[6.4%]	-0.57	(-0.1)
Seller-initiated								
All	17.93	888	[100.0%]	14.40	1356	[100.0%]	-3.53	(-1.8)
Small	12.60	664	[74.8%]	9.70	942	[69.5%]	-2.90	(-1.5)
Medium	23.91	179	[20.1%]	24.03	318	[23.5%]	0.12	(0.0)
Large	51.14	45	[5.1%]	22.49	96	[7.1%]	-28.64	(-5.0)

Panel C. Proportion of buyer-initiated minus seller-initiated trades (percent of trades)

Trade Size	Non-event period Mean	Avg Trds	[% Trds]	Pre-announcement period Mean	Avg Trds	[% Trds]	Difference Mean	(t-stat)
All	2.31	1826	[100.0%]	9.43	3026	[100.0%]	7.12	(8.3)
Small	1.28	1351	[74.0%]	8.87	2081	[68.8%]	7.60	(8.6)
Medium	4.87	378	[20.7%]	12.40	742	[24.5%]	7.53	(5.7)
Large	6.62	98	[5.3%]	2.47	203	[6.7%]	-4.15	(-2.2)
Continuations								
All	3.32	1255	[100.0%]	13.39	2115	[100.0%]	10.07	(8.3)
Small	1.99	929	[74.1%]	12.49	1450	[68.6%]	10.49	(8.8)
Medium	7.21	261	[20.8%]	16.95	527	[24.9%]	9.74	(5.2)
Large	6.76	64	[5.1%]	6.91	138	[6.5%]	0.15	(0.1)
Reversals								
All	0.08	571	[100.0%]	0.26	911	[100.0%]	0.18	(2.1)
Small	-0.29	421	[73.8%]	0.63	631	[69.3%]	0.92	(1.8)
Medium	-0.37	116	[20.3%]	1.13	215	[23.6%]	1.50	(1.0)
Large	6.36	34	[5.9%]	-7.30	65	[7.1%]	-13.66	(-4.9)

Sample: 51 NYSE tender offer target companies in 1994 and 1995 with the largest price run-ups in the pre-announcement period. Non-event period is days -249 to -220 relative to date of the first tender offer announcement in the Wall Street Journal; pre-announcement period is days -31 to -2. The table reports estimates of effective spreads (calculated as the absolute difference between trade price and prevailing midquote as a percentage of midquote price), adverse selection component of the spread (as a percentage of effective spread), proportion of buyer-initiated minus seller-initiated trades (as a percentage of total trades), and proportion of total midquote returns classified by trade size, sequence and whether buyer- or seller-initiated. In the pre-announcement period, transactions for all securities are pooled, and reported numbers are time-series averages and t-statistics from daily statistics. Small, medium and large trade categories are based on the 75th and 95th percentiles of trade sizes for each company in the 30-day non-event period. A continuation is a trade following a prior same-day trade of the same sign (both trades initiated by buyers or both by sellers). A reversal is a trade following a prior same-day trade of a different sign (one trade initiated by a buyer and the other by a seller). Only regular trades (excluding opening and after market close) and BBO-eligible quotes with positive spreads originating on the NYSE were used.

Table 8. Weighted least-squares regression estimates of the difference in cumulative returns between pre-announcement and non-event periods on dummy variables for trade size and sequence, and differences in share volume occurring in that category

Regressor	Coefficient	(t-stat)
Small	2.38	(3.75)
Medium	1.35	(2.11)
Large	0.22	(0.36)
Continuations	1.82	(2.85)
Volume	-0.03	(-0.08)
R^2	0.096	
F-value	12.924	
p-value	0.0001	
# Obs	612	

Sample: 102 NYSE tender offer target companies in 1994 and 1995. The pre-announcement period is days -31 through -2 in relation to date of first tender-offer announcement in the Wall Street Journal; and the non-event period is days -249 through -220. Table 8 presents the results from estimating the following regression equation

$$EXRET_{i,size,seq} = \sum_{size} \hat{\beta}_{size} D_{size} + \hat{\beta}_{seq} D_{seq} + \hat{\beta}_v Vol_{i,size,seq}$$

where the dependent variable $EXRET_{i,size,seq}$ is the difference between the pre-announcement and non-event periods for company i of cumulative midquote returns from all trades in the same size/sequence category . Trades are classified into categories by size (Small, Medium or Large) and sequence (Reversals or Continuations). D_{size} is a dummy variable corresponding to he three trade size categories, and D_{seq} is a dummy variable indicating if the trade is a continuation sequence. Vol_{ic} is the difference in share volume for company i in trade size/sequence category c between the pre-announcement and non-event period, in millions of shares. The weights are equal to the absolute difference in cumulative stock midquote returns for company i between the pre-announcement and non-event periods.

Figure 2. Effective Spread (percent of price)

By Trade Size

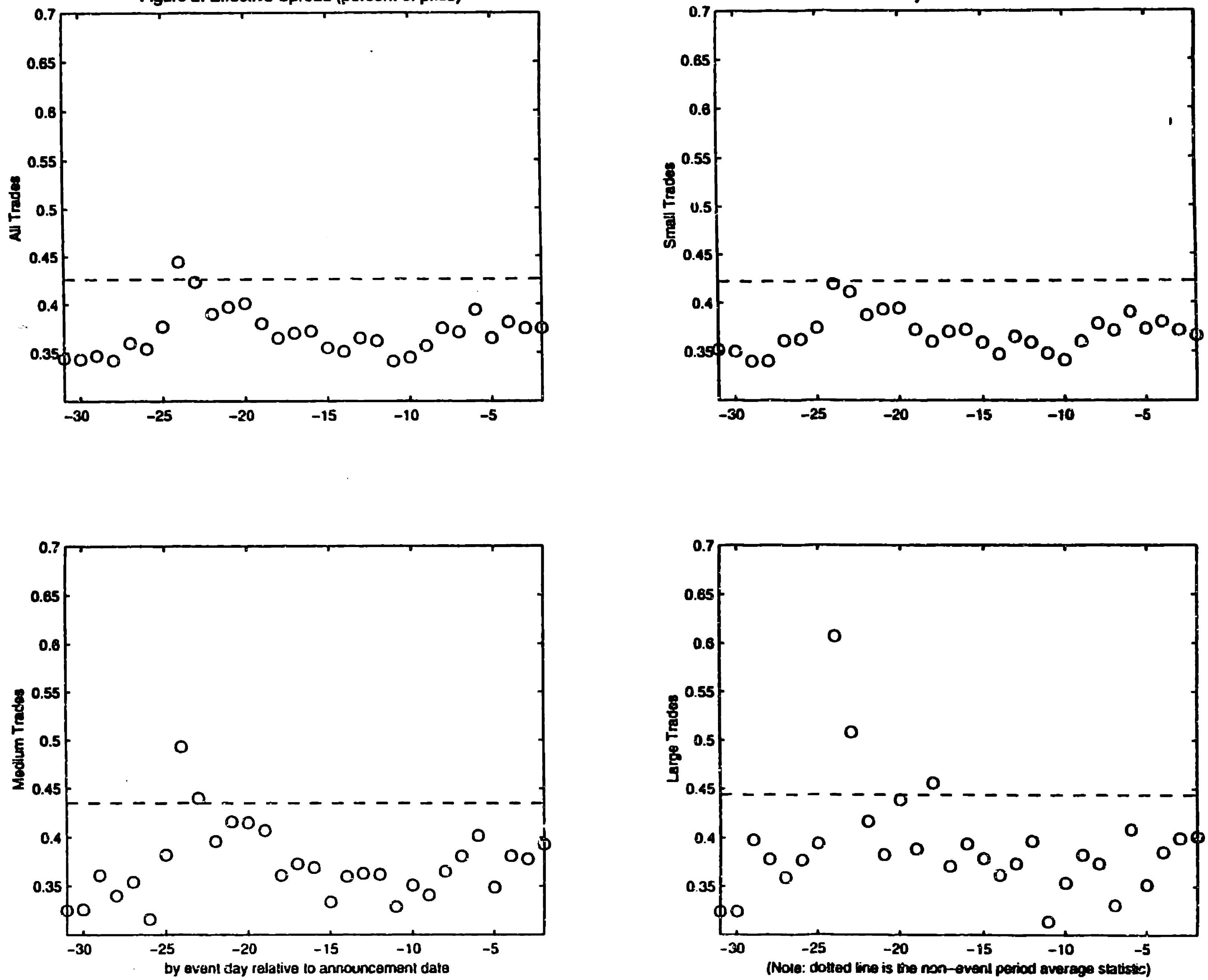


Figure 3. Adverse Selection Component (percent of spread)

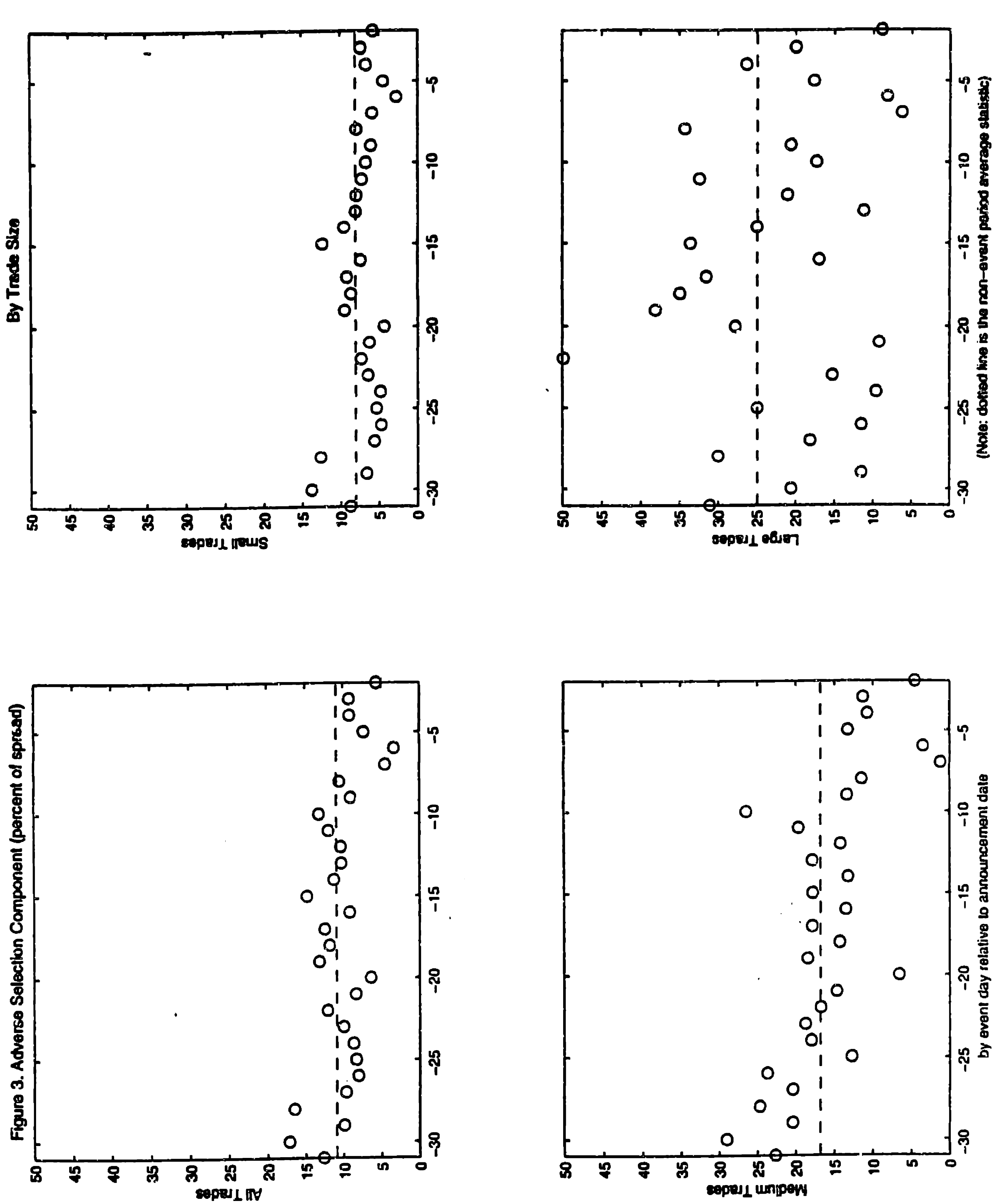
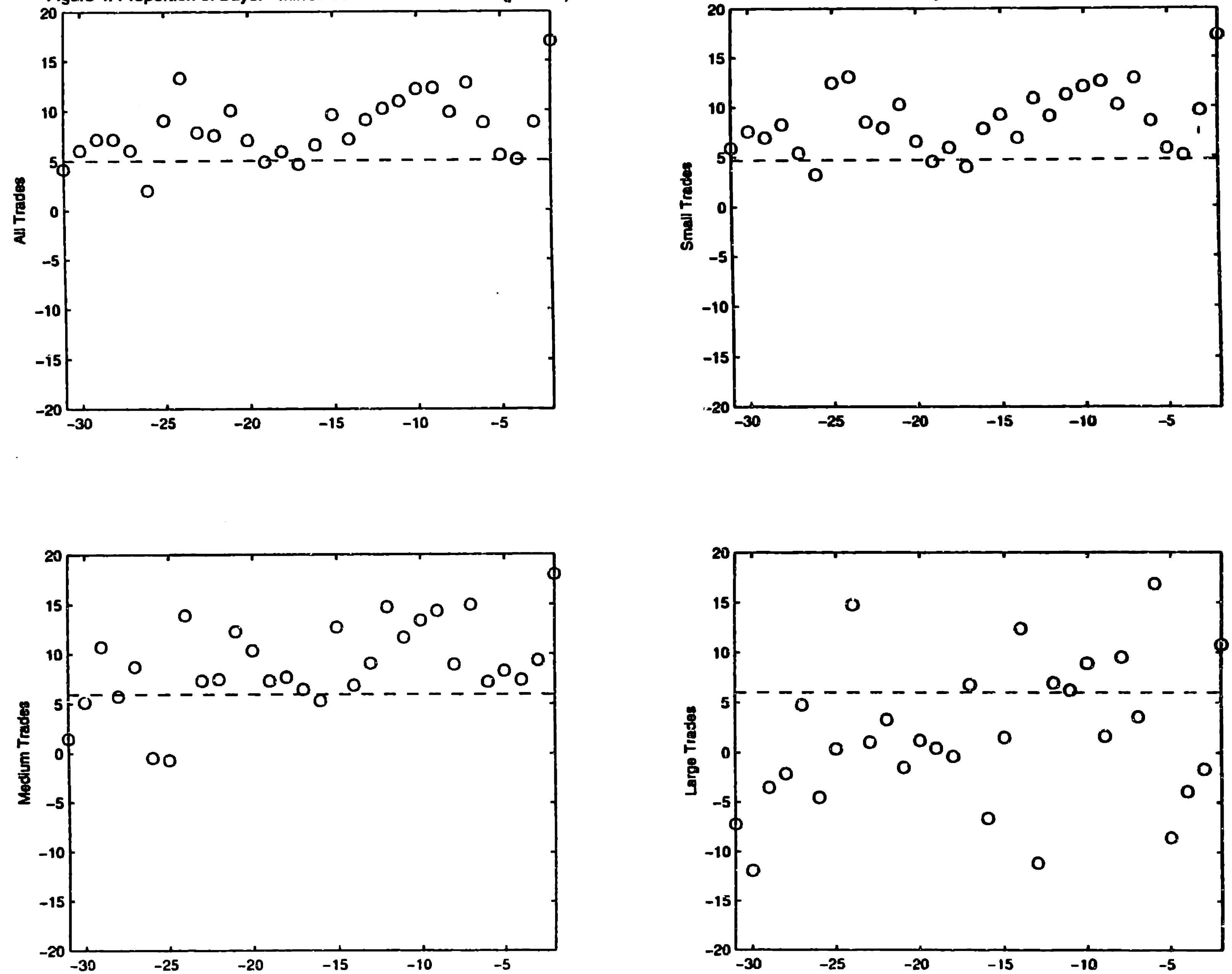


Figure 4. Proportion of Buyer- minus Seller-Initiated Trades (percent)

By Trade Size

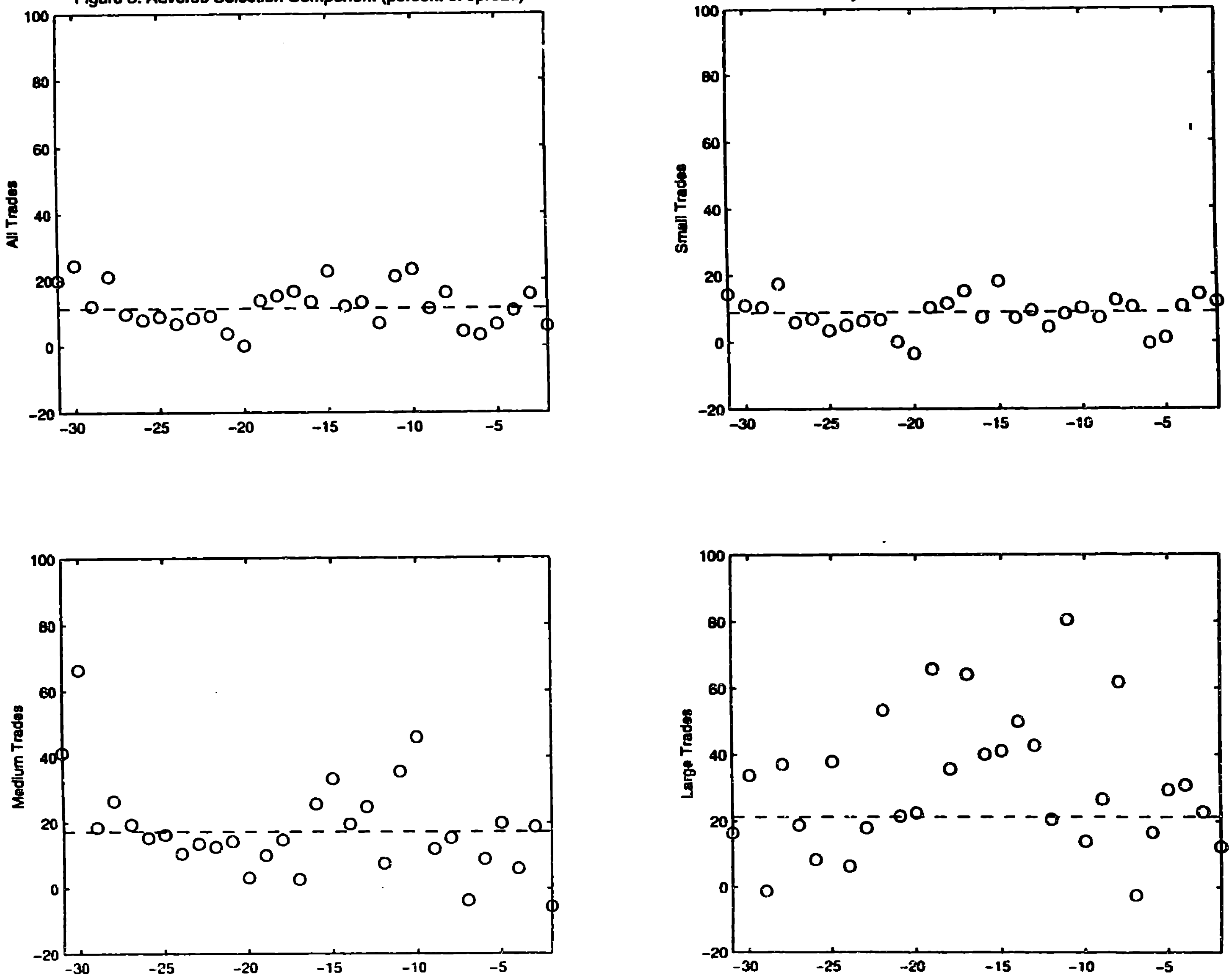


by event day relative to announcement date

(Note: dotted line is the non-event period average statistic)

