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and the Profitability of Momentum Strategies
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ABSTRACT

A number of theories have been proposed to explain the medium-term momentum in stock returns identified by Jegadeesh and Titman (1993). We test one such theory--based on the graduate-information-diffusion model of Hong and Stein (1997)--and establish three key results. First, once one moves past the very smallest stocks (where thin market-making capacity appears to be an issue) 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, there is a strong asymmetry: the effect of analyst coverage is much more pronounced for stocks that are past losers than for stocks that are past winners. These findings are consistent with the hypothesis that firm-specific information, especially negative information, diffuses only gradually across the investing public.

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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 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

[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.

[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.

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 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

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[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).

[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.

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 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

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[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.

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 (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

[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.

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.

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.

[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.

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

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 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

[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.

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 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

[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.

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] 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

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[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.

[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.

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 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

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[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 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.

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 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

[19]See also Hayes (1996).

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 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]

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

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

[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.

independent sort to generate ten subsamples, with the breakpoints determined by NYSE/AMEX deciles. Figure 1 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

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[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 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

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 million vs. $180 million). Evidently, due to non-linearities in the analyst-size

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.

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

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 underperform P1/SUB3 stocks by 0.70% per month. This difference is also highly significant,

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[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 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.

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 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

[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.

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 <u>differential</u> 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 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

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

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-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

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[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.

[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.

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 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

[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.

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.

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

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

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.

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 T-bills), 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):

[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.

$$r_{it} = b_i m_t + e_{it} \tag{1}$$

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, $(\mathrm{cov}(m_t, m_{t-1}) = 0)$ a regression of r_{it} on r_{it-1} produces the following theoretical coefficient ρ_i^*:

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

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

[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.

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 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

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

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 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

[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.

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.

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.

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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	46.7%
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	6356	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	6	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^2
1	.54	.03												NO	.61
	(52.67)	(0.99)													
2	.56	.04												YES	.63
	(52.90)	(1.21)													
3	.55	.05	.12											NO	.61
	(53.03)	(1.50)	(3.15)												
4	.57	.07	.17											YES	.63
	(52.22)	(2.00)	(4.30)												
5	.50	.07		.38										NO	.64
	(48.41)	(2.28)		(11.54)											
6	.51	.09		.40										YES	.65
	(46.11)	(2.62)		(10.94)											
7	.57	.09			-.52	-1.27	-.50	-.28	-.28	-.04	-.16			YES	.65
	(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	.64
	(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 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.

		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: 20th-40th Percentile	2: 40th-60th Percentile	3: 60th-80th Percentile	4: 80th-100th 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=0.01389 (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	464	
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 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 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 20^{th} 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. Note: 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	0.8990
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

