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RESEARCH ARTICLE

The behavior of stock analysts: empirical evidence of "economic rents" across market capitalization accruing from consensus forecast EPS errors

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Abstract

Many investors employ investment strategies based upon revisions to analysts' earnings per share (EPS) estimates begging the question, inter alia, "How accurate are those estimates?" This paper fills a gap in the current literature on the matter. Stocks of large capitalization companies are deemed to offer little in the way of earnings surprises. As a result of so many analysts following such well-known companies, all available information is considered fully incorporated into consensus EPS forecasts. Stocks of small capitalization companies with relatively little analyst coverage and low headline profiles are considered to offer greater earnings surprise potential. All prices and consensus estimates are deemed to fully reflect all available information and any heretofore "unknown" information will be quickly and efficiently incorporated so as to eliminate any investment advantage. The author concludes herein that there is essentially an equal chance of the existence of a consensus forecast EPS error (defined as missing by greater than ten percent of actual earnings) among large, medium and small capitalization stocks –irrespective of the level of analyst coverage or consensus forecast earnings growth. If one objective of stock selection is to achieve abnormal portfolio returns, then the selection should be based upon anticipating changes in the consensus forecast rather than absolute changes in earnings-related data– the famous Keynesian "beauty contest." Indeed, the author has identified six earnings data of statistical significance with respect to signaling a potential short-term demand shock. Consensus and individual analyst EPS estimates –the focus of this paper– is but one datum. Results (not included) of an investment strategy focused upon anticipating changes in the consensus forecast rather than absolute changes in earnings estimates demonstrated consistent abnormal profits in the long, short, and combined long/short portfolios over the sixty month period June, 2001, through May, 2006, evincing "economic rents" (Lo, 2005) theoretically gained by "information traders" at the expense of "noise traders" (Black, 1986). A brief, rather abstract and qualitative examination of the information requirements of the efficient capital markets hypothesis in light of the results herein is also undertaken.

Keywords: Consensus, Earnings, Estimates, Errors, Revisions, Portfolio, Returns, Information, Access, Behavior, Efficient, Markets, Momentum, Anomaly.

JEL Classification: G02, G11, G12, G14, G24.

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El comportamiento de los analistas de valores: **evidencia empírica sobre "rentas económicas" según capitalización bursátil derivadas de los errores en las predicciones de consenso sobre las ganancias por acción**

Sexton, Jeffrey A.

Resumen

Muchos inversores utilizan estrategias de inversión basadas en las revisiones de las estimaciones de las ganancias por acción (EPS) realizadas por los analistas, lo que nos lleva a preguntarnos, entre otras cosas, "¿cuál es la fiabilidad de tales estimaciones?" Este artículo cubre este vacío en la literatura actual sobre la cuestión. Se supone que las acciones de empresas con una gran capitalización tienen pocas sorpresas que ofrecer en lo que a ganancias se refiere. Como consecuencia de tantos analistas siguiendo tales bien conocidas empresas, toda la información disponible se considera incorporada en la predicciones de consenso sobre las EPS. Lo contrario ocurre con las acciones de empresas con reducida capitalización, con una cobertura relativamente pequeña por parte de los analistas y un perfil menos popular. Se supone que todos los precios y estimaciones de consenso reflejan plenamente toda la información disponible y cualquier información "desconocida" se incorporará de manera rápida y eficiente, eliminándose cualquier ventaja de inversión. El autor llega a la conclusión de que, básicamente, las posibilidades de existencia de error en la predicción de consenso de las EPS (definido como diferencia de más del diez por ciento sobre las ganancias reales) entre las acciones de empresas con capitalización grande, mediana y pequeña son las mismas — con independencia del nivel de cobertura de los analistas o del pronóstico de consenso sobre el incremento de las ganancias. Si uno de los objetivos de la selección de valores es el logro de rendimientos atípicos en la cartera, ésta debería basarse en anticipar los cambios en la predicción de consenso más que en los cambios absolutos en la información relacionada con las ganancias — el famoso "concurso de belleza" keynesiano. De hecho, el autor ha identificado seis variables relacionadas con las ganancias estadísticamente significativas en lo que se refiere a la señalización de un potencial shock de demanda a corto plazo. Las estimaciones de consenso y de los analistas individuales de las EPS —que constituyen el objeto de este artículo— no son sino un dato de una variable. Los resultados (que no se incluyen) de una estrategia de inversión basada en la anticipación de las revisiones del pronóstico de consenso en lugar de en los cambios en valor absoluto en las estimaciones de ganancias, han demostrado constantes ganancias anómalas en carteras a corto y largo plazo, así como en aquellas que combinan el corto y largo plazo, en el período de sesenta meses comprendido entre Junio de 2001 y mayo de 2006, evidenciándose "rentas económicas", en el sentido de Lo (2005) teóricamente obtenidas por los "operadores de la información" a expensas de los "operadores ruidosos" (Black, 1986). También se ha realizado un breve examen, más bien abstracto y cualitativo, de los requerimientos de información de la hipótesis de eficiencia en los mercados de capital a la luz de los resultados contenidos en este artículo.