Figure 5. Adverse Selection Component (percent of spread)

Buyer-Initiated Trades, by Trade Size



by event day relative to announcement date

(Note: dotted line is the non-event period average statistic)

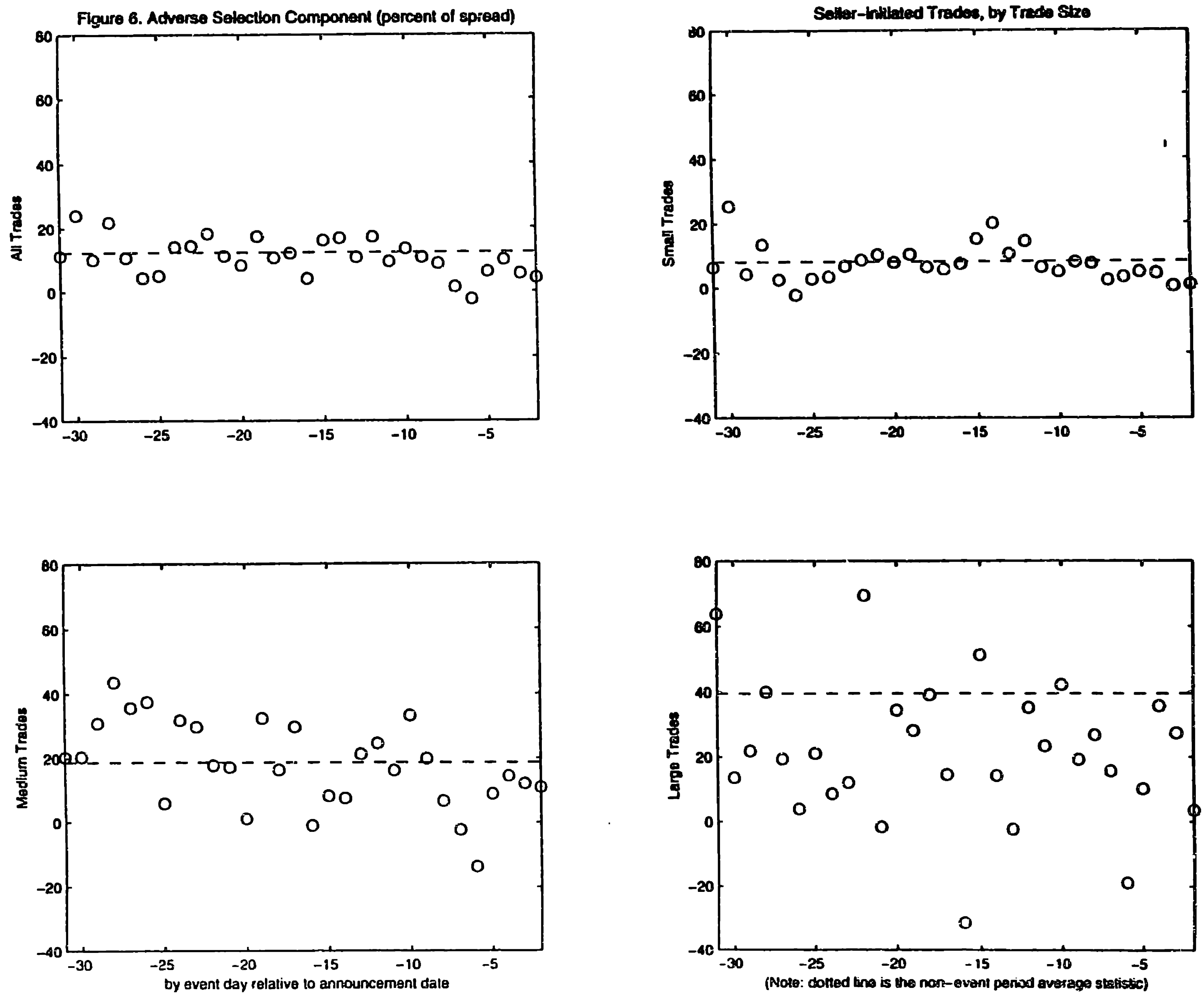
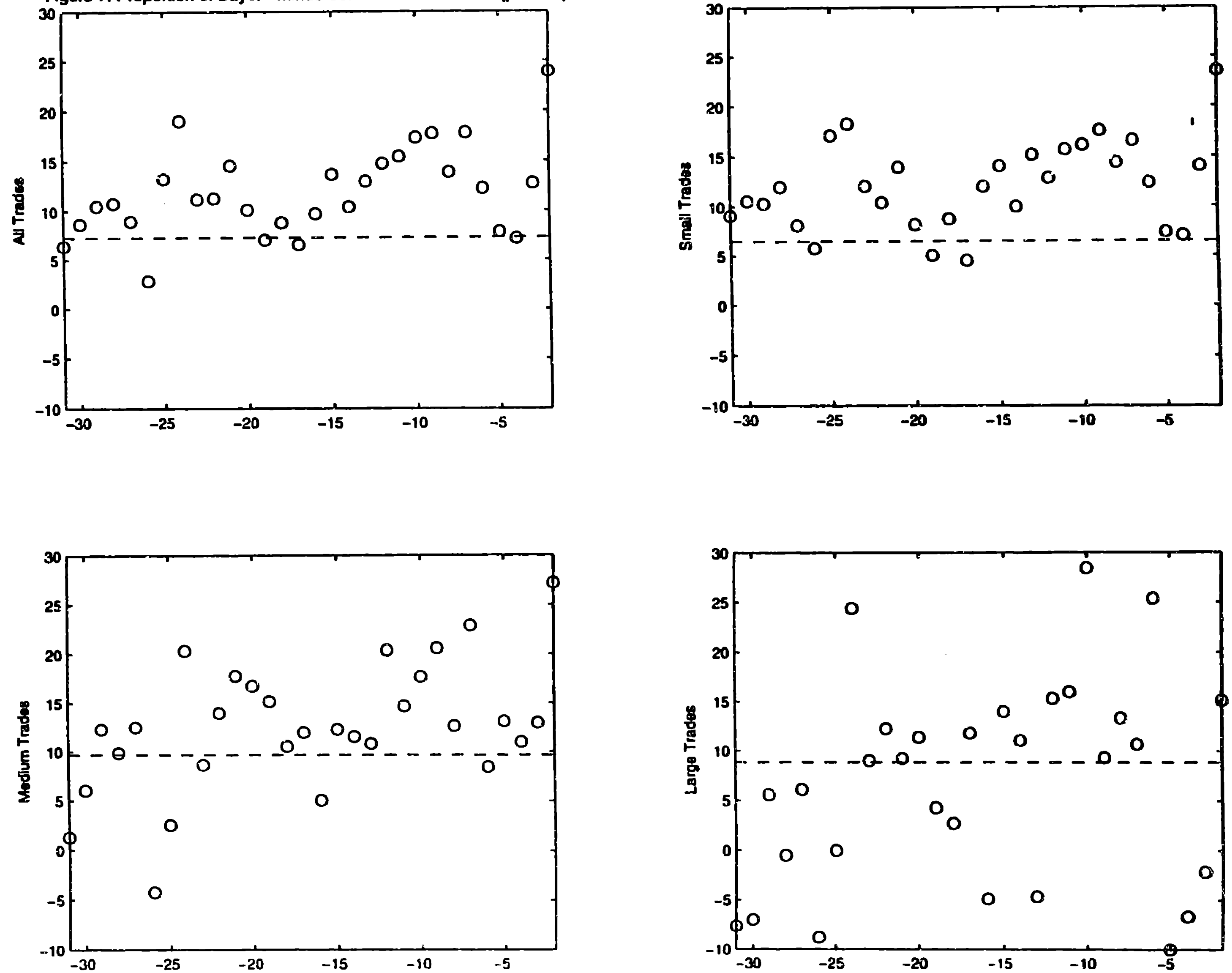


Figure 6. Adverse Selection Component (percent of spread)
Seller-Initiated Trades, by Trade Size
All Trades
Small Trades
Medium Trades
Large Trades
by event day relative to announcement date
(Note: dotted line is the non-event period average statistic)

Figure 7. Proportion of Buyer- minus Seller-initiated Trades (percent)

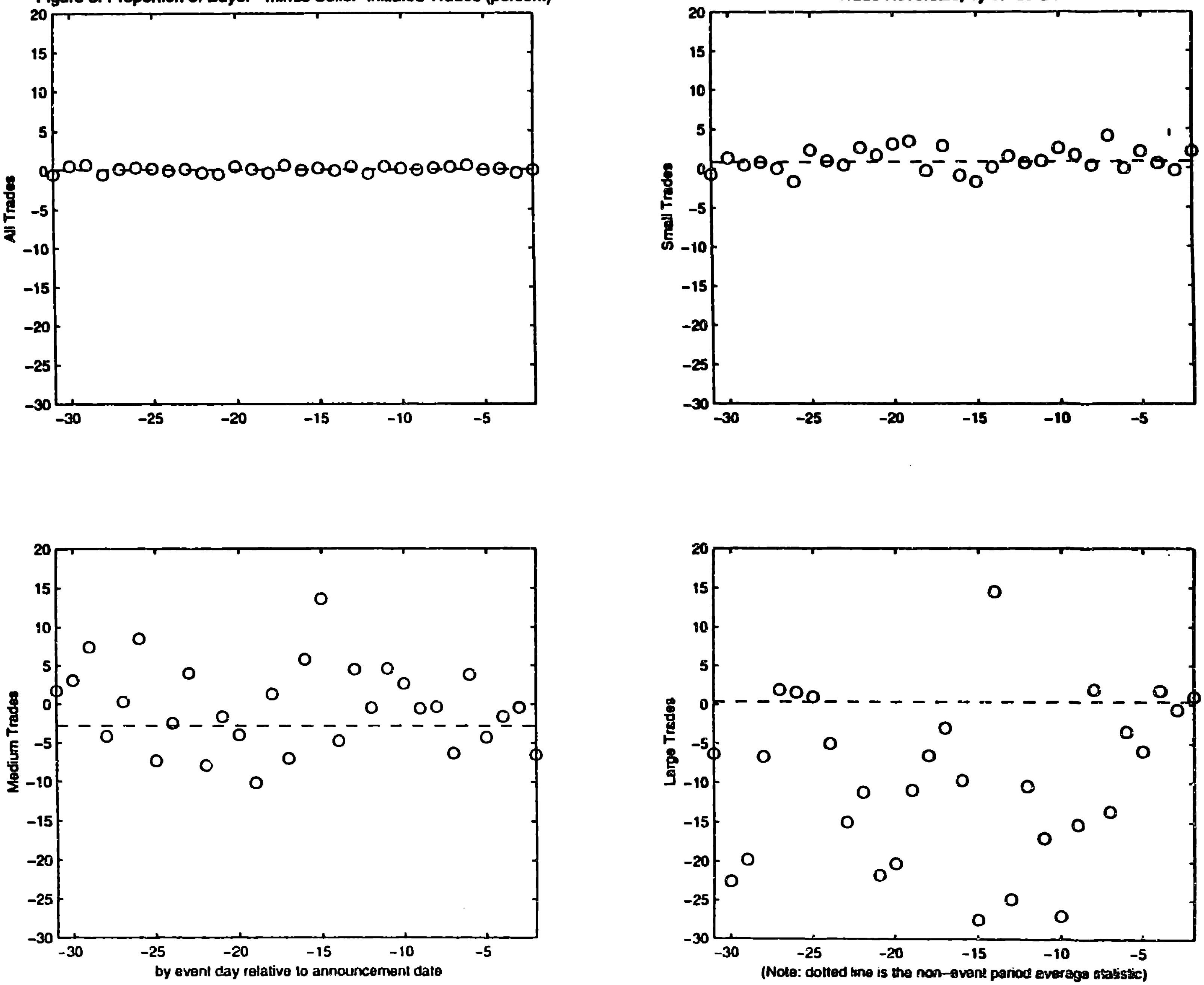
Trade Continuations, by Trade Size



(Note: dotted line is the non-event period average statistic)

Figure 8. Proportion of Buyer- minus Seller-initiated Trades (percent)

Trade Reversals, by Trade Size



Chapter 3

Introduction

A large body of research has examined analysts' earnings forecasts to test the rational expectations hypothesis, treating the forecasts as if they were the expectations of the analysts. Earnings estimates from sell-side brokerage firms are routinely collected by services such as I/B/E/S, Zacks, Standard and Poor's and First Call, and disseminated to institutional investors, along with the names of the analysts making the estimates. Their forecasts are routinely held to the "market test" every three months when actual company earnings are announced. Since analysts' livelihoods[1] depend directly on the accuracy of their forecasts, and since we can observe the same forecasts that the analyst sells, it appears plausible that these forecasts accurately measure the analysts' expectations.

Existing empirical evidence indicates that analyst forecasts of corporate earnings do not meet the standards of the rational expectations hypothesis. In particular, previous research has documented analysts' tendency to overestimate corporate earnings in frequency and magnitude. Examples are Abarbanell (1989), Brown, Foster and Noreen (1985) and Stickel (1990) using Value Line, I/B/E/S and Zacks data sources respectively.

In this paper, we consider an environment in which analysts forecast company

[1]Stickel (1992) documents that analysts who make the Institutional Investors' All-Star Team, an important factor in determining analysts' compensation, produce more accurate earnings forecasts than other analysts.

earnings (and are compensated based on the accuracy of their forecasts) but where the company's management is a key source of firm-specific information. In this environment, analysts seek to minimize the mean squared error of earnings forecasts, but their optimal reported forecasts are positively biased. This result can be understood by observing that mean squared error can be decomposed into two components: the (squared) bias and variance of the forecast. By reporting a positively biased forecast in order to cultivate management relations, analysts seek to obtain access to better information that could reduce the variance and hence the conditional expected total error of their reported forecast. In other words, analysts are rationally biased: the optimal forecast that minimizes mean squared error differs from the expected value by a positive amount.

There is significant anecdotal evidence of the pressure on analysts to produce accurate forecasts and, at the same time, maintain management relationships and access. The Wall Street Journal[2] reported the dismissal of "widely-quoted aerospace analyst" by Prudential Securities, his employer of 13 years.

> [The analyst] had fallen from grace at Prudential for calls on prospects for two companies – General Dynamics Corp and Boeing Co. [The analyst] also said Prudential had wanted its analysts named to an "all-star" list produced by Institutional Investor magazine, which he hadn't made since 1989. [The analyst] added that he believes the firing may also have reflected complaints to Prudential by General Dynamics managers. In 1991 first quarter, with General Dynamics' stock trading at about $30 a share, [the analyst] urged investors to sell General Dynamics' stock.

Top management and investment contacts at followed firms may limit or eliminate the analyst's flow of information if he issues unfavorable ratings. Pratt (1993) reports that General Motors has been known to tell analysts explicitly that their phone calls will not be returned if they drop its ratings below neutral. Following the much-publicised dismissal of a Janney Montgomery Scott casino analyst who angered

[2]Wall Street Journal, November 5, 1992.

billionaire Donald Trump by suggesting that Trump's lavish new Taj Mahal Casino Resort might not succeed, the St Petersburg Times[3] reported that

> most [analysts] learn early on that telling the unvarnished truth is no way to win friends in the executive suite. The most frequent punishment companies mete out is the "deep freeze". Take St. Petersburg stock analyst Harry Katica, who earlier this year was recommending stock in Silk Greenhouse Inc. to clients of Raymond James & Associates. When he stopped saying "buy" and advised investors to "hold", officials at the Tampa retailer simply stopped returning his telephone calls.

In the next section, we examine this "management access" story more formally, and show that it generates some auxiliary empirical implications that can be tested by examining the cross-section of earnings forecasts. To preview, we expect that companies with more uncertain information environments would be associated with more optimistic forecasts since analysts have more to gain informationally by being positively biased. Also, analysts for whom cultivating relationships are more important for gaining management access, such as those employed by smaller regional brokerage firms rather than a large top-tier broker, would tend to issue more optimistic forecasts.