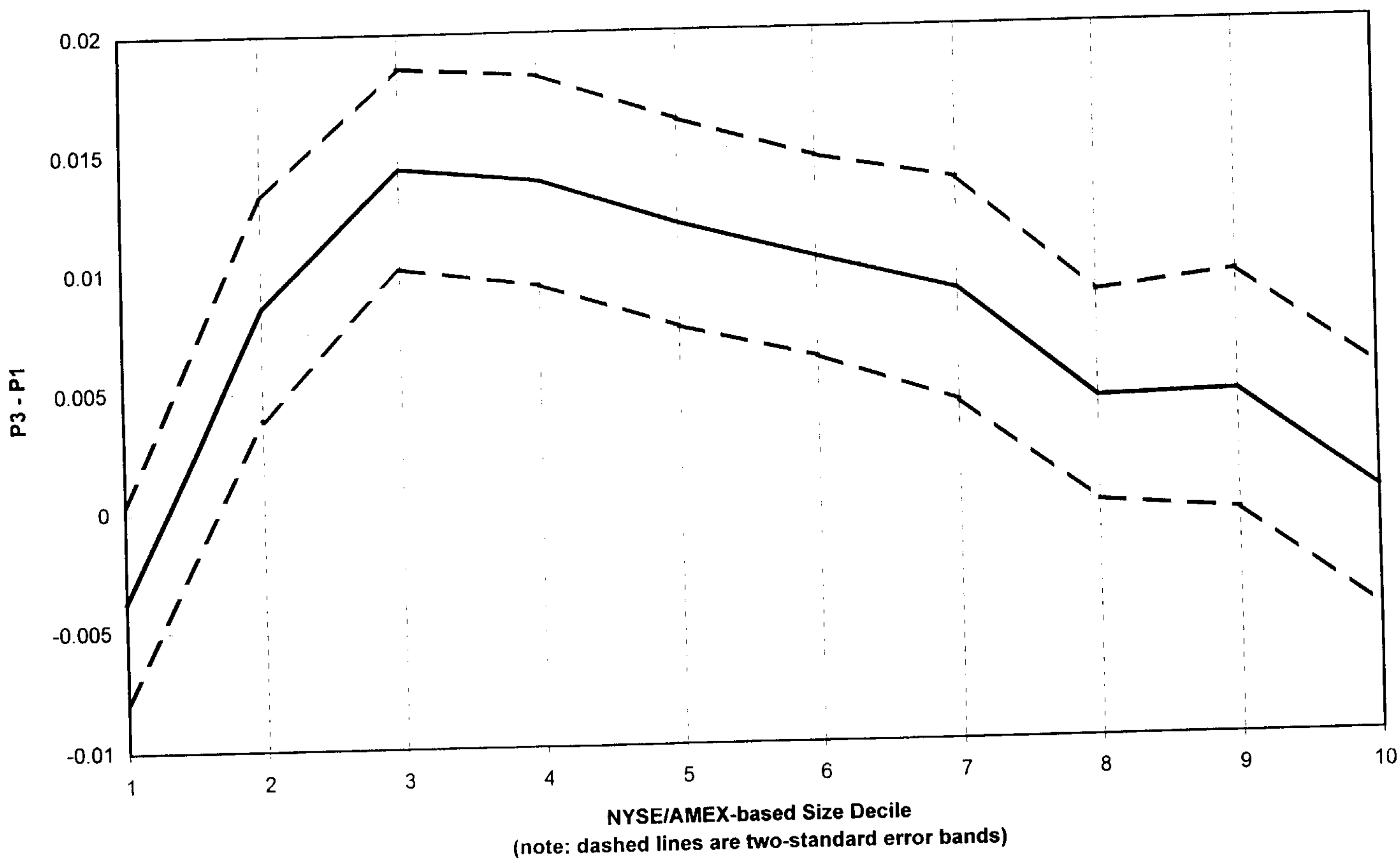

Figure 2: Cumulative Beta-Adjusted Returns in Event Time
Panel A: Momentum Profits for SUB1 and SUB3

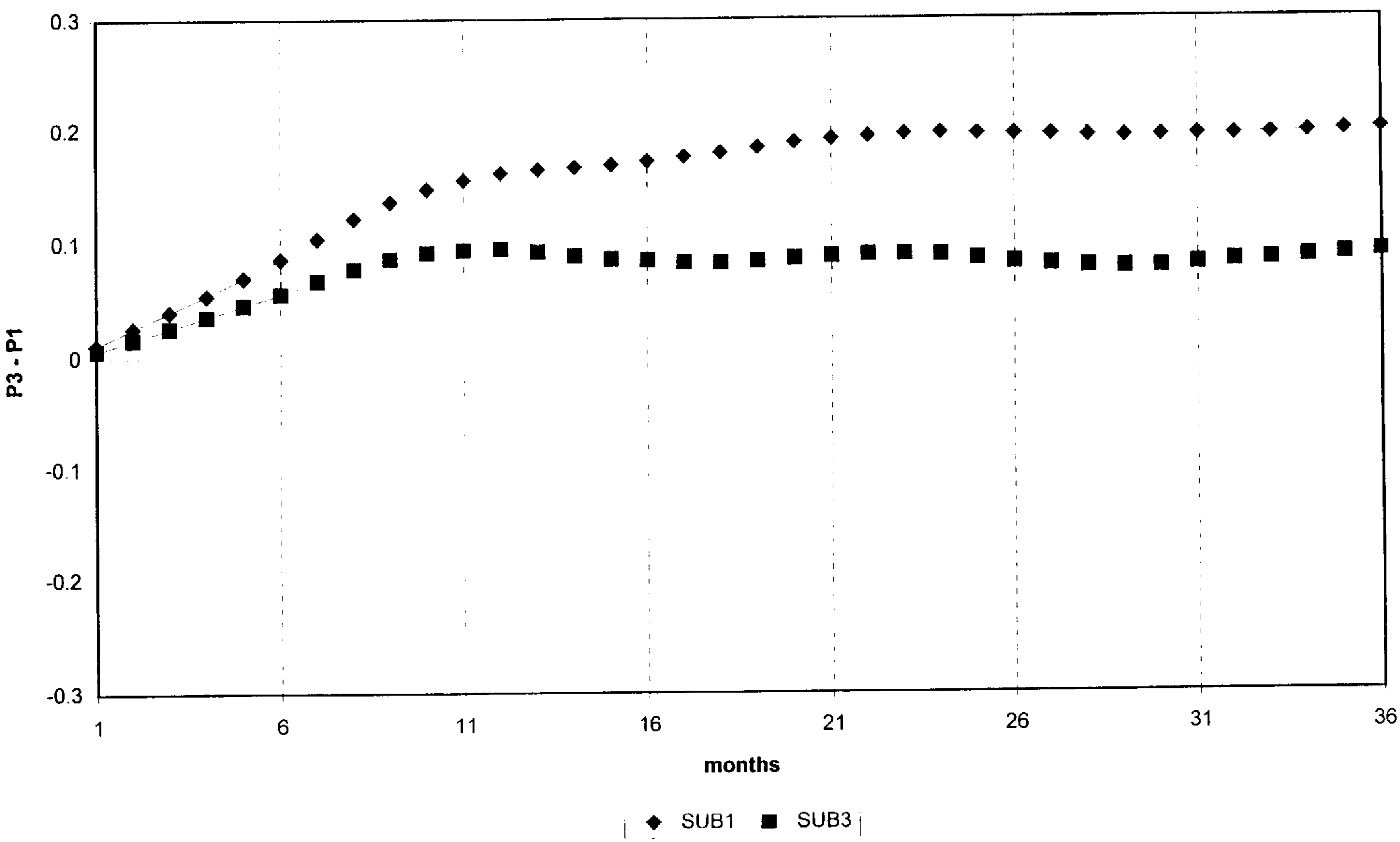

Figure 2: Cumulative Beta-Adjusted Returns in Event Time
Panel B: Profits to the LAST Strategy