Palabras clave: Consenso, ganancias, estimaciones, errores, revisiones, cartera, rendimientos, información, acceso, comportamiento, eficiente, mercados, momentum, anomalía.

1. Introduction and methodology

Many investors select stocks on the basis of revisions to analysts' forecast earnings per share (EPS). How accurate are those forecasts in the first place? Moreover, since an efficient market will already have incorporated these prospects in share prices, such investors should not outperform the market (see Elton *et al.*, 1981; Fama, 1970; Mandelbrot, 1966; Samuelson, 1965; inter alia). Using institutional earnings forecasts compiled by the Institutional Brokers Estimate System (I/B/E/S), now part of Thomson Financial, which, in turn, is available on Wharton Research Data Services (WRDS), I compared forecast earnings per share growth with actual earnings per share growth for all constituent companies of the S&P 500, S&P Mid Cap 400 and S&P Small Cap 600 indices for fiscal years 1993 to 2004, as well as for those constituent companies whose fiscal year coincided with the calendar year over the same period. Using the difference as a surrogate for ultimate change in the earnings forecast, I compared the price performance during the year with both the magnitude of the original EPS growth forecast and the magnitude of the ultimate change.

2. Actual EPS forecast errors

No relation was found between the original forecast EPS growth and actual price performance. Alternatively, regardless of whether the fiscal year coincided with the calendar year or spanned the calendar year, portfolios of companies whose consensus EPS forecasts underestimated actual earnings growth outperformed the market on average, whereas portfolios of companies whose consensus forecasts overestimated the actual earnings growth underperformed the market. These results suggest that, if one objective of stock selection is to achieve abnormal portfolio returns, the selection should perhaps be based upon anticipating changes in the consensus forecast rather than absolute changes in earnings. The author has successfully extended this analysis to other earnings–related data, as well, which are not covered in this paper at this time.

Stocks of large capitalization companies are deemed to offer little in the way of earnings surprises (Chen, 1997; Roulstone, 2003). Because so many analysts are following such well-known companies, all available information is considered fully incorporated into the prevailing consensus EPS forecast. Any heretofore "unknown" information will be quickly and efficiently incorporated into the consensus forecast. Conversely, stocks of small capitalization companies with relatively little analyst coverage and low headline profiles are considered to offer greater earnings surprise potential.

I conclude that in any given year there exists an almost equal chance of the existence of a forecast EPS error greater than ten percent of actual earnings for stocks in the

S&P 500, S&P Mid Cap 400, and S&P Small Cap 600 indices irrespective of the level of analyst coverage. Of all 12,868 company fiscal years for which consensus forecast EPS were issued from 1993 to 2004, there were errors in 7,731 (60.07%) years:

- 2,465 (31.88%) were S&P 500 Index constituents
- 2,049 (26.50%) were S&P Mid Cap 400 Index constituents
- 3,217 (41.60%) were S&P Small Cap 600 Index constituents

Any notion of increased consensus forecast EPS accuracy resulting from greater analyst coverage of large cap stocks (S&P 500 Index) is a fallacy. Similarly, any notion that S&P Small Cap 600 Index constituent stocks offer materially different earnings surprise potential than S&P 500 Index constituent stocks is also a fallacy. Furthermore, S&P Mid Cap 400 Index constituent stocks should receive equal consideration for allocation in a portfolio selected on the basis of anticipating changes in the consensus forecast.