Prior research has suggested and tested alternative hypotheses to explain the optimistic bias in analysts' forecasts. Some papers have suggested that analysts face payoff structures that provide incentives to produce forecasts which do not minimize forecast errors. McNichols and O'Brien (1996) suggest that analysts initiate coverage of a stock only when they tend to have an optimistic view of the stock, because buy ideas generate more commissions than sell recommendations – they term this tendency a "self-selection" bias. Michealy and Womack (1995) and Lin and McNichols (1997) document that the conflicts of interest that affect brokers who also have an investment banking relationship with the company could pressure analysts to issue more positive forecasts. Ito (1990) finds that exchanges rates forecasts are systematically biased

[3]St. Petersburg Times, August 5, 1990.

toward scenarios that would benefit the forecaster's employer. These studies have been more successful empirically in explaining why analysts tend to issue more"buy" recommendations than "sells", but have not been able to explain biases in earnings forecasts. Whereas *earnings forecasts* are objective and are easily subjected to the market test, analysts' *recommendations* are qualitative and subjective, that depend on judgements of stock price valuations and longer term prospects, and hence more easily influenced by the alternative incentive schemes suggested above than minimum forecast error considerations.

For forecasts collected by I/B/E/S, Philbrick and Ricks (1991) and Keane and Runkle (1997) have pointed out that because I/B/E/S forecasts are generally of ordinary continuing earnings, comparisons with reported earnings may be affected by unusual accounting items. In particular, management may report discretionary charges, usually large asset write-offs or restructuring expenses, as above-the-line special items. These cases may generate extreme negative earnings that skew measures of overall forecast bias.

We identify those forecasts in our sample that are most likely to be affected by these alternative "self-selection" and "conflict-of-interest" hypotheses, or are affected large discretionary accounting charges. We find that these factors do not explain away the positive bias in earnings forecasts. Our main empirical tests suggest that consensus forecast bias is concentrated in small and volatile companies, or that have recently experienced negative earnings surprises or stock returns. Also, relative to others following the same company, analysts employed by smaller brokerage firms tend to issue more optimistic forecasts.

In a study of Value Line forecasts, Francis and Philbrick (1993) show that in when stock recommendations are prepared by other persons, but analysts are responsible for earnings forecasts and management relations, analysts do not produce forecasts with minimal error, but issue forecasts that are optimistic for "sell" stocks than for "buy" stocks. However, their results relate to a specific, perhaps unusual, environment for analysts employed by a particular company, Value Line.

We also do not directly address the "efficiency" property of rationality, which has been the subject of other research. DeBondt and Thaler (1990) suggest that analysts exhibit behavioral biases by overreacting to past information, while Ababanell (1992) provides evidence that analysts underreact to the information in past earnings announcements. Related research using macroeconomic forecasts have argued that forecasters may deliberately garble their own forecasts to gain reputation or publicity. Scharfstein and Stein (1992) demonstrates that reputation concerns can lead to herding of forecasts. Lamont (1995) hypothesizes that a forecaster's willingness to make predictions that deviate from the consensus may vary systematically with his level of experience or seniority. Analyzing forecasts of GNP and GDP from an annual Business Week survey, he finds that forecasters who have been in the industry longer exhibit a greater willingness to deviate from the consensus. Laster, Bennett and Geoum (1996) develop a model that shows how forecasters' efforts to balance twin objectives of accuracy and publicity can lead them to produce biased macroeconomic forecasts. Forecasters seeking publicity will predict values that are not tightly clustered around a consensus, as these forecasts would then have little or no chance of winning them widespread attention. However, while these stories predict that the distribution of errors may be too tight or too disperse, they do not address why the mean bias is positive.

The rest of our study proceeds as follows. In Section 2, we describe more formally how management access considerations lead analysts to trade off bias and precision in forming minimum error forecasts of earnings, and the auxiliary empirical implications that this story generates. In Section 3 we perform some preliminary exploratory analyses of the I/B/E/S database of individual analysts' forecasts, and show that the specific factors described above do not drive away the optimistic bias. Section 4 reports our main empirical tests of the predicted relationships between forecast bias and company and analyst characteristics. We conclude in Section 5.

3.1 Rational Bias

Assume that the analyst is tasked to publish an earnings forecast which minimizes expected squared deviation between the forecast and actual earnings. Furthermore, he is able to observe a noisy private signal of company's earnings, presumably through research and company visits. Our key assumption is that the analyst, in publishing a biased forecast, can control the precision of his private signal. Through cultivating management relations by appearing to be favorable, the analyst can gain access to publicly-unavailable company information.

Specifically, assume that the analyst observes I_t, a noisy signal of company's earnings X. He publishes a forecast $\hat{X}$, so as to minimize mean squared error, which can be decomposed into a conditional squared bias and a conditional variance term.

$$Min_{\hat{X}}\ E_t[(\hat{X} - X)^2 | I_t] \equiv Min_b\ b^2 + Var_t(X|I_t) \tag{3.1}$$

where b is the conditional bias $\hat{X} - \overline{X}$.

Let

1. X be normal with mean 0 (without loss of generality) and variance σ_0^2 (or precision τ_0)
2. the signal be $I_t = X + \epsilon_t$
3. and the noise term ϵ_t be normal with mean 0 and variance σ^2 a function of bias b (or precision $\tau(b)$); then
4. the conditional expectation of X is $\frac{\tau(b)}{\tau(b)+\tau_0} I_t$
5. the conditional variance of X is $\frac{1}{\tau(b)+\tau_0}$

Hence the loss function can be written as

$$Min_b\ b^2 + \frac{1}{\tau_0 + \tau(b)} \tag{3.2}$$

and the first-order condition is

$$b = \frac{\tau'(b)}{2(\tau_0 + \tau(b))^2} \tag{3.3}$$

A static analysis of this first order condition immediately suggests the two following propositions.

PROPOSITION 1

If earnings are less predictable (τ_0 is small), then optimism b increases. Intuitively, if public news about the company's earnings prospects are unavailable, then the analyst has more to gain informationally when giving up some positive bias. Companies that are small or volatile are likely to have more uncertain information environments.

PROPOSITION 2

Greater optimism is observed if cultivating management relations is more important for gaining access to private information, i.e. τ' is positive. This corresponds to the case when the analyst is most able to improve the precision τ of his private signal. Analysts employed by smaller, regional brokerage firms, which possess fewer research resources or weaker distribution networks, are probably more reliant on management relations to gain company information.

This result that a biased estimator can possess the desirable property of having lower sampling variability has several analogies in the field of statistical decision theory. For example, James and Stein (1961) demonstrated a biased estimator in a linear regression setup with more than 2 regressors that dominated the conventional least squares-maximum likelihood estimator under a mean squared loss performance measure.

We also note that the first order condition to the analyst's forecasting problem resembles closely the form for the optimal predictor under the "linex" loss function introduced by Varian (1974) and further studied by Zellner (1986). The linex loss function, an algebraically convenient example of an asymmetric utility function, is given by:

$$L(x) = b[e^{ax} - ax - 1] \tag{3.4}$$

The linex loss function is so-named for its almost linear shape on one side of the origin, and almost exponential slope on the other. The parameter a plays an important role in the shape of the linex loss function. Quadratic loss is approximately nested within linex loss, because if a is small, one can approximate the loss function by its first two Taylor expansion terms which yields just a quadratic loss function. When x is a Gaussian variate (with mean 0 and standard deviation σ, without loss of generality), the optimal predictor is given by:

$$\hat{y} = \frac{a}{2}\sigma^2 \tag{3.5}$$

By comparison to our setup, if the slope of the relationship function $\tau(b)$ is constant, then our stylized model of the analyst's forecasting problem can be expressed as a linex loss function. This result links our work to recent developments in economic theory (such as the "loss aversion" utility theory of Kahneman and Tversky (1979)) and demonstrates an example of how asymmetric loss may arise quite naturally in economic problems.

3.2 Data

Our forecast data is from the Institutional Brokers Estimate System, or I/B/E/S. We use both the Detail and Summary versions of the data. The Detail database consists of individual analysts' forecasts of earnings per share made between 1983 and 1997 by analysts at over 300 brokerage firms. The individual forecasts are used by I/B/E/S to compute monthly Summary information, such as means, medians and standard deviations.

Each entry in the database represents an individual forecast and contains the company ticker, broker identifier, analyst identifier, estimate and forecast date. Analyst codes are used to identify analysts on the academic tape. These codes remain with an analyst as he moves from broker to broker. Some entries to the dataset are forecasts supplied by individual analysts and others are supplied by teams of analysts. The analyst codes on the academic tapes do not distinguish between individuals and teams. While all major brokerage firms are included in the dataset, most of the brokers are regional firms. It is not known what percentage of the overall analyst population is included in the detail tape, but analysts have an incentive to supply forecasts to I/B/E/S. The corporate version of the tape includes analysts' names and is sold to money managers. This provides the analysts with exposure. Also, any analyst who is employed by a broker that provides forecasts to I/B/E/S is required to supply forecasts to I/B/E/S for any firms followed.

I/B/E/S also supplies an Actuals file that reports actual earnings per share. Some companies are followed on a primary EPS basis and others are followed on a fully diluted EPS basis. I/B/E/S makes any necessary adjustments to forecasts so they are on the same basis that the firm is normally followed. I/B/E/S culls earnings reports from newswires, newspapers and brokers themselves. However, there are known problems with data alignment in the reported I/B/E/S earnings data. Philbrick and Ricks (1991) examine this issue in detail. They identified numerous cases where the actual I/B/E/S EPS for quarter t was, in fact, the actual EPS for quarter $t-1$. Once this misalignment arose for particular firm, it persisted through all remaining quarters. They report that these problems with actual EPS appear have been mitigated for recent reported earnings. Because of this alignment problem, and to be consistent with the literature, we use data for actual EPS from Compustat's Industrial Quarterly files of active and inactive companies[4].

Table 1 provides some summary characteristics of the I/B/E/S Detail File. Panel A is based on firms with quarterly earnings forecasts in the I/B/E/S Detail File. Quarterly detail estimates from I/B/E/S became available starting in late 1983. 2451 companies with fiscal quarter end dates in 1984 were covered, and this rose to 5973 in 1996. Most of the increase can be attributed to improved coverage of small and medium-sized companies (CRSP decile 7 and smaller) and of NASDAQ-listed compa-

[4]We matched companies from the CRSP, Compustat and I/B/E/S using 8-digit CUSIP identifiers.

nies. Panel B reports the number of brokerage firms that reported either a quarterly or annual earnings estimate for a fiscal period ending in each year; and the the distribution of the number of analysts employed by each broker. The number of brokerage firms ranged from 140 at the beginning of our sample to 303 in 1996 of 1996. Each broker employed about 18 analysts; most of the brokerage firms (80 percent) employed fewer than 30 analysts, but the very largest brokers (at the 95th percentile) employed at least 60 to 70 analysts. Panel C shows the number of analysts providing annual or quarterly earnings forecasts in each year, as well as the distribution of the number of companies each analyst followed. An average analyst covered about 15 different companies.

3.2.1 The Distribution of Forecast Bias

We now examine the distribution of quarterly consensus earnings estimates. The consensus estimate for a company is taken to be the median of the unrevised estimates of a quarter's earnings across all brokerage firms in the Detail file[5]. When a broker issues more than one forecast for the same firm for the same quarter, we use the most recent. The consensus forecast bias is computed by subtracting the Compustat earnings per share before extraordinary items expressed on the same primary or diluted share basis as recorded in I/B/E/S. We report forecast bias both in terms of cents per share (denoted as BIAS), and as a percentage of quarter end stock price (denoted as PCTBIAS) to eliminate heteroskedasticity[6].

Figure 1 graphs the time series of each quarter's mean consensus forecast bias across all companies, as well as for companies stratified by size according to the size decile assigned by CRSP at its quarter end[7]. The optimistic bias has been consistent

[5]Note that this figure may differ from the Summary median estimate reported by I/B/E/S each month to its clients and in the academic historical tapes, because I/B/E/S calculates its summaries at fixed dates in the middle of each month.

[6]However, in the main empirical analyses later, we will normalize forecast bias by split-adjusted stock price twelve months prior to the beginning of the quarter, to control for any simultaneity effects between price and our other measures.

[7]Large companies are those in deciles 8 through 10; medium companies in deciles 5 through 7; and small companies in deciles 1 through 4. CRSP reassigns size deciles every year, hence a company may be in a different size class at different quarter end dates.

every quarter, although the level has been somewhat reduced in the second half of the sample period, particularly for small companies. Table 2 provides more summary statistics on the distribution of consensus forecast bias. Panel A reports that the time series mean is 7.5 cents per share (or 0.93 percent of stock price), and ranged from 10.7 cents for small companies to 7.2 cents per share for large companies (3.3 percent to 0.5 percent of stock price respectively).

Panels B and C report summary statistics for the pooled sample of forecast bias values. The overall median bias of 0.2 cents per share is lower than the mean of 7.0 cents (0.01 percent and 0.91 percent of stock price respectively). 50.0 percent of the forecasts were positively biased compare to to 42.1 percent that were negative. These panels and Figure 2 shows that the distribution is positively skewed, with large positive biases appearing more frequently than large negative biases.

Panel D summarizes the forecast bias for each of the 29 industries (by 2-digit SIC code provided by Compustat) with data pertaining to at least 60 companies. All of the industries exhibited statistically significant optimistic bias when measured as a percentage of stock price; and all but two industries (Food and kindred products and Insurance carriers) evidenced optimistic bias in terms of cents per share. Except for companies in two industries, the proportion of positive forecast biases exceeded negative biases: the two exceptions are Nondepository credit institutions and Insurance carriers.

3.2.2 Special Accounting Charges

I/B/E/S analysts forecast earnings from continuing operations; the forecast which I/B/E/S publishes after discontinued operations, extra-ordinary charges, and other non-operating items have been backed out[8]. This usually corresponds to what GAAP calls "income before extraordinary items" and reported by Compustat. I/B/E/S provides no specific instructions to individual analysts about the treatment of extraordinary items. They refer to extraordinary items as "write downs which are at the

[8]See the I/B/E/S Glossary: A Guide to Understanding I/B/E/S Terms and Conventions.

discretion of management", while according to GAAP, not all discretionary write-downs qualify as extraordinary. Special items are above-the-line, nonrecurring gains and losses that Compustat includes in pretax EPS before extraordinary items and discontinued operations. According to GAAP, they are "unusual" or "infrequent" charges (but not both) that can be taken at the discretion of management, but not as an adjustment to ordinary income. Philbrick and Ricks (1991) reported that on average I/B/E/S forecasts appear to exclude special items, while I/B/E/S actuals are inconsistent in the treatment of such items.

Most large special items are restructuring charges and write-offs. Philbrick and Ricks (1991) add back the entire amount of the discretionary accruals after attempting to adjust for tax effects, while Keane and Runkle (1997) eliminated those observations with large special items charges. We will follow the latter approach, reasoning that it is difficult for a researcher to to come up with an unbiased after-tax estimate of what the analysts are trying to predict if such a discretionary accrual did not occur.

Panels A and B of Table 3 show that of the 106477 observations of firm-quarter forecast estimates, 12923 were associated with non-zero special items charges, of which 5200 were in the fourth quarter. Elliott and Shaw (1988) find that most (almost two thirds) of their sample of firms also took large write-offs in the fourth quarter. The majority of special items were negative charges to income, with a mean (median) of -29.7 (-6.0) cents per share or -3.0 (-0.35) percent of stock price. This reflects the conservative nature of accounting: management can take large discretionary write-downs of assets, but assets cannot be written up.

As shown in panel C, if we removed all these observations, mean forecast bias would still be positive, but reduced by almost half from 7.0 cents to 3.6 cents per share (or from 0.91 percent to 0.49 percent of stock price). Hence discretionary accounting charges cannot by itself explain why earnings forecasts on average are positively biased. Note that most of this adjustment comes from eliminating the largest (in absolute terms) special item charges. Eliminating the 2473 observations (roughly twenty percent of all special item charges) with special items larger than two standard deviations of the forecast bias (ie two times 37.6 cents) would bring mean forecast bias down to the 4.4 cents per share or 0.62 percent of stock price, with a standard deviation of 34.8 cents or 5.02 percent[9]. We feel that this is a sensible cut-off for removing extreme cases of special items charges, and the remainder of our analysis uses the censored sample.

3.2.3 Stale Forecasts

A number of prior studies have documented that forecast bias is not constant across forecast horizons. Figure 3 plots the average consensus forecast bias observed at forecast horizons from 11 months before to 1 month after quarter end. At each month, relative to quarter end, the consensus forecast bias is computed as before, but only based on forecasts available at month end. For all three class sizes, forecast bias is positive and decreases as the quarter end approaches. The rate of change increases most at one month before quarter end. This corresponds to the time immediately after, for most companies, actual earnings from the prior quarter have been announced. Kang, O'Brien and Sivaramakrishnan (1994) conclude that this horizon effect is independent of informational factors that cannot be explained by adaptive formation of expectations and conjecture that forecast rules for earnings for the same quarter from different points in time are different. Whereas forecasts closest to the announcements date would be subject to the market test, earlier forecasts, which the analyst has the option to revise later, may be influenced more by other conflicting incentives.

Brown (1991) compares "timely composites" to the mean forecast and shows that earnings forecast accuracy can be improved by discarding old earnings forecasts. Further, he finds that a 30-day average of recent forecasts is significantly more accurate than the most recent forecast for large firms, but are approximately as accurate for small firms. For large firms, aggregating recent forecasts can improve forecast accuracy because these firms are followed by many analysts, whereas few analysts follow small firms

[9]By comparison but not reported here, the consensus forecast bias computed using I/B/E/S actuals had approximately identical means (4.5 cents or 0.61 percent of price) but higher standard deviations (45.4 cents and 7.34 percent of price).

In Table 4, we consider a similar timely measure of the consensus forecast bias based on the median of unrevised forecasts submitted by a broker for a company no more than three months prior to quarter end; if no forecasts are available, then the single more recent forecast of all forecasts made for the company is used. The three month recency requirement ensures that the analyst has available information from the prior quarter's performance. On average, using this more recent measure of consensus forecast reduced the mean number of forecasts from 4.8 to 4.1 per company; the mean and standard deviation of forecast bias also declined. The average bias still remains positive, reduced slightly to 4.1 cents per share or 0.59 percent of stock price.