Finally, if 60.07% of consensus EPS forecasts for all corporate fiscal years 1993-2004 are inaccurate, then how accurate, i.e., efficient, can share prices really be at any given time? Can they fully reflect all available information as posited by the efficient markets hypothesis (EMH)? (Samuelson, 1965; Mandelbrot, 1966; Fama, 1970) The rub is in the meaning of the words "available" and "information." Perhaps certain information exists that is unavailable. Just because something cannot be seen, smelled, touched, heard or tasted does not mean that it does not exist or that it cannot be measured. Consider the proven yet unseen existence of black holes (Einstein, 1916).

3. Errors in forecast EPS and attendant price returns

Chapter 12 of Keynes' The General Theory of Employment Interest and Money describes a behavioral jungle stock analysts must navigate daily: never, ever be wrong on your own; be in bad company as it is safe within the herd; the game is career risk—manage it safely (see Mikhail *et al*., 1997 and 1999; Hong *et al*., 2000; Banerjee, 1992; and Bikhehandani *et al*., 1992, for research about analyst turnover, reputation, and career concerns). Picture a National Geographic film of a zebra herd crossing a crocodile-infested African river. The lead zebra, those on the margins of the herd, and the sickly bringing up the rear are at greatest risk of consumption. Keynes did not believe financial markets behaved rationally and wrote about "animal spirits" which can drive participants to behave in elemental ways no different than the zebra herd. Indeed, according to the "Adaptive Markets Hypothesis" (Lo, 2005), financial—not physical—survival is of paramount concern to market participants rather than seeking the highest return for a given level of risk per the CAPM. Once the emotions associated with survival of any kind are triggered, specific chemical reactions take place within our bodies, specifically our gut and our brains, and the rational investor behavior reflected in the Capital Asset Pricing Model (CAPM) and essential to market efficiency disappears. What seems to be irrational behavior in terms of investment decisions is, however, perfectly rational in the context of survival. Perhaps one can take man out of the proverbial jungle, but one cannot really take the jungle out of man.

Behavioral psychologists and experimental economists have documented a number of deviations from the predicted EMH outcomes. They have noted specific behavioral biases associated with human decision-making under uncertainty not all of which lead to the most desirable outcome for individual economic welfare, e.g., over-confidence (Fischoff and Slovic, 1980; Barber and Odean, 2001; Gervais and Odean, 2001), overreaction (DeBondt and Thaler, 1986), loss aversion (Kahneman and Tversky, 1979; Shefrin and Statman, 1985; Odean, 1998), herding (Huberman and Regev, 2001; Ashiya and Doi, 2001; Hong *et al*., 2000), psychological accounting (Tversky and Kahneman, 1981), miscalibration of probabilities (Lichtenstein *et al*., 1982), hyperbolic discounting (Laibson, 1997), and regret (Bell, 1982; Clarke *et al*., 1994). According to Lo (2005), all of these critics of EMH argue that investors are often—if not always—irrational, exhibiting predictable and financially ruinous behavior.

Several researchers have extended the above analyses to the behavior of stock analysts. Ehrbeck and Waldmann (1996), Ashiya and Doi (2000), Givoly and Lakonishok (1984), Brown *et al*. (1985), Mikhail *et al*. (1999), Hong *et al*. (2000), Trueman (1994), Tyszka and Zielonka (2002), Korn and Laird (1999), inter alia, all concluded the existence of herd behavior by stock analysts with respect to individual earnings estimates and revisions as well as consensus recommendations and revisions. Keynes' "animal spirits" are alive and well within the analyst community.

This naturally begs the question of errors by the herd with respect to those estimates and revisions. While there has been a great deal of research on the topic of analyst errors (Elton *et al*., 1981 and 1984; Bulkley and Harris, 1997; Givoly, 1985; De Bondt and Thaler, 1985; and, Barber *et al*., 2001), inter alia, a gap exists in the literature. None simply established the first principles:

1. How many errors do analysts actually make in EPS forecasts?
2. How large are the errors?
3. How is price performance related to errors?
4. How does market capitalization factor into the errors?