Our subsequent empirical tests use this timely method of computing consensus forecast bias to minimize the forecast horizon effect.

3.2.4 Investment Banking Relationships

A number of studies have examined the impact of underwriting relationships on analysts forecasts and recommendations. Michealy and Womack (1996) document how conflicts of interest in investment banks bias the recommendations of the firms they underwrite. Analysts working for brokerage firms that either have investment banking relationships or want tc cultivate them are pressured to maintain positive recommendations. As an example, the two factors that were reported[10] to be most important to AT&T's choice of investment bankers for the $3 billion IPO of AT&T's equipment business (Lucent Technologies) were the attitude of the firm's analysts toward AT&T and who the firms used as its primary long-distance carrier. Allen and Faulhaber (1989) argued that investment bankers will have superior information on the firm. This story leads to differing forecasts, with underwriter analysts producing more accurate forecasts because of an informational advantage gained during the due diligence process. An investment banking relationship is a double-aged sword: while analysts probably have more accurate information, they probably must refrain from negative comments.

[10]Wall Street Journal, February 1, 1996.

Lin and McNichols (1993) and Dugar and Nathan (1995) examine whether the relationship between the investment banker and the issuing firm affects the investment banker's earnings forecasts and recommendations. They find that despite the fact that underwriter analysts produce more optimistic recommendations, forecasted earnings were not any more biased.

Unfortunately, because the academic version of the I/B/E/S files do not reveal the identities of the analysts or brokerage firms, providing only numerical codes, we are precluded from identifying forecasts from brokerage firms with investment banking relationships with the company. Instead, we exclude those observations for which either had no analyst coverage a year ago, or is only covered by a single analyst. The first filter includes any IPO's in the original sample[11], while the second is based on the presumption that if a company has an analyst following of one, that analyst most likely comes from a brokerage firm with an investment banking relationship.

Table 5 reveals that overall, new single-analyst companies had an average consensus forecast bias of 0.89 percent of stock price compared with 0.49 percent for old, multi-analyst companies. However, all of this decline appears to be driven by a size effect. New, single-analyst companies are predominantly small. A size decile-by-decile comparison shows that there is no evidence new or single-analyst companies are associated with a more positive bias when controlled for size[12].

3.2.5 New Initiation of Coverage

McNichols and O'Brien (1996) suggest that analysts with favorable views are more likely than those with unfavorable views to initiate coverage of a company. Most sell-side analysts are directly or indirectly compensated for commission business they generate for their brokerage firms. Buy recommendations generate more commissions because their clients can always add stocks to their portfolio, but cannot sell stock (or

[11] A more precise study of how underwriting relationships affect forecast bias is underway through identifying IPO's and SEO's in the SDC database.

[12] In comparison, Ali (1996), using summary annual earnings forecasts, found a positive forecast bias for small (smallest three deciles) IPO and SEO firms only, and no bias for single-coverage companies.

is prohibitively expensive due to institutional constraints) they do not own. Hence optimistic views will be under-represented in samples of observed forecasts.

We examine if this conjecture holds up for earnings forecasts. Table 6 compares the average consensus forecast bias, dropping analysts who had newly initiated coverage. Specifically, we compute the new measure of consensus forecast bias (dropping new analysts) as the median of *seasoned* analysts (those who had submitted a quarterly or annual earnings forecast for the company for an earlier fiscal end) submitted no more than three months prior to quarter end; or the most recent of all brokers' forecasts if, as before, no eligible forecasts of three months recency are available. We detect practically no change in the estimated consensus forecast bias in the overall sample or in size-based subsamples.

3.3 Empirical Results

3.3.1 Company Characteristics

We begin our main empirical tests by examining the cross-sectional relationship between forecast bias and company characteristics. Proposition 1 states that firms that have more uncertain earnings should be associated with more optimistically biased forecasts. Prior studies such as Brown (1997) have suggested that firm size and analyst coverage are related to a company's information environment, since information about smaller firms is gathered and processed relatively infrequently. The precision of alternative time series-based models of quarterly earnings should also affect the value of management access and hence determine analysts' bias. Finally, the volatility of stock price returns, net of market-wide effects, should also reflect how market participants view the extent of company-specific uncertainty. For each company-quarter, we measure the following proxy variables:

1. SIZE is the log market capitalization, from CRSP, 12 months prior to the beginning of the quarter. We use this "stale" measure of company size to reduce any endogeneity effects related to forecast bias.

2. COVER is the log of one plus the number of analysts, based on the I/B/E/S Summary File, providing FY1 (annual) earnings forecasts 12 months prior to the beginning of the quarter. In the I/B/E/S database, some analysts who provided annual earnings forecasts did not provide quarterly forecasts, particularly earlier in the sample period. Although our study focuses on quarterly forecast bias, the number of analysts providing annual forecasts is a better measure of analyst coverage.

3. EPSVAR is the standard error from a trend regression of past quarterly earnings, for the eight quarters up to two quarters prior to the current quarter, scaled by stock price. This crude proxy should bear some relationship with how unpredictable the company's earnings have been; although it does not capture the contribution of other public or more recent sources of information, and is only estimated from a limited number of data points.

4. STDEXR is the standard error from a market model regression of daily stock returns on value-weighted market returns over the year ending at the start of the quarter. This provides a somewhat more timely measure of company-specific uncertainty as revealed by the capital markets.

Prior studies such as Abarbanell (1989) and Klein (1990) have documented that analysts appear to underreact to past stock prices and earnings announcements. These suggest that we also consider the following variables:

1. BIAS1 is the consensus forecast bias from the prior quarter. For all our analysis, consensus forecast bias is expressed as a percentage of stock price 12 months prior to the beginning of the quarter for which earnings are forecasted.

2. ALPHA is the intercept from a market model regression of daily stock returns on value-weighted market returns over the year ending at the start of the quarter.

3. BP is the book to price ratio, twelve months prior to the start of the quarter.

Table 7 describes the correlations between these company characteristic variables and forecast bias. It reports the time-series mean of the pair-wise correlation coefficients computed each quarter from the cross-section of stocks. Forecast bias is positively correlated with the standard deviation of residual returns, past earnings variability and prior forecast bias; and negatively correlated with size, analyst coverage, past returns, and book to price ratio. Each of these correlations has the predicted sign, but we shall turn to multivariate tests below.

Next, we look at the average consensus forecast bias of groups of companies sorted by company characteristics. For Panel A of Table 8, we sort our companies each quarter into ten groups based on ALPHA, BIAS1, SIZE or STDEXR. Because of the correlation between STDEXR and other characteristics such as SIZE, COVER and BP, we also sort the companies by residual STDEXR, where the residuals come from a quarter-by-quarter cross-sectional regression of STDEXR on SIZE, COVER and BP.

The average consensus forecast bias is computed for each group every quarter, and the time series means and standard errors are reported. These reveal a generally increasing relationship with forecast bias across the deciles, although for some pairs of adjacent deciles the relationship is essentially flat. For all the the company characteristic variables considered, the relationship with forecast bias is strikingly steeper in the larger deciles.

For (minus) ALPHA, the relationship is approximately flat in the first six deciles (large positive ALPHA values), and most positive for deciles seven through ten (negative ALPHA values). BIAS1 shows more of a positive relationship for all deciles, but is again, steepest for deciles seven through ten. This is consistent with the "underreaction" found by prior studies, but we uncover a the striking asymmetry. Forecast bias is much more positive for firms that have bad prior surprises or prior stock returns. This could be interpreted by an informal story that management access is more important when the company is sitting on bad news. When firms have good news, managers probably have every incentive to push this news out to investors as fast as possible. In contrast, when there is bad news, managers are likely to be less forthcoming, sometimes even delaying quarterly announcements, hence management relations become more important as a source of information.

The sorts on (minus) SIZE, EPSVAR and STDEXR show similar patterns. The relationship with forecast bias is generally monotonic, but most of the positive bias is concentrated in the three largest deciles – the smallest or most volatile companies. We test further the relationship that STDEXR, as a proxy for company-specific uncertainty, bears with forecast bias. Since this variable was found to be strongly correlated with SIZE, as well as other company characteristics, we want to ensure it does not merely capture the size effect. Hence we sort the companies by residual STDEXR, which are the residuals formed from regressing STDEXR on SIZE, BP and COVER. To provide even better control for any size effect, we use a two-level sort in Panel B. First, all companies are sorted, each quarter, by size into five groups. Then for each group separately, residual STDEXR is estimated from cross-sectional regressions of STDEXR on SIZE, COVER and BP each quarter, and used to further classify each group into five smaller quintiles. Panel B shows that even controlling for size, and other characteristics, STDEXR is able to capture a positive relationship with forecast bias. The largest two quintiles (most volatile) of stocks exhibit the most positive bias. Comparing the average of each residual STDEXR quintile across size groups, the mean forecast bias increases gradually from between 0.21 and 0.30 percent of price in the first three quintiles, then jumps to 0.48 percent and 0.73 percent in quintiles four and five. The mean size values for these quintiles showed a fairly reasonable control for size, with mean market cap varying from a low of $936 million in quintile 1 to $1796 million in quintile 3, then *declining* to $1195 million in quintile 5. The mean coverage and book-to-price values also showed little systematic variation.

Table 9 provides a more structured multivariate regression analysis. We pool all the observations and examine the regression of consensus forecast bias on the company characteristic variables. To control for any time effects, we include dummy variables corresponding to each calendar quarter. Our preliminary analyses in tables 3 and 5 suggested that we also include dummy variables to account for fourth quarter effects (when more discretionary charges are likely to be taken) and newly-covered firms (firms for which analyst coverage was initiated within the past twelve months). We also perform some sensitivity analyses of the regression model, by examining subperiods and size-based subsamples, and by adding regressors to control for book-to-price, analyst coverage and industry effects.

The estimated coefficients are all of the predicted sign, and are consistent with what we observed with the portfolio sorts. Forecast bias is greatest for companies that (1) are small, (2) are more volatile (as measured by STDEXR), (3) experienced prior negative earnings surprise (the prior quarter's consensus forecast bias BIAS1) or (4) experienced poor stock returns (as measured by ALPHA). Similar results were obtained when the full sample period was split into two halves and when the sample of companies was split into three size-based groups. Adding additional regressors for book-to-price, analyst coverage and industry dummies also did not matter materially.

3.3.2 Analyst Characteristics

We next examine the properties of the individual analyst forecasts that make up the company consensus forecasts. We shall use a regression approach to relate relative analyst forecast bias to analyst characteristics. Proposition 2 suggests that analysts who are less reliant on management relations and access as a source of company information should exhibit less positive bias. Analysts who are employed by large brokerage firms are likely to have more or superior resources available from their employers, such as administrative support and access to databases, and easier access to the private information of the managers at the companies they follow. Stickel (1995) provides empirical evidence that capital market participants respond more to the buy and sell recommendations of analysts employed by large brokerage house relative to other analysts because larger firms have more advanced distribution networks to better disseminate their analysts' recommendations into the capital markets. Analyst coverage is important to companies, particularly new companies that are not known to the marketplace, because their stock value will be enhanced when investors, especially institutional investors, hear about them. Hence coverage by a well-known analyst or brokerage firm represents an important marketing tool for companies. We predict brokerage firm size to be related to relative forecast bias. Analysts employed by smaller, regional brokerage firms without the resources or reputation of top-tier brokers are likely to depend on management relations and hence publish more positive forecasts.

Results from prior research suggest that analyst experience forecast age, company and time effects should be controlled for when evaluating differences in analysts' forecasts. Mikhail, Walther and Willis (1997) found that analyst forecast errors declined as firm-specific experience increases; they conclude that analysts' general skills as well as firm-specific knowledge improve over time consistent with a "learning-by-doing" hypothesis. A number of studies also document that forecast accuracy decreases with the length of the forecast horizon (e.g. Brown, Foster and Noreen (1985)), while our analysis of Table 4 indicates that forecast bias also decreases with horizon. We use only the latest forecast from each analyst, submitted no more than three months prior to quarter end, so that we only compare forecasts of a maximum horizon; as well as include the forecast's age as a regressor variable. To control for company and time effects, we compute each analyst's forecast relative to other analysts who followed the same firm during the same time period.

Since we are examining differences between individual analysts' forecasts, we require that the companies whose forecasts we include be from at least two analysts for the quarter, and that the mean absolute forecast deviation, computed as the average deviation of each forecast from the mean forecast for all eligible forecasts for the company that quarter, be at least one cent per share. For each eligible analyst forecast, we extract the following variables:

1. RELPCTB is the forecast minus the mean forecast across all analysts covering the company, scaled by stock price 12 months prior to the start of the quarter.

2. DAGE is the experience of the analyst, defined as the number of years since first fiscal end that the analyst published a quarterly or annual earnings forecast for the company, less the average experience of all analysts covering the company

that quarter.

3. DSTALE is quarter end dates minus the the date of the estimate, expressed as a fraction of years, less the average for all analysts covering the company that quarter. This variable is designed to control for forecast horizon, since forecasts are released on different days.

4. DANAL is the fractional rank of the size of the brokerage firm, less the average for analysts covering the company that quarter. The brokerage firm rank is obtained by ranking all firms by the number of analysts employed within twelve months prior to the quarter end date.

Since some of these variables require data from searching back in time and I/B/E/S Detail data only begins providing substantive information after 1984, we begin our analysis in 1986 so that earlier data is available to allow some variation in these variables.

Panel A of Table 10 shows the distribution of the raw analyst characteristics variables. Distributions of the raw regression variables are reported because by construction the means of the differenced variables are zero. The average analyst followed a company an average of 3.5 years out of 11 years of data. The average age of a forecast is 0.075 years (or 0.9 months) indicating that an average forecast is submitted a little over two months after the prior quarter end. The pair-wise correlations reported in Panel B show that relative forecast bias is negatively correlated with analyst experience and employer size, and positively correlated with the age of the forecast.

Table 11 reports results from the pooled regression of relative forecast bias (RELPCTB) on the analyst characteristic variables (DAGE, DSTALE and DANAL). For sensitivity analysis, we also report regression results from subperiods and company size-based subsamples.

The coefficient for brokerage size in the pooled regression is reliably negative as predicted. However, the coefficient of -0.03, which implies that the relative difference of forecasts between the largest and smallest brokers is 0.03 percent of stock price, may not be an economically large value. Nevertheless, the results are robust in subperiods and size-based subsamples, and the effect is somewhat stronger (-0.044 percent) in recent years.

The positive coefficient for DSTALE confirms the relationship between forecast horizon and bias. The coefficient of 0.25 indicates that for every month (recall that DSTALE is expressed in years), forecasts tend to be more biased by 0.02 percent of stock price. DAGE has a negative coefficient, indicating that experienced analysts are not as positively biased, but this relationship is statistically weaker.

3.4 Conclusion

Our results suggest that forecast bias differs predictably across analysts and companies, and market expectations studies may be improved by modeling analysts' and company characteristics. The evidence is consistent with an environment where analysts publish forecasts to appear as if they share management's positive sentiments in order to gain improved management access and information.

A possible direction for future research is to test the capital market implications of our findings. Lee (1997) shows that earnings estimates can help explain cross-sectional differences in stock price valuations; it is not known if predictable biases in earnings forecasts are incorporated in earnings expectations or stock price valuations.

Little is understood about the dynamics of the market for analysts' forecasts and the incentives to provide forecasting services, or what information analysts' earnings forecasts actually represent. We have focused on one aspect of their task – management access to gain better company information – and provided evidence consistent with notion that the systematic optimistic bias in analysts' forecasts is rational.

3.5 References

Abarbanell, J.S. and V. L. Bernard, 1992, "Tests of Analysts' Overreaction/Underreaction to Earnings Enformation as an Explanation for Anomalous Stock Price Behavior, *Journal of Finance* 47, 1181-1207.

Ackert, L. and W. Hunder, 1994, "Rational Expectations and the Dynamic Adjustment of Security Analysts Forecasts to New Information", *Journal of Financial Rescarch* 17, 387-401.

Ackert, L. and W. Hunder, 1995, "Rational Expectations and Security analysts Forecasts", *Financial Review* 30, 427-443.

Aigner, D., T. Amemiya and D. Poirier, 1976, "On the Estimation of Production Frontiers: Maximum Likelihood Estimation of the Parameters of a Discontinuous Density Function", *International Economic Review* 17, 377-396.

Alexander, J., D. Goff, and P. Peterson, 1989, "Profitability of a Trading Strategy Based on Unexpected Earnings", *Financial Analysts Journal* 45, no. 4, 65-71.

Ali, A., 1996, "Bias in Analysts' Earnings Forecasts as an Explanation for the Long-Run Underperformance of Stocks Following Equity Offerings", working paper, University of Arizona.

Ali, A., A. Klein, and J. Rosenfeld, 1992, "Analysts' Use of Information about Permanent and Transitory Earnings Components in Forecasting Annual EPS", *The Accounting Review* 67, 183-199.

Ball, R., and E. Bartov, 1995, "How Naive is the Stock Market's Use of Earnings Information", working paper, University of Rochester.

Bernard, V., 1993, "Stock Price Reactions to Earnings Announcements: a Summary of Recent Anomalous Evidence and Possible Explanations", in *Advances in Behavioral Finance*, edited by Richard Thaler, Russell Sage Foundation.

Bernard, V., and J. Thomas, 1989, "Post-earnings Announcement Drift: Delayed Price Response or Risk Premium?", *Journal of Accounting Research* 27, 1-48.

Bernard, V., and J. Thomas, 1990, "Evidence that Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings" *Journal of Accounting and Economics* 13, 305-340.

Bernard, V., J. Thomas, and J. Whalen, 1997, "Accounting-based Stock Market Anomalies: Separating Market Inefficiencies and Risk", *Contemporary Accounting Research.*

Bhushan, R., 1989, "Firm Characteristics and Analysts Following", *Journal of Accounting and Economics*, 255-274.

Bhushan, R., 1994, "An Informational Efficiency Perspective on the Post-earnings-announcement Drift", *Journal of Accounting and Economics* 18, 45-65.

Bonham, C., and R. Cohen, 1995, "Testing the Rationality of Price Forecasts: Comment" *American Economic Review* 85, 284-289.