To answer the first question, I analyzed 12,868 company fiscal years of which common data was available for 12,508 years in the Standard & Poor's (S&P) COMPUSTAT, I/B/E/S and Center for Research in Security Prices (CRSP) databases containing constituent index information and institutional earnings forecasts, respectively, for the period 1993-2004. Why stop at 2004? The data is cleaner and clearer. The past decade has muddied the waters greatly in terms of analyst employment and coverage. Wall Street firms now employ fewer analysts and cover fewer stocks across all market cap strata due in large part to the regulatory fallout of the global settlement with then-New York Attorney General Eliot Spitzer, as well as Regulation FD and the market crash of 2008/2009 and ensuing extraordinary market (bond, stock, money and interest rate) intervention and outright manipulation by governments around the world. I leave it up to the reader to determine whether he or she believes the environment in which they find themselves reading this paper is more like the period covered by my analysis, less like the period or a "new normal" or "new neutral" in which no one (from the Fed Chairman or Chairwoman and equity analysts all the way down to the local shoe shine) really has any clue what the hell is going on or what is going to happen in the coming weeks and months and, therefore, really have no idea how to formulate EPS forecasts for the companies they cover like they used to.

Unlike other authors, I included those companies that reported negative earnings as well as those with fiscal years not ending on December 31st. I did not analyze dispersion of analyst forecasts. I simply examined whether the consensus EPS forecast underestimated actual EPS by more than 10%, fell on target (between -10% and +10%), or overestimated actual EPS by more than 10%. For example, the consensus forecasts of EPS growth for companies in Portfolio A-1 of Table 1 (all above 39.42%) turned out to have underestimated actual earnings growth by at least 10%, while those for companies in Portfolio E-3 (less than 4.87% forecast growth in EPS) turned out to have overestimated actual earnings growth by at least 10%. I define an error as overestimation of actual EPS by 10% or underestimation by 10%. The following are the results of my analysis:

Fiscal Years Analyzed	Fiscal Years With Errors	Std. Dev.	Mean	Median	Percentile 1st	5th	10th	90th	95th	99th
12,868	7,731 (60.07%)	419.23%	-58.48%	-0.83%	-1,811%	-250%	-111%	25%	38.18%	75.05%

Interestingly enough, the median error is essentially dead-on accurate—score one for the analysts! On the whole, however, the fat tail of negative errors supports the general finding in the literature (the breadth of which I will not attempt to reference here) that analyst forecasts are generally over optimistic.

To answer the second question, I employed the cross-sectional testing methodology of Elton *et al*. (1981 and 1984), Bulkley and Harris (1997), Givoly (1985), and Barber *et al*. (2001). I updated pertinent data and I logically extended the analysis to consider for the first time the effect within market capitalization strata, specifically, the S&P

500, S&P Mid Cap 400, and S&P Small Cap 600 indices. I/B/E/S provides a consensus forecast for the next fiscal year earnings per share (EPS) made as of the end of the current fiscal year. "Range of Consensus Forecasts of Individual Company EPS Growth as of Prior FY-End" is the percentage difference between the next year consensus EPS forecast and actual prior year earnings. Price performance is the percentage difference between the price as of the prior year-end and the next year-end.

I ranked the 12,508 company fiscal years by next year forecast EPS growth and created five portfolios of approximately equal size—companies with forecast EPS growth (A) above 39%, (B) between 19% and 39%, (C) between 12% and 19%, (D) between 4% and 12% and (E) less than 4%. I then calculated the actual, equal-weighted price change of each of those five portfolios for the period 1993-2004. Technically, the portfolios consist of any stock during the period 1993-2004 for which the next fiscal year forecast EPS growth happens to fall into the appropriate quintile of my final ranking. Therefore, different fiscal years for the same company might appear in any given quintile depending upon the forecast EPS growth of a particular fiscal year.

Table 1. 1993-2004 Price performance of portfolios with differing consensus forecasts and forecast errors