Brennan, M., and P. Hughes, 1991, "Stock Prices and the Supply of Information", *Journal of Finance*, 1665-1691.

Brown, L., R. Hagerman, P. Griffin, and M. Zmijewski, 1987, "Security Analyst Superiority Relative to Univariate Time-series Models in Forecasting Quarterly Earnings", *Journal of Accounting and Economics*, 61-87.

Brown, L., 1991, "Forecast Selection When All Forecasts Are Not Equally Recent, *International Journal of Forecasting* 7, 349-356.

Brown, L., 1993, "Earnings Forecasting Research: Its Implications for Capital Markets Research", *International Journal of Forecasting* 9, 295-320.

Brown, L., 1996, "Analyst Forecasting Errors and Their Implications for Security Analysis: An Alternative Perspective, *Financial Analysts Journal* 52, 40-47.

Brown, L., 1997, "Earnings Surprise Research: Synthesis and Perspectives", *Financial Analysts Journal* 53, 13-19.

Brown, L., 1997, "Analyst Forecasting Errors: Additional Evidence", *Financial Analysts Journal*, 81-88.

Brown, L., J. Han, E. Keon and W. Quinn, 1996, "Predicting Analysts' Earnings Surprise', *The Journal of Investing* 17-23.

Butler, K. and L. Lang, 1991, "The Forecast Accuracy of Individual Analysts: Evidence of Systematic Optimism and Pessimism", *Journal of Accounting Research* 29, 150-156.

Cheyman, M. and R. Schwartz, 1994, "Falling in Love Again - Analysts Estimates and Reality", *Financial Analysts Journal* 50, 66-68.

Christoffersen, P., and F. Diebold, 1994, "Optimal Prediction Under Asymmetric Loss", NBER Technical Working Paper No. 167.

Clement, M., 1997, "Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter?", working paper, University of Texas at Austin.

Conrad, J., and G. Kaul, 1993, "Long-term Overreaction or Biases in Computed Returns?", *The Journal of Finance*, 48, 39-63.

De Bondt, W. and R. Thaler, 1990, "Do Security Analysts Overreact?", *American Economic Review* 80, 52-57.

Dreman, D., and M. Berry, 1995, "Analyst Forecasting Errors and Their Implications for Security Analysis", 30-41.

Dugar, A. and S. Nathan, 1995, "The Effect of Investment Banking Relationships on Financial Analysts Forecasts and Investment Recommendations", *Contemporary Accounting Research.*

Dutta, S., and B. Trueman, 1997, "Optimists, Pessimists and Managerial Disclosures", working paper, University of California, Berkeley.

Ehrbeck, T., and R. Waldman, 1996, "Why are Professional Forecasters Biased? Agency versus Behavioral Explanations" *Quarterly Journal of Economics*, February:21-40

Francis, J., and D. Philbrick, 1993, "Analysts' Decisions as Products of a Multi-task Environment", *Journal of Accounting Research* 31, 216-230.

Frankel, R. and C. Lee, 1996, "Accounting Valuation, Market Expectations and the Book-to-Market Effect", working paper.

Granger, C. W. J., 1969, "Prediction with a Generalized Cost of Error Function", *Operational Research Quarterly* 20, 199-207.

Huberts, L., and R. Fuller, 1995, "Predictability Bias in the U.S. Equity Market, *Financial Analysts Journal* 51, 12-28.

Ito, T., 1990, "Foreign Exchange Rate Expectations: Micro Survey Data" *American Economic Review* 80, 434-49.

Jacob, J., T. Lys and M. Neale, 1996, "Experience, Expertise and the Forecasting Performance of Security Analysts", working paper, Stanford University.

Jeong, J., and G.S. Maddalla, 1996, "Testing the Rationality of Survey Data Using the Weighted Double-Bootstrapped Method of Moments" *Review of Economics and Statistics*, May:296-302.

Kahneman, D., and A. Tversky (1979), "Prospect Theory: An Analysis of Decision Under Risk", *Econometrica*, 47, 263-291.

Kang, S., J. O'Brien, and K. Sivaramakrishnan, 1994, "Analysts' interim Earnings Forecasts: Evidence on the Forecasting Process", *Journal of Accounting Research*

32, 103-112.

Keane, M. and D. Runkle, 1990, "Testing the Rationality of Price Forecasts: New Evidence from Panel Data", *American Economic Review* 80:4, 714-735.

Keane, M. and D. Runkle, 1995, "Testing the Rationality of Price Forecasts: Reply", *American Economic Review* 85:1, 289.

Keane, M. and D. Runkle, "Are Financial Analysts Forecasts of Corporate Profits Rational", working paper.

Klein, A., 1990, "A Direct Test of the Cognitive Bias Theory of Share Price Reversals", *Journal of Accounting and Economics* 13, 155-166.

Koenker, R. and G. Basset Jr., 1978, "Regression Quantiles", *Econometrica* 46, 33-50.

Koenker, R. and G. Basset Jr., 1982, "Robust Tests for Heteroskedasticity Based on Regression Quantiles", *Econometrica* 50, 43-61.

Lamont, O., 1995, "Macroeconomic Forecasts and Microeconomic Forecasters", Working paper 5284, National Bureau of Economic Research.

Lang, L., R., Litzenberger and V. Madrigal, 1992, "Testing Financial Market Equilibrium Under Asymmetric Information", *Journal of Political Economy* 100, 317-348.

Laster, D., P. Bennett and I. S. Geoum, 1996, "Rational Bias in Macroeconomic Forecasts", Working Paper, Federal Reserve Bank of New York.

Lin, H., and M., McNichols, 1997, "Underwriting Relationships and Analysts' Earnings Forecasts and Investment Recommendations", working paper 1435, Stanford University.

Lys, T., and S. Sohn, 1990, "The Association Between Revisions of Financial Analysts' Earnings Forecasts and Security Price Changes", *Journal of Accounting and Economics* 13, 341-364.

Lys, T., and L. Soo, 1995, "Analysts' Forecast Precision as a Response to Competition", *Journal of Accounting, Auditing and Finance* 10, 751-765.

Maddala, G., and M. Nimalendran, 1995, "An Unobserved Component Panel Data Model to Study the Effect of Earnings Surprises on Stock Prices, Trading Volumes and Spreads, *Journal of Econometrics* 68, 229-242.

McNichols, M., and P. O'Brien, 1996, "Self-selection and Analyst Coverage", working paper, Stanford University Graduate School of Business.

Michealy, R., and K. Womack, 1996, "Conflict of Interest and the Credibility of Underwriter Analyst Recommendations", working paper, Cornell University.

Mikhail, M., B. Walther, and R. Willis, 1997, "Do Security Analysts Improve Their Performance with Experience", *Journal of Accounting Research*, forthcoming.

Muth, J. F., 1961, "Rational Expectations and the Theory of Price movements", *Econometrica* 29, 315-335.

O'Brien, P., 1988, "Analysts' Forecasts as Earnings Expectations", *Journal of Accounting and Economics* 10, 53-83.

O'Brien, P., 1990, "Forecast Accuracy of Individual Analysis in Nine Industries", *Journal of Accounting Research*, 28, 286-304.

O'Brien, P., 1994, "Are Analyst Overestimates Due to Macroeconomic Shocks or Bias", working paper, University of Michigan Business School.

Olsen, R., 1996, "Implications of herding behavior for earnings estimation, risk assessment, and stock returns", *Financial Analysts Journal*, 37-41.

Peters, D., 1993a, "Are Earnings Surprises Predictable?", *Journal of Investing* 2, 47-51.

Peters, D., 1993b, "The Influence of Size on Earnings Surprise predictability", *Journal of Investing* 2, 47-51.

Philbrick, D.R. and W. E. Ricks, 1991, "Using Value line and IBES Analyst Forecasts in Accounting Research", *Journal of Accounting Research* 29, 397-417.

Pratt, T., 1993, "Wall Street's Four-Letter Word", *Investment Dealers Digest*, March, 18-22.

Scharfstein, D. and J. Stein, 1990, "Herd Behavior and Investment", *American Economic Review* 80, 465-479.

Sinha, P., L., Brown, and S. Das, 1997, "A Re-examination of Financial Analysts' Differential Earnings Forecast Accuracy", *Contemporary Accounting Research* 14, 1-42.

Stickel, S., 1990, "Predicting Individual Analyst Earnings Forecast", *Journal of Accounting Research* 28, 409-417

Stickel, S., 1991, "Common Stock Returns Surrounding Earnings Forecast Revisions: More Puzzling Evidence" *The Accounting Review* 66, 402-416.

Stickel, S., 1992, "Reputation and Performance Among Security Analysts", *Journal* *of Finance*, 1811-1836,

Stickel, S., 1993, "Accuracy Improvements From a Consensus of Updated Individual Analyst Earnings Forecasts", *International Journal of Forecasting* 9, 345-353.

Stickel, S., 1995, "The Anatomy of the Performance of Buy and Sell Recommendations", *Financial Analysts Journal* 25-39.

Stober, T., 1992, "Summary Financial Statement Measures and Analysts' Forecasts of Earnings", *Journal of Accounting and Economics* 15, 347-372.

Stockman, A. C., 1987, "Economic Theory and Exchange Rate Forecasts", *International Journal of Forecasting* 3, 3-15.

Teuman, B., 1994, "Analysts Forecasts and Herding Behavior, *Review of Financial Studies* 7, 97-124.

Womack, K., 1996, "Do Brokerage Analysts' Recommendations have investment value?", *Journal of Finance* 52, 137-167.

Zellner, A., 1986, "Bayesian Estimation and Prediction Using Asymmetric Loss Functions", *Journal of the American Statistical Association*, 81, 446-451.

Table 1. Sample Characteristics of I/B/E/S Detail File

Panel A. Companies with Quarterly Earnings Forecasts

Year	Firms	CRSP Size Decile 1	2	3	4	5	6	7	8	9	10	Exchange NYSE	AMEX	NASD
84	2451	1	8	18	54	118	207	300	432	538	570	1268	191	808
85	2939	6	17	38	76	161	245	345	480	553	604	1335	218	997
86	3187	4	18	48	93	158	267	384	473	579	654	1346	221	1148
87	3475	5	23	75	133	195	327	400	503	603	668	1363	246	1367
88	3394	6	29	91	148	232	326	400	472	542	661	1224	269	1455
89	3369	8	26	87	172	261	321	402	460	547	637	1203	290	1470
90	3283	9	30	69	142	256	336	390	480	528	630	1206	284	1421
91	3320	11	37	77	173	267	328	402	489	534	633	1230	267	1491
92	3575	12	42	94	186	312	391	463	514	570	668	1330	249	1717
93	4056	25	73	161	266	364	419	492	546	622	721	1450	243	2066
94	4760	33	128	235	349	412	521	536	595	659	774	1596	254	2505
95	5265	43	144	272	378	476	557	573	632	699	805	1708	238	2767
96	5973	83	181	325	462	544	599	647	689	747	846	1829	259	3198

Panel B. Brokerage Firms and Analysts Employed

Year	# Brokers	Mean	# Analysts Employed at Percentiles P20	P40	P60	P80	P90	P95	Max
84	140	22.6	5	11	16	37.5	52.5	62	215
85	158	21.6	5	11	17	32	54	63	221
86	164	20.6	4	10	17	30	57	65	207
87	186	19.4	3	10	16	25	52	71	186
88	217	17.1	2	7	15	25	44	62	140
89	223	16.2	2	7	13	23	34	60	127
90	226	15.6	3	7	13	24	34	61	115
91	221	15.7	3	7	13	24	35	56	114
92	240	15.0	2	6	12	23	34	61	137
93	260	15.8	2	5	11	26	38.5	63	166
94	255	17.1	2	6	13	26	41	75	183
95	274	17.3	2	6	13	26	42	71	197
96	303	17.8	2	5	13	27	44	64	253

Panel C. Analysts and Number of Firms Followed

Year	# Analysts	Mean	# Firms Followed at Percentiles Min	5	25	50	75	95	Max
83	2523	11.7	1	1	3	8	16	35	119
84	2796	13.7	1	1	4	10	19	39	127
85	2993	14.2	1	1	4	11	19	40	139
86	2924	15.5	1	1	5	13	21	41	122
87	3065	15.9	1	1	6	13	21	41	129
88	3121	15.3	1	1	6	13	21	40	151
89	2995	16.0	1	1	7	13	21	41	378
90	2882	16.0	1	1	7	13	21	40	416
91	2769	16.0	1	1	6	14	21	40	420
92	2858	15.6	1	1	6	14	21	39	374
93	3188	15.6	1	1	6	13	21	39	138
94	3444	14.8	1	1	5	13	20	38	169
95	3815	14.3	1	1	4	12	20	38	131
96	4374	13.8	1	1	4	11	20	37	130

Table 2. Distribution of Concensus Forecast Bias

Panel A. Time Series of Forecast Bias 1984-1996

		Cents per Share			Percent of Price		
Company Size	# Qtrs	Mean	Stderr	Median	Mean	Stderr	Median
All	52	7.47	(0.51)	6.37	0.93	(0.06)	0.83
Small	52	10.74	(0.98)	8.49	3.28	(0.32)	2.31
Medium	52	7.52	(0.43)	7.22	1.33	(0.10)	1.24
Large	52	7.15	(0.62)	6.11	0.53	(0.05)	0.45

Panel B. Distribution of Concensus Forecast Bias by Size 1984-1996 (cents per share)

							Forecast Bias at Percentile											EPS
Size	N	Mean	StdErr	Std	Skew	Kurt	5	10	25	40	50	60	75	90	95	% Pos	% Neg	(cents)
Pooled	106466	7.0	(0.1)	47.4	5.8	106.1	-19.0	-10.0	-3.0	-1.0	0.2	2.0	7.0	25.0	50.5	50.0	42.1	30.6
Large	63428	6.9	(0.2)	52.4	5.3	95.7	-23.0	-12.0	-3.5	-1.0	0.0	2.0	7.0	25.0	52.0	48.8	43.5	44.6
Medium	33054	6.8	(0.2)	39.1	6.8	118.9	-15.0	-8.0	-2.5	-0.5	0.5	2.0	7.0	24.0	47.0	51.2	40.8	12.4
Small	9984	8.6	(0.4)	38.2	7.0	94.0	-12.0	-7.0	-2.0	0.0	1.0	3.0	8.0	26.5	52.5	54.1	37.3	2.4

Panel C. Distribution of Concensus Forecast Bias by Size 1984-1996 (percent of price)

							Forecast Bias at Percentile											Price
Size	N	Mean	StdErr	Std	Skew	Kurt	5	10	25	40	50	60	75	90	95	% Pos	% Neg	($)
Pooled	106466	0.91	(0.02)	7.36	30.0	1652.8	-1.00	-0.53	-0.15	-0.03	0.01	0.11	0.44	1.88	4.40	50.0	42.1	23.32
Large	63428	0.52	(0.02)	5.04	39.4	2768.9	-0.79	-0.42	-0.12	-0.03	0.00	0.07	0.29	1.13	2.46	48.8	43.5	30.68
Medium	33054	1.19	(0.05)	8.68	29.2	1557.6	-1.23	-0.64	-0.19	-0.03	0.04	0.19	0.69	2.69	5.95	51.2	40.8	13.82
Small	9984	2.47	(0.13)	12.77	15.1	406.9	-1.84	-0.95	-0.24	0.00	0.13	0.43	1.49	5.82	12.44	54.1	37.3	8.04

Panel D. Distribution of Concensus Forecast Bias, by Industry

				cents per share						percent of price						percent	
SIC	Industry	Firms	Obs	Mean	StdErr	Std	P25	P50	P75	Mean	StdErr	Std	P25	P50	P75	Pos	Neg
13	Oil and Gas Extraction	162	2269	10.5	(1.2)	55.8	-3.0	1.0	8.5	1.3	(0.2)	9.4	-0.2	0.1	0.7	54.7	40.0
20	Food and Kindred Products	138	2967	0.9	(1.0)	56.2	-3.0	0.4	6.0	0.4	(0.0)	2.6	-0.1	0.0	0.3	50.2	40.1
22	Textile Mill Products	61	1184	6.3	(1.1)	36.3	-3.5	0.0	7.8	0.8	(0.1)	5.0	-0.2	0.0	0.6	49.9	43.2
23	Apparel and Other Finished Pds	67	1111	10.9	(1.6)	53.9	-3.0	0.0	9.0	1.9	(0.3)	11.1	-0.2	0.0	0.6	47.5	44.2
26	Paper and Allied Products	77	1914	7.4	(0.9)	40.7	-5.0	1.0	10.0	0.5	(0.1)	4.7	-0.2	0.0	0.4	52.6	42.5
27	Printing,Publishing and Allied	91	2208	2.9	(0.9)	41.1	-3.0	0.5	5.4	0.4	(0.1)	5.5	-0.1	0.0	0.2	50.7	41.7
28	Chemicals and Allied Products	424	7527	5.3	(0.5)	44.7	-3.0	0.0	5.8	0.4	(0.0)	3.6	-0.1	0.0	0.3	47.6	44.5
30	Rubber and Misc Plastics Prods	76	1306	6.4	(1.0)	35.7	-3.0	0.0	6.0	0.8	(0.1)	5.3	-0.1	0.0	0.3	47.0	44.6
33	Primary Metal Industries	108	2331	9.1	(1.4)	65.2	-5.5	1.0	12.0	1.1	(0.3)	14.3	-0.3	0.0	0.8	51.4	44.1
34	Fabr Metal,Ex Machy,Trans Eq	88	1692	7.5	(1.2)	48.5	-3.0	1.0	7.5	0.6	(0.1)	5.4	-0.2	0.0	0.4	52.1	42.0
35	Indl,Comml Machy,Computer Eq	485	8640	11.7	(0.6)	59.8	-3.0	0.5	9.0	1.4	(0.1)	7.2	-0.2	0.0	0.6	51.0	42.0
36	Electr, Oth Elec Eq, Ex Cmp	432	7568	6.7	(0.4)	31.4	-2.5	0.0	7.0	1.0	(0.1)	5.1	-0.1	0.0	0.5	49.2	42.3
37	Transportation Equipment	129	2548	6.8	(1.2)	63.0	-4.5	0.5	9.6	0.8	(0.1)	6.9	-0.2	0.0	0.5	50.4	43.6
38	Meas Instr;Photo Gds;Watches	422	6576	7.6	(0.5)	40.7	-2.0	0.5	6.5	0.9	(0.1)	5.4	-0.1	0.0	0.5	51.2	39.1
39	Misc Manufacturng Industries	80	1238	10.9	(1.4)	49.6	-2.5	1.0	11.0	2.0	(0.3)	9.7	-0.1	0.1	0.9	55.7	37.8
48	Communications	176	2200	6.9	(1.1)	52.3	-3.0	1.0	9.0	0.6	(0.1)	3.5	-0.1	0.0	0.4	54.5	39.8
49	Electric, Gas, Sanitary Serv	201	5436	5.7	(0.6)	45.1	-5.0	1.0	9.0	0.6	(0.1)	8.1	-0.2	0.0	0.4	52.1	43.1
50	Durable Goods-Wholesale	158	2438	5.6	(0.6)	28.6	-2.0	0.5	6.0	0.9	(0.1)	6.1	-0.1	0.0	0.5	51.6	40.0
51	Nondurable Goods-Wholesale	79	1324	6.5	(0.9)	33.0	-2.5	1.0	6.5	0.5	(0.1)	3.4	-0.1	0.0	0.4	52.7	38.1
56	Apparel and Accessory Stores	63	1213	5.1	(0.9)	32.4	-2.0	0.0	5.0	1.5	(0.4)	13.1	-0.1	0.0	0.4	48.4	41.2
58	Eating and Drinking Places	106	1604	6.1	(0.7)	26.4	-1.0	0.5	4.0	1.1	(0.2)	6.4	-0.1	0.0	0.3	50.9	33.5
59	Miscellaneous Retail	130	1815	6.8	(0.8)	32.5	-1.0	0.5	6.0	1.1	(0.2)	10.3	-0.1	0.0	0.5	50.7	36.3
60	Depository Institutions	521	6884	7.9	(0.8)	65.6	-4.0	0.0	6.0	1.0	(0.1)	12.2	-0.2	0.0	0.2	47.0	46.6
61	Nondepository Credit Instn	85	959	4.4	(0.9)	29.1	-3.0	0.0	4.5	0.9	(0.2)	5.9	-0.2	0.0	0.3	41.2	47.9
63	Insurance Carriers	204	3931	0.2	(0.9)	59.2	-11.5	-1.5	6.5	0.3	(0.1)	3.9	-0.4	-0.1	0.3	39.5	56.4
67	Holding,Other Invest Offices	107	973	6.6	(1.7)	54.0	-1.0	1.0	8.0	0.9	(0.2)	7.7	-0.1	0.1	0.6	57.7	32.8
73	Business Services	638	7440	7.6	(0.4)	32.6	-2.0	0.0	6.0	1.0	(0.1)	4.9	-0.1	0.0	0.5	49.3	40.3
80	Health Services	149	1791	6.5	(0.8)	34.0	-1.0	0.0	3.5	1.0	(0.1)	6.1	-0.1	0.0	0.3	44.7	39.8
87	Engr,Acc,Resh,Mgmt,Rel Svcs	103	1273	6.2	(0.7)	23.9	-1.0	1.0	6.0	0.9	(0.1)	4.0	-0.1	0.1	0.6	57.0	31.8

The concensus forecast bias for a company in a quarter is the median of all brokers' latest estimate of that quarter's earnings, less the actual earnings subsequently reported. The concensus forecast bias is reported both in terms of cents per share, and as a percentage of the company's stock price at quarter end. Panel A reports summary statistics for the quarterly cross-sectional mean concensus forecast bias across all companies. Panels B and C describe the distribution of the pooled sample of concensus forecast bias values for all companies and quarters.

Table 3. Concensus Forecast Bias, Dropping Large Special Items Charges

Panel A. Concensus Forecast Bias, Trimmed by Amount of Special Items Charges

		Cents per Share					Percent of Price						
Trim	N	Mean	Std	Skew	Kurt	Median	Mean	Std	Skew	Kurt	Median	% Pos	% Neg
None	106466	7.0	47.4	5.8	106.1	0.2	0.91	7.36	30.0	1652.8	0.01	50.0	42.1
$\geq \pm 5\sigma$	105528	5.3	36.9	5.5	148.2	0.0	0.74	5.52	27.8	1739.6	0.00	49.8	42.3
$\geq \pm 4\sigma$	105219	5.0	36.3	5.7	158.9	0.0	0.70	5.31	29.4	1979.4	0.00	49.7	42.4
$\geq \pm 3\sigma$	104794	4.8	35.7	5.9	169.7	0.0	0.67	5.20	31.1	2160.5	0.00	49.6	42.5
$\geq \pm 2\sigma$	103993	4.4	34.8	6.1	183.5	0.0	0.62	5.02	33.8	2485.7	0.00	49.3	42.6
$\geq \pm 1\sigma$	102332	3.9	34.1	6.4	199.5	0.0	0.56	4.79	37.6	2990.2	0.00	48.9	42.9
0	93543	3.6	34.4	7.0	205.3	0.0	0.49	4.78	40.8	3307.6	0.00	47.9	43.7

Panel B. Distribution of Special Items Charges, by Fiscal Qtr (cents per share)

Qtr	N	# Special	Mean	Std	Min	P5	P10	P25	P50	P75	P90	P95	Max
1	24727	2013	-5.7	94.8	-1167.5	-114.9	-53.3	-14.3	-1.9	8.6	33.5	73.1	1396.4
2	26275	2704	-20.6	99.0	-1535.3	-146.7	-82.5	-25.5	-4.2	4.9	25.5	55.0	901.5
3	27198	3006	-28.1	115.3	-1090.7	-208.4	-105.1	-31.9	-5.3	3.4	24.0	52.4	1762.2
4	28266	5200	-44.7	128.8	-1639.7	-247.0	-142.6	-50.5	-10.9	0.3	15.6	38.5	1500.0
All	106466	12923	-29.7	115.8	-1639.7	-199.0	-109.7	-33.9	-6.0	3.1	22.5	51.2	1762.2

Panel C. Distribution of Special Items Charges, by Fiscal Qtr (percent of price)

Qtr	N	# Special	Mean	Std	Min	P5	P10	P25	P50	P75	P90	P95	Max
1	24727	2013	-0.74	7.63	-158.31	-6.98	-3.42	-0.92	-0.11	0.40	1.58	3.84	63.18
2	26275	2704	-2.34	17.36	-551.62	-12.52	-6.52	-1.81	-0.24	0.26	1.36	3.07	53.52
3	27198	3006	-2.87	11.61	-184.63	-16.27	-8.64	-2.26	-0.32	0.18	1.28	3.13	64.46
4	28266	5200	-4.28	15.47	-380.25	-20.67	-11.76	-3.73	-0.72	0.02	0.90	2.17	55.95
All	106466	12923	-2.99	14.19	-551.62	-15.66	-8.48	-2.41	-0.35	0.17	1.21	2.80	64.46

The concensus forecast bias for a company in a quarter is the median of all brokers' latest estimate of that quarter's earnings, less the actual earnings subsequently reported. The concensus forecast bias is reported both in terms of cents per share, and as a percentage of the company's stock price at quarter end. Panel A describes the distribution of the pooled sample of concensus forecast bias values for all companies and quarters, after trimming the sample of outliers. Outliers are identified as observations for which special items charges are larger than a multiple of the standard deviation of concensus forecast errors (excluding all observations with non-zero special item charges). Panels B and C describe the distribution of special items charges that appear in the pooled sample.

Table 4. Concensus Forecast Bias Dropping Stale Forecasts

Panel A. Concensus Forecast Bias (cents per share)

YR	Companies	All Forecasts # Forecasts	All Forecasts Mean	All Forecasts StdErr	All Forecasts Std	# Stale Forecasts Dropped	Recent Forecasts # Forecasts	Recent Forecasts Mean	Recent Forecasts StdErr	Recent Forecasts Std	Difference in Mean
84	5093	3.0	4.9	(0.6)	39.5	0.4	2.6	4.7	(0.6)	39.5	-0.2
85	5569	3.9	8.0	(0.5)	38.5	0.5	3.4	7.6	(0.5)	38.4	-0.4
86	6061	4.0	9.3	(0.6)	48.7	0.4	3.6	9.0	(0.6)	48.8	-0.3
87	6358	4.1	7.0	(0.6)	49.1	0.6	3.4	6.9	(0.6)	49.4	-0.1
88	6267	4.5	3.9	(0.5)	40.0	0.4	4.1	3.7	(0.5)	39.7	-0.1
89	6658	5.1	6.4	(0.5)	41.1	0.5	4.5	6.2	(0.5)	40.7	-0.2
90	6745	5.2	7.5	(0.5)	39.1	0.6	4.6	7.1	(0.5)	38.8	-0.4
91	7021	5.4	4.7	(0.4)	33.2	0.6	4.8	4.3	(0.4)	33.0	-0.4
92	8084	5.2	3.4	(0.3)	31.1	0.6	4.7	3.1	(0.3)	30.7	-0.2
93	8993	5.0	1.8	(0.4)	33.6	0.7	4.3	1.6	(0.4)	33.4	-0.2
94	11297	5.2	1.8	(0.2)	24.3	0.7	4.4	1.6	(0.2)	24.1	-0.2
95	12050	5.2	2.6	(0.2)	24.3	0.9	4.3	2.2	(0.2)	23.8	-0.4
96	13797	4.9	2.9	(0.2)	25.0	1.0	3.9	2.5	(0.2)	24.3	-0.5
Pooled	103993	4.8	4.4	(0.1)	34.8	0.7	4.1	4.1	(0.1)	34.6	-0.3

Panel B. Concensus Forecast Bias (percent of price)

YR	Companies	All Forecasts # Forecasts	All Forecasts Mean	All Forecasts StdErr	All Forecasts Std	# Stale Forecasts Dropped	Recent Forecasts # Forecasts	Recent Forecasts Mean	Recent Forecasts StdErr	Recent Forecasts Std	Difference in Mean
84	5093	3.0	0.61	(0.05)	3.87	0.4	2.6	0.59	(0.05)	3.84	-0.02
85	5569	3.9	0.80	(0.07)	5.02	0.5	3.4	0.78	(0.07)	5.00	-0.03
86	6061	4.0	1.03	(0.09)	7.39	0.4	3.6	1.00	(0.09)	7.34	-0.03
87	6358	4.1	0.81	(0.10)	8.05	0.6	3.4	0.78	(0.10)	7.64	-0.03
88	6267	4.5	0.70	(0.10)	7.93	0.4	4.1	0.68	(0.10)	7.89	-0.03
89	6658	5.1	0.72	(0.06)	4.77	0.5	4.5	0.69	(0.06)	4.70	-0.03
90	6745	5.2	1.09	(0.08)	6.79	0.6	4.6	1.03	(0.08)	6.66	-0.06
91	7021	5.4	0.62	(0.05)	4.12	0.6	4.8	0.58	(0.05)	4.09	-0.04
92	8084	5.2	0.38	(0.03)	2.57	0.6	4.7	0.36	(0.03)	2.53	-0.02
93	8993	5.0	0.44	(0.04)	3.93	0.7	4.3	0.42	(0.04)	3.91	-0.02
94	11297	5.2	0.38	(0.03)	3.15	0.7	4.4	0.35	(0.03)	3.08	-0.03
95	12050	5.2	0.47	(0.03)	3.49	0.9	4.3	0.42	(0.03)	3.37	-0.05
96	13797	4.9	0.57	(0.03)	4.05	1.0	3.9	0.51	(0.03)	3.92	-0.06
Pooled	103993	4.8	0.62	(0.02)	5.02	0.7	4.1	0.59	(0.02)	4.92	-0.04

Table 5. Concensus Forecast Bias Dropping Newly-covered and Single-analyst Companies

Panel A. Concensus Forecast Bias 1984-1996, by Size Class (cents per share)

	All Companies			New/Single-Analyst			Old/Multi-Analyst			Difference in	
Size	N	Mean	StdErr	N	Mean	StdErr	N	Mean	StdErr	Mean	(t-test)
10	24406	3.0	0.3	795	3.0	2.0	23611	3.0	0.3	-0.0	(-0.03)
9	20579	3.9	0.2	2298	1.5	0.7	18281	4.2	0.2	-2.7	(-3.56)
8	16742	4.2	0.3	3533	2.1	0.5	13209	4.7	0.3	-2.6	(-4.72)
7	13521	4.2	0.2	4352	3.3	0.5	9169	4.7	0.3	-1.4	(-2.34)
6	10851	4.4	0.3	4600	3.9	0.5	6251	4.9	0.4	-0.2	(-1.58)
5	8082	4.9	0.3	3933	4.8	0.4	4149	5.0	0.4	-0.2	(-0.41)
4	5296	4.9	0.3	3065	4.8	0.4	2231	5.1	0.5	-0.3	(-0.45)
3	2995	6.0	0.5	2021	6.0	0.6	974	6.1	0.9	-0.1	(-0.16)
2	1254	8.6	0.8	1018	8.9	1.0	236	7.2	1.3	1.7	(1.00)
1	267	5.7	2.3	217	6.1	2.5	50	3.7	6.1	2.4	(0.35)
Pooled	103993	4.1	0.1	25832	3.9	0.2	78161	4.1	0.1	-0.2	(-0.93)

Panel B. Concensus Forecast Bias 1984-1996, by Size Class (percent of price)

	All Companies			New/Single-Analyst			Old/Multi-Analyst			Difference in	
Size	N	Mean	StdErr	N	Mean	StdErr	N	Mean	StdErr	Mean	(t-test)
10	24406	0.15	0.01	795	0.18	0.08	23611	0.15	0.01	0.03	(0.45)
9	20579	0.34	0.03	2298	0.31	0.12	18281	0.34	0.03	-0.03	(-0.25)
8	16742	0.48	0.03	3533	0.33	0.05	13209	0.52	0.04	-0.19	(-2.96)
7	13521	0.65	0.04	4352	0.61	0.08	9169	0.67	0.04	-0.06	(0.63)
6	10851	0.84	0.07	4600	0.73	0.09	6251	0.93	0.11	-0.20	(-1.39)
5	8082	0.98	0.05	3933	0.99	0.07	4149	0.96	0.08	0.03	(-0.25)
4	5296	1.24	0.08	3065	1.25	0.11	2231	1.23	0.13	0.02	(0.08)
3	2995	1.82	0.16	2021	1.77	0.17	974	1.94	0.32	-0.17	(-0.45)
2	1254	2.63	0.28	1018	2.75	0.33	236	2.11	0.39	0.64	(1.25)
1	267	3.85	1.02	217	3.80	1.04	50	4.06	3.00	-0.26	(-0.08)
Pooled	103993	0.59	0.02	25832	0.89	0.04	78161	0.49	0.02	0.40	(10.1)

The concensus forecast bias for a company in a quarter is the median of all brokers' latest estimate of that quarter's earnings, submitted no more than three months prior to quarter end; or the most recent of all brokers' estimates if none of the brokers submitted a forecast of less than three months recency. New/single-analyst companies are those for whom analyst coverage (number of analysts providing FY1 forecasts) a year ago is zero, or for whom analyst coverage at quarter end is no more than one. The table reports the number and cross-sectional mean and standard error of the concensus forecast bias, by company size class as defined by its CRSP size decile (10 denotes the largest size decile).

Table 6. Concensus Forecast Bias, Dropping New Analysts

Panel A. Concensus Forecast Bias (cents per share)

		All Analysts			Dropping New Analysts		
Size	N	# Forecasts	Mean	StdErr	# Forecasts	Mean	StdErr
10	24406	8.7	3.0	0.3	8.5	3.1	0.3
9	20579	4.2	3.9	0.2	4.1	3.9	0.2
8	16742	3.0	4.2	0.3	2.9	4.2	0.3
7	13521	2.3	4.2	0.2	2.2	4.3	0.3
6	10851	2.0	4.4	0.3	1.9	4.4	0.3
5	8082	1.7	4.9	0.3	1.6	4.9	0.3
4	5296	1.5	4.9	0.3	1.4	4.9	0.3
3	2995	1.3	6.0	0.5	1.3	6.0	0.5
2	1254	1.2	8.6	0.8	1.2	8.6	0.8
1	267	1.1	5.7	2.3	1.1	5.5	2.3
Pooled	103993	4.1	4.1	0.1	4.0	4.1	0.1

Panel B. Concensus Forecast Bias (percent of price)

		New and Seasoned Analysts			Dropping New Analysts		
Size	N	# Forecasts	Mean	StdErr	# Forecasts	Mean	StdErr
10	24406	8.7	0.15	0.01	8.5	0.15	0.01
9	20579	4.2	0.34	0.03	4.1	0.34	0.03
8	16742	3.0	0.48	0.03	2.9	0.48	0.03
7	13521	2.3	0.65	0.04	2.2	0.66	0.04
6	10851	2.0	0.84	0.07	1.9	0.84	0.07
5	8082	1.7	0.98	0.05	1.6	0.98	0.05
4	5296	1.5	1.24	0.08	1.4	1.24	0.08
3	2995	1.3	1.82	0.16	1.3	1.82	0.16
2	1254	1.2	2.63	0.28	1.2	2.63	0.28
1	267	1.1	3.85	1.02	1.1	3.85	1.02
Pooled	103993	4.1	0.59	0.02	4.0	0.59	0.02

Seasoned (new) analysts are those that had (had not) submitted a quarterly or annual earnings forecast for an earlier fiscal end date. The concensus forecast bias (all analysts) for a company in a quarter is the median of all brokers' latest estimate of that quarter's earnings, submitted no more than three months prior to quarter end; or the most recent of all brokers' estimates if none of the brokers submitted a forecast of less than three months recency. The concensus forecast bias (dropping new analysts) for a company in a quarter is the median of all brokers' latest estimate from seasoned analysts of that quarter's earnings, submitted no more than three months prior to quarter end; or the most recent of all brokers' estimates if none of the brokers submitted a forecast of less than three months recency. The table reports the mean number of forecasts per company, and the cross-sectional mean and standard error of the concensus forecast bias, by company size class as defined by its CRSP size decile (10 denotes the largest size decile).

Table 7. Correlation Coefficients of Company Characteristics Variables

	BIAS	BIAS1	BP	SIZE	COVER	ALPHA	STDEXR	EPSVAR
BIAS	1.000 (0.000)	0.300 (0.008)	-0.027 (0.007)	-0.086 (0.006)	-0.076 (0.006)	-0.135 (0.006)	0.104 (0.006)	0.043 (0.006)
BIAS1	0.300 (0.008)	1.000 (0.000)	-0.012 (0.008)	-0.067 (0.007)	-0.055 (0.007)	-0.203 (0.007)	0.097 (0.006)	0.046 (0.006)
BP	-0.027 (0.007)	-0.012 (0.008)	1.000 (0.000)	-0.037 (0.015)	0.010 (0.010)	0.094 (0.017)	-0.201 (0.014)	0.403 (0.010)
SIZE	-0.086 (0.006)	-0.067 (0.007)	-0.037 (0.015)	1.000 (0.000)	0.794 (0.002)	-0.189 (0.020)	-0.658 (0.012)	-0.197 (0.007)
COVER	-0.076 (0.006)	-0.055 (0.007)	0.010 (0.010)	0.794 (0.002)	1.000 (0.000)	-0.181 (0.016)	-0.487 (0.012)	-0.110 (0.007)
ALPHA	-0.135 (0.006)	-0.203 (0.007)	0.094 (0.017)	-0.189 (0.020)	-0.181 (0.016)	1.000 (0.000)	-0.016 (0.026)	0.016 (0.013)
STDEXR	0.104 (0.006)	0.097 (0.006)	-0.201 (0.014)	-0.658 (0.012)	-0.487 (0.012)	-0.016 (0.026)	1.000 (0.000)	0.182 (0.007)
EPSVAR	0.043 (0.006)	0.046 (0.006)	0.403 (0.010)	-0.197 (0.007)	-0.110 (0.007)	0.016 (0.013)	0.182 (0.007)	1.000 (0.000)

Table reports the time series mean (from December 1984 through December 1996) of the quarterly cross-sectional correlations (with time series standard errors in parentheses) of company characteristics variables, for companies with quarter end dates in March, June, September and December.

1. BIAS is the concensus forecast bias (scaled by split-adjusted stock price 12 months prior to the beginning of the quarter), defined as the median of all brokers' latest estimate of that quarter's earnings, submitted no more than three months prior to quarter end; or the most recent of all brokers' estimates if none of the brokers submitted a forecast of less than three months recency.
2. BIAS1 is concensus forecast bias from the previous quarter.
3. BP is the book to price ratio 12 months prior to the beginning of the quarter.
4. SIZE is the log market capitalization 12 months prior to the beginning of the quarter.
5. COVER is the log of 1 + number of analysts providing FY1 earnings forecasts 12 months prior to the beginning of the quarter.
6. ALPHA is the intercept from the market model regression of daily stock returns on value-weighted market returns, for the year ending at the beginning of the quarter.
7. STDEXR is the standard error from the market model regression of daily stock returns on the value-weighted market return, for the year ending at the beginning of the quarter.
8. EPSVAR is the standard error from a trend regression of quarterly earnings for the eight quarters up to two quarters prior.

Table 8. Concensus Forecast Bias, by Company Characteristics

Panel A. Mean Forecast Bias

Grouped by	Decile 1	2	3	4	5	6	7	8	9	10	All
(minus) ALPHA	0.22	0.22	0.22	0.21	0.25	0.27	0.37	0.40	0.61	1.13	0.39
	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.10)	(0.02)
BIAS1	-0.19	0.03	0.07	0.07	0.13	0.21	0.29	0.49	0.84	1.95	0.39
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.10)	(0.02)
(minus) SIZE	0.05	0.14	0.24	0.29	0.26	0.31	0.47	0.53	0.62	0.98	0.39
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.07)	(0.02)
EPSVAR	0.14	0.13	0.20	0.20	0.27	0.33	0.33	0.44	0.67	1.13	0.38
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.05)	(0.10)	(0.02)
STDEXR	0.10	0.11	0.15	0.21	0.23	0.36	0.37	0.52	0.66	1.19	0.39
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.09)	(0.02)
Residual STDEXR	0.22	0.21	0.24	0.25	0.28	0.33	0.38	0.35	0.54	1.11	0.39
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.08)	(0.02)

Panel A reports the time-series means and standard errors (in parentheses) of the quarterly cross-sectional mean concensus forecast bias, grouped each quarter by company characteristic variables, from December 1984 through December 1996. Concensus forecast bias is the median (scaled by split-adjusted stock price from 12 months prior to the beginning of the quarter) of all brokers' latest estimate of that quarter's earnings, submitted no more than three months prior to quarter end; or the most recent of all brokers' estimates if none of the brokers submitted a forecast of less than three months recency.

1. BIAS1 is the concensus forecast bias from the prior quarter.
2. SIZE is the log market capitalization, 12 months prior to the beginning of the quarter.
3. ALPHA is the intercept from the market model regression of daily stock returns on value-weighted market returns, for the year ending at the beginning of the quarter.
4. EPSVAR is the standard deviation of the trend-adjusted quarterly earnings from the eight quarters prior to the previous quarter, scaled by the split-adjusted stock price 12 months prior to the beginning of the quarter.
5. STDEXR is the standard error from the market model regression of daily stock returns on the value-weighted market return, for the year ending at the beginning of the quarter.
6. Residual STDEXR are the cross-sectional residuals $\hat{\epsilon}_{it}$ from the following regression, estimated every quarter t:

$$STDEXR_{it} = \hat{\beta}_0 + \hat{\beta}_1 SIZE_{it} + \hat{\beta}_2 BP_{it} + \hat{\beta}_3 COVER_{it} + \hat{\epsilon}_{it}$$

   (a) $SIZE_{it}$ is the log market capitalization, 12 months prior to the beginning of the quarter t.
   (b) BP_{it} is the book to price ratio for company i, 12 months prior to the beginning of the quarter t.
   (c) $COVER_{it}$ is the log of 1 + number of analysts providing FY1 earnings forecasts for company i, 12 months prior to the beginning of the quarter t.

Panel B. Mean Forecast Bias, Grouped by SIZE and Residual STDEXR

SIZE	Residual STDEXR 1	2	3	4	5	All
Small	0.52	0.44	0.61	1.05	1.37	0.80
	(0.07)	(0.06)	(0.06)	(0.10)	(0.10)	(0.05)
2	0.21	0.32	0.31	0.63	1.03	0.50
	(0.04)	(0.06)	(0.04)	(0.08)	(0.11)	(0.04)
3	0.13	0.13	0.26	0.32	0.60	0.29
	(0.02)	(0.02)	(0.05)	(0.05)	(0.07)	(0.02)
4	0.13	0.20	0.25	0.29	0.48	0.27
	(0.03)	(0.05)	(0.05)	(0.04)	(0.08)	(0.03)
Large	0.07	0.08	0.07	0.08	0.17	0.10
	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.02)
All	0.21	0.23	0.30	0.48	0.73	0.39
	(0.02)	(0.02)	(0.02)	(0.04)	(0.05)	(0.02)
Mean size ($Mil)	936	1352	1796	1710	1195	1399
Mean coverage	8.7	9.1	9.3	9.4	9.5	9.2
Mean book-to-price	0.70	0.68	0.68	0.68	0.69	0.69

Each quarter, all companies are sorted into 5 group by SIZE, and each size group is then sorted by Residual STDEXR. Panel B reports the time-series means and standard errors (in parentheses) of the quarterly cross-sectional mean concensus forecast bias for each SIZE/Residual STDEXR subgroup, from December 1984 through December 1996.

Concensus forecast bias is the median (scaled by split-adjusted stock price 12 months prior to the beginning of the quarter) of all brokers' latest estimate of that quarter's earnings, submitted no more than three months prior to quarter end; or the most recent of all brokers' estimates if none of the brokers submitted a forecast of less than three months recency.

Residual STDEXR are the cross-sectional residuals $\hat{e}_{it}$ from the following regression, estimated every quarter t:

$$STDEXR_{it} = \hat{\beta}_0 + \hat{\beta}_1 SIZE_{it} + \hat{\beta}_2 BP_{it} + \hat{\beta}_3 COVER_{it} + \hat{e}_{it}$$

1. $SIZE_{it}$ is the log market capitalization, 12 months prior to the beginning of the quarter t.
2. BP_{it} is the book to price ratio for company i, 12 months prior to the beginning of the quarter t.
3. $COVER_{it}$ is the log of 1 + number of analysts providing FY1 earnings forecasts for company i, 12 months prior to the beginning of the quarter t.

Table 9. Regression of Concensus Forecast Bias on Company Characteristics

	SIZE	STDEXR	BIAS1	ALPHA	NEW	D4Q	BP	COVER	D_q	D_{sic}	AdjR2	N
Pooled 1984-1996	-0.035 (-17.27)	2.804 (10.50)	0.021 (22.69)	-52.237 (-28.31)	0.073 (8.99)	0.046 (5.92)			yes		0.114	62826
Subperiod 1984-1990	-0.049 (-13.16)	4.407 (7.18)	0.020 (13.72)	-66.505 (-17.59)	0.062 (3.94)	0.049 (3.57)			yes		0.148	24975
Subperiod 1991-1996	-0.023 (-9.72)	2.653 (9.49)	0.022 (17.85)	-43.139 (-21.49)	0.079 (8.76)	0.044 (4.92)			yes		0.079	37845
Large Stocks 1984-1996	-0.032 (-12.56)	2.139 (5.40)	0.021 (16.90)	-49.150 (-20.33)	0.056 (4.07)	0.036 (3.78)			yes		0.087	41307
Medium Stocks 1984-1996	-0.062 (-4.75)	3.026 (5.85)	0.021 (11.97)	-61.887 (-15.87)	0.048 (3.60)	0.066 (4.34)			yes		0.140	16659
Small Stocks 1984-1996	-0.149 (-5.12)	3.858 (4.83)	0.017 (6.67)	-64.644 (-7.77)	0.066 (2.54)	0.064 (1.97)			yes		0.190	4242
Pooled 1984-1996	-0.029 (-8.66)	4.035 (12.35)	0.019 (19.75)	-55.579 (-27.13)	0.072 (6.61)	0.043 (5.07)	0.057 (7.31)	-0.013 (-2.10)	yes	yes	0.122	53921

Table reports the coefficients and t-statistics (in parentheses) of the regression of concensus forecast bias on company characteristics variables. Large, medium and small stocks are classified by CRSP size deciles 8 to 10, 5 to 7, and 1 to 4 respectively.

1. BIAS is the concensus forecast bias (scaled by split-adjusted stock price 12 months prior to the beginning of the quarter), defined as the median of all brokers' latest estimate of that quarter's earnings, submitted no more than three months prior to quarter end; or the most recent of all brokers' estimates if none of the brokers submitted a forecast of less than three months recency.
2. SIZE is the log of market capitalization 12 months prior to the beginning of the quarter.
3. STDEXR is the standard error from the market model regression of daily stock returns on the value-weighted market return, for the year ending at the beginning of the quarter.
4. BIAS1 is BIAS lagged by one quarter.
5. ALPHA is the intercept from the market model regression of daily stock returns on the value-weighted market return, for the year ending at the beginning of the quarter.
6. NEW is an indicator variable that takes on value of 1 if analyst coverage for the company was initiated within twelve months prior to quarter end.
7. D4Q is an indicator variable that takes on value of 1 for fourth fiscal quarters.
8. BP is the book to price ratio 12 months prior to the beginning of the quarter.
9. COVER is the log of 1 + number of analysts providing FY1 earnings forecasts 12 months prior to the beginning of the quarter.
10. D_q are dummy variables for each calendar quarter.
11. D_{sic} are industry dummy variables based on two-digit SIC codes.

Table 10. Distribution of Analyst Characteristics Variables

Panel A. Distribution of raw variables 1986-1996

	Mean	Std Dev	Skewness	Kurtosis	Percentile 5	25	50	75	95
RELPCTB	0.000	0.686	5.322	743.38	-0.464	-0.096	-0.004	0.090	0.475
AGE	3.449	2.966	1.127	0.581	0.250	1.000	2.500	5.000	9.750
STALE	0.075	0.090	0.257	-0.511	-0.052	0.003	0.071	0.137	0.222
ANAL	0.864	0.164	-1.968	4.166	0.526	0.816	0.930	0.973	1.000

Panel B. Correlation Coefficients 1986-1996

	RELPCTB	DAGE	DSTALE	DANAL
RELPCTB	1.000	-0.007	0.075	-0.013
DAGE	-0.007	1.000	-0.001	0.001
DSTALE	0.075	-0.001	1.000	0.015
DANAL	-0.013	0.001	0.015	1.000

1. RELPCTB is an analyst's latest forecast, submitted no more than three months prior to quarter end, minus the mean forecast for analysts following the company that quarter, scaled by stock price at quarter end.
2. DAGE is the number of years since the analyst first published an annual or quarterly earnings forecast for the company, less the average for analysts following the company that quarter.
3. DSTALE is the quarter end date minus the submission date of the estimate, expressed as a fraction of years, less the average for analysts following the company that quarter.
4. DANAL is the fractional rank of the size of the brokerage firm that employed the analyst, less the average for analysts following the company that quarter. The fractional rank is obtained by ranking all brokerage firms by the number of analysts employed within twelve months prior to the quarter end date.

Table 11. Regression of Relative Analyst Forecast Bias on Analyst Characteristics

		DAGE	DSTALE	DANAL	AdjR2	N
Pooled	1986-1996	-0.001	0.250	-0.032	0.009	182582
		(-2.84)	(39.01)	(-9.79)		
Size Decile	10	-0.001	0.189	-0.023	0.006	119587
		(-3.00)	(26.72)	(-6.07)		
	9	-0.001	0.329	-0.049	0.013	33476
		(-1.02)	(20.25)	(-6.40)		
	1-8	-0.000	0.443	-0.049	0.016	28299
		(-0.02)	(20.83)	(-4.75)		
Year	1986-1991	-0.001	0.300	-0.017	0.009	81633
		(-2.18)	(27.11)	(-3.15)		
	1992-1996	-0.000	0.220	-0.044	0.009	100945
		(-2.21)	(28.70)	(-10.54)		

Table 11 reports the coefficients and t-statistics (in parentheses) of the multiple regression of relative analyst bias as a percentage of quarter end stock price (RELPCTB, on analyst characterics variables (DAGE, DSTALE, and DANAL).

1. RELPCTB is an analyst's latest forecast, submitted no more than three months prior to quarter end, minus the mean forecast for for a company-quarter, as a percentage of stock price at quarter end.
2. DAGE is the number of years since the analyst first published an annual or quarterly earnings forecast for the company, less the average for analysts following the company that quarter.
3. DSTALE is the quarter end date minus the submission date of the estimate, expressed as a fraction of years, less the average for analysts following the company that quarter.
4. DANAL is the fractional rank of the size of the brokerage firm that employed the analyst, less the average for analysts following the company that quarter. The fractional rank is obtained by ranking all brokerage firms by the number of analysts employed within twelve months prior to the quarter end date.

Figure 1A. Mean Concensus Forecast Bias by Quarter (All Stocks) 1984–1996

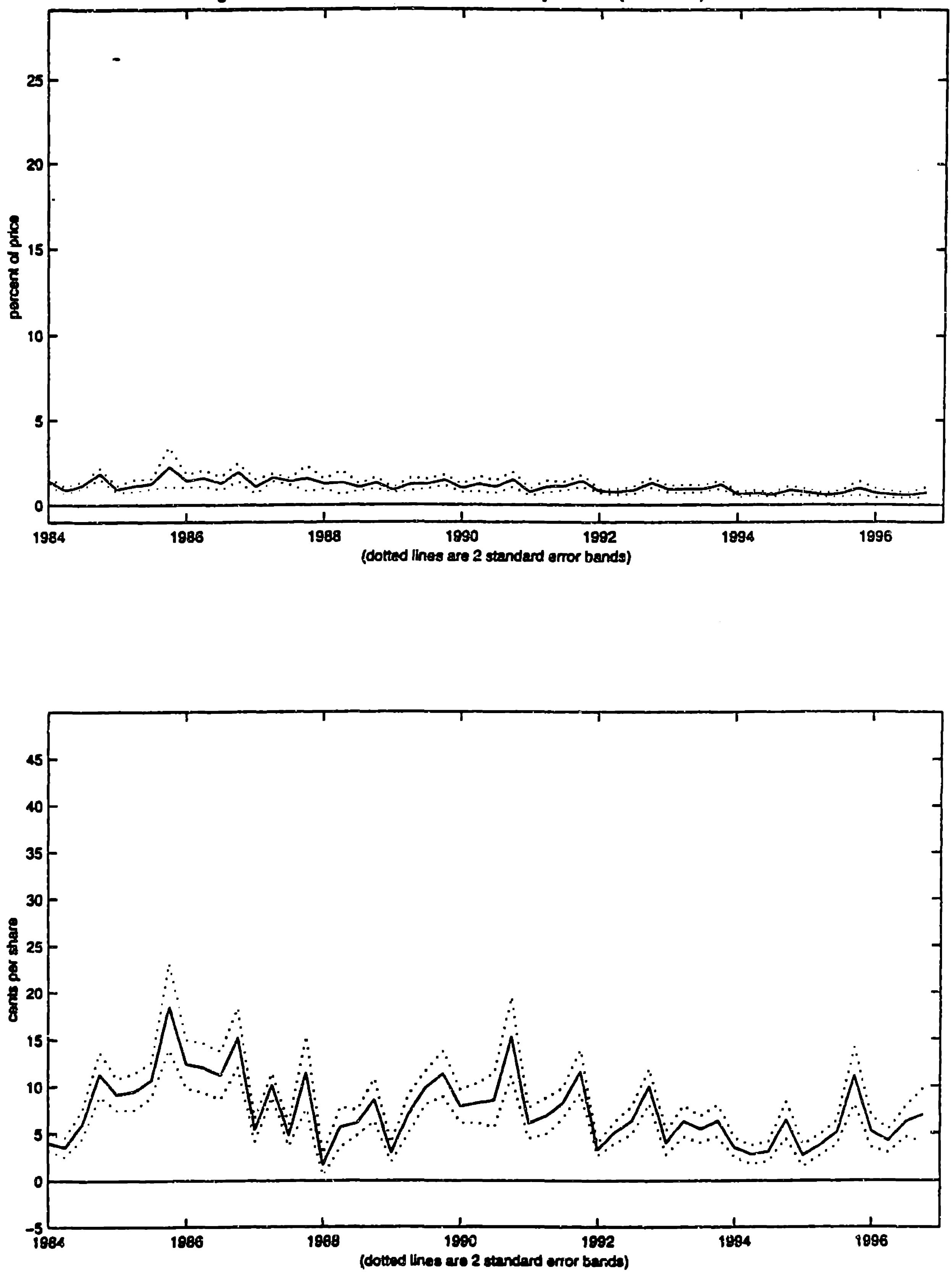


Figure 1B. Mean Concensus Forecast Bias by Quarter (Small Stocks) 1984–1996

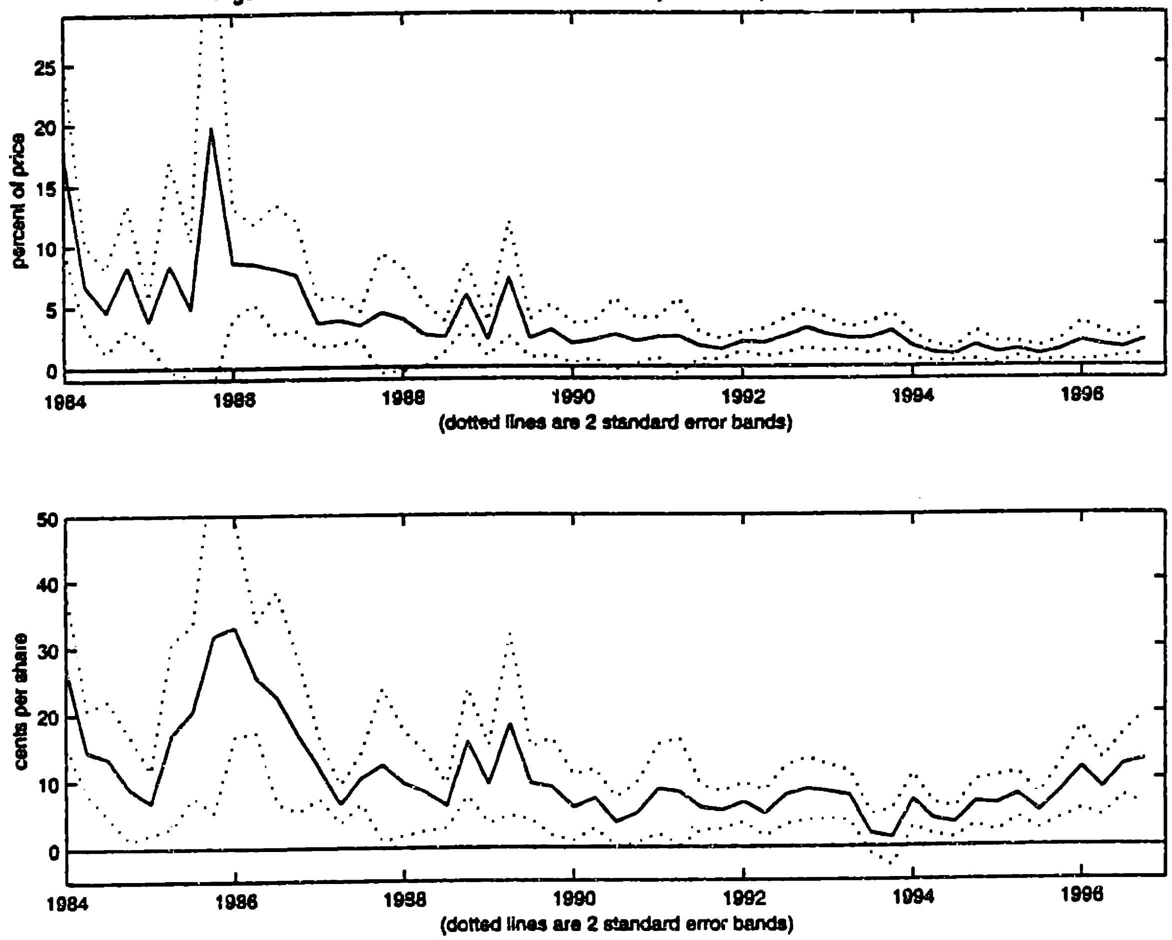


Figure 1C. Mean Concensus Forecast Bias by Quarter (Medium Stocks) 1984–1996

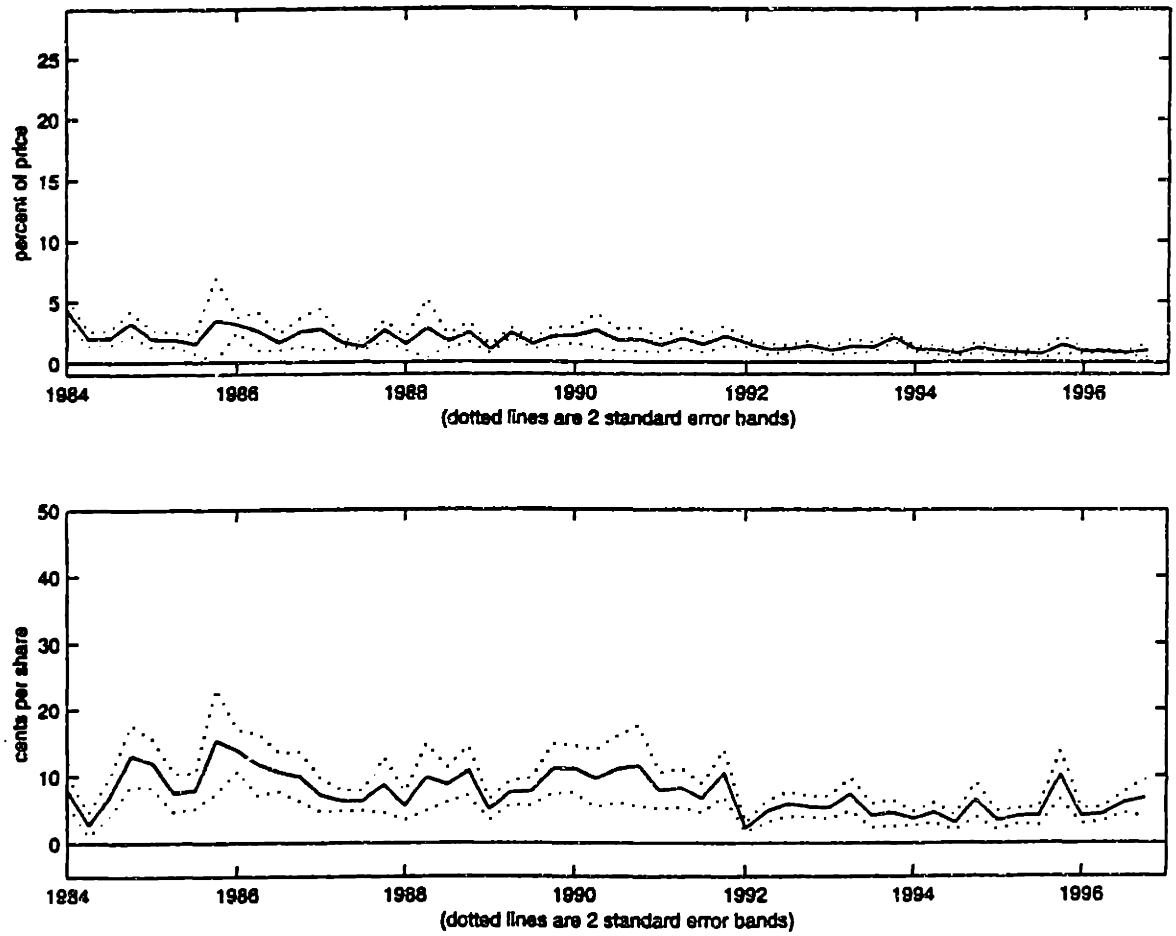
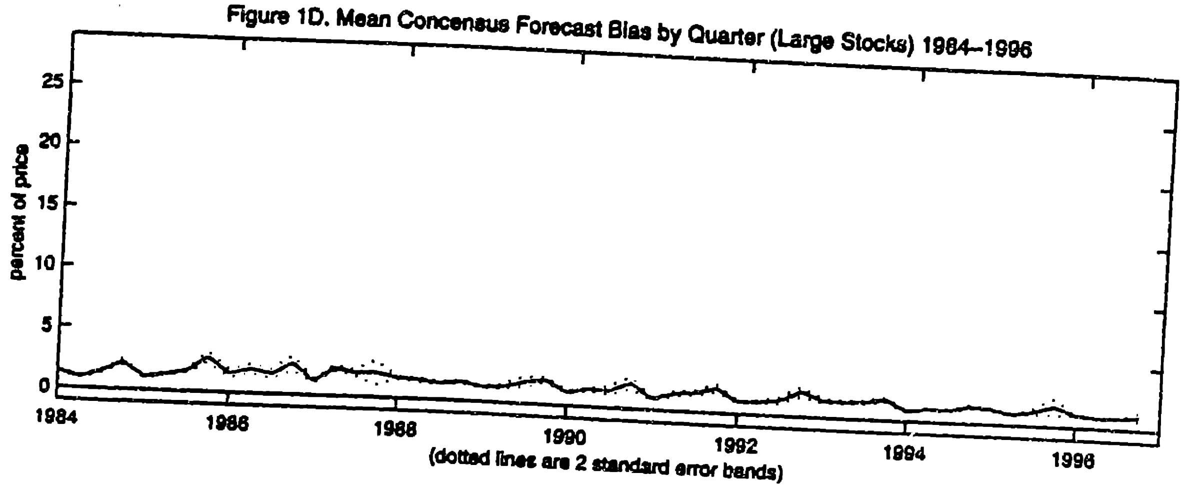


Figure 1D. Mean Concensus Forecast Bias by Quarter (Large Stocks) 1984–1996



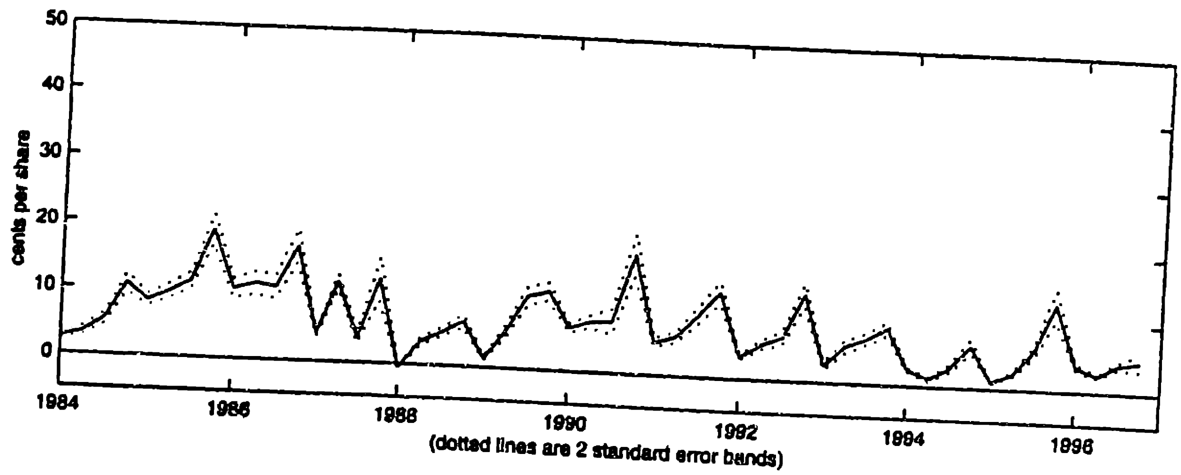
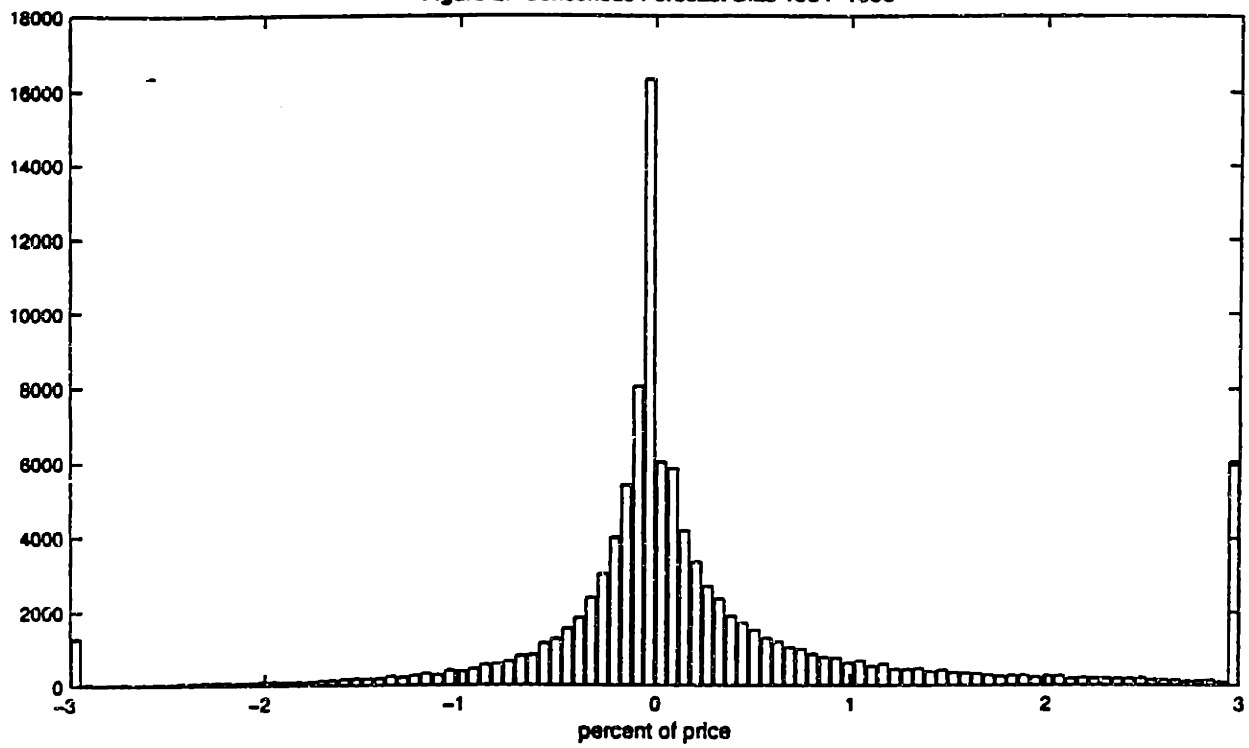


Figure 2. Concensus Forecast Bias 1984–1996



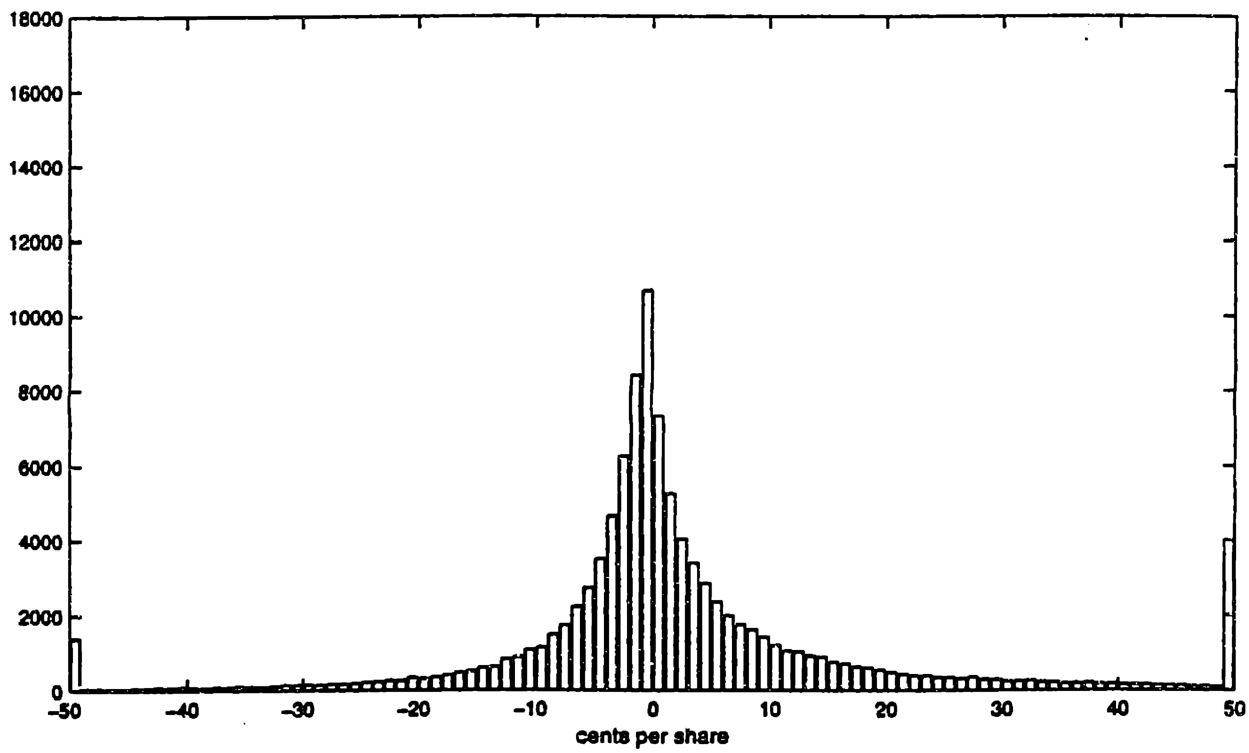


Figure 3. Concensus Forecast Bias by Horizon 1984–1996 (cents per share)