Portfolio	Range of Consensus Forecasts of Individual Company EPS Growth as of Prior FY-End		Portfolio Price Performance 1993-2004	Sub-Portfolio	Range of Forecast Errors		Sub-Portfolio Price Performance 1993-2004	Number of Securities in Sub-Portfolio
	From	To			From	To		
A	39,42%	9400,00%	31,43%	A-1	+10%	4100,00%	50,98%	700
				A-2	-10%	+10%	65,96%	467
				A-3	-13200%	-10%	9,81%	1319
B	19,51%	39,39%	15,62%	B-1	+10%	1550,00%	40,17%	545
				B-2	-10%	+10%	15,21%	930
				B-3	-16765%	-10%	3,14%	1032
C	12,65%	19,51%	14,05%	C-1	+10%	4500,00%	37,35%	484
				C-2	-10%	+10%	12,35%	1352
				C-3	-2600%	-10%	1,02%	671
D	4,87%	12,65%	9,48%	D-1	+10%	83,31%	28,02%	470
				D-2	-10%	+10%	8,03%	1474
				D-3	-3433%	-10%	-2,10%	568
E	-700,00%	4,87%	0,31%	E-1	+10%	900,00%	10,21%	841
				E-2	-10%	+10%	2,69%	850
				E-3	-4900%	-10%	-12,56%	805

As Table 1 shows, at the comprehensive level there appears to be some relation between forecast EPS growth and performance. When I break down my analysis to only consider stocks for which the fiscal year coincides with the calendar year then I find no relation between forecast growth and performance, as stated previously. Indeed, the low forecast growth Portfolios D & E in many years perform better than high forecast growth Portfolios A & B. At this level of calendar year analysis, my findings are consistent with Elton *et al*. (1981) and EMH: forecast data such as EPS estimates (whether increases or decreases) appear to be fully incorporated into price by the time they become measurable.

Contrary to Elton *et al*. (1984), I find no evidence that firms for which analysts make large errors in forecasting in one year are the same as those for which they make large errors in the adjacent year. However, I examined all fiscal years and Elton *et al*. (1984) only examined fiscal years that coincided with the calendar year. Those authors also cited their findings as support for the proposition that firms for which analysts prepare poor forecasts in any year tend to be the same firms for which they prepare poor forecasts in the subsequent year. I also find no evidence to support this claim. Moreover, five years before Elton *et al*. (1984), Brown and Rozeff (1979) specifically found that analysts exhibit adaptive behavior and "learn" from prior their estimates.

So as to maintain a consistent methodology for comparison with Elton *et al*. (1981 and 1984), Bulkley and Harris (1997), Givoly (1985), and Barber *et al*. (2001), I abandoned the analysis of fiscal years spanning the calendar year. To further analyze price performance at the sub-portfolio level, I examined the relation between price movement and changes in consensus EPS forecasts by focusing, for example, on the error in the December 2002 consensus forecast of 2003 EPS as a surrogate for changes in the forecast of 2003 EPS over the period December, 2002 to December, 2003. Using the percentage difference between each company's actual 2003 EPS and the consensus forecast of its EPS made as of December, 2002, I divided each portfolio, A through E, into three sub-portfolios according to whether the forecast underestimated EPS by more than 10%, fell on target (between -10% and +10%), or overestimated EPS by more than 10%.

I then compared the price performance of each sub-portfolio with the magnitude of the original EPS growth forecast and the magnitude of the error. The A-2 through E-2 sub-portfolios with on-target forecast errors (-10 to +10%) all performed about the same as or even a little worse than the S&P 500 in every year with the exception of years when that index produced negative returns. In those years (2002, 2001, 2000, and 1994) sub-portfolios A-2, B-2, and C-2 tended to outperform, but D-2 and E-2 tended to underperform. These findings are consistent with those of Elton *et al*. (1981).

Most significantly, sub-portfolios with consensus forecasts that underestimated EPS growth by at least 10% (Portfolios A-1, B-1, C-1, D-1 and E-1) all substantially outperformed the S&P 500 Index every year. With the exceptions again of years with negative S&P 500 returns, sub-portfolios A-3, B-3, C-3, D-3, and E-3 (sub-portfolios of companies with consensus forecasts that overestimated EPS growth by at least 10%) all substantially underperformed the S&P 500 Index. Anticipating changes in consensus forecasts does indeed seem to be a key determinant of abnormal portfolio returns; accuracy is not enough.

Interestingly, while the empirical evidence indicates returns of portfolios of stocks with forecast errors greater than 10% are positively correlated, I cannot confirm a positive or a negative statistical correlation between forecast error and price return at the individual stock level. Neither can I confirm or reject the evidence found by Bulkley and Harris (1997) ". . . that realised returns are negatively correlated with analysts' forecast errors . . ." thereby confirming that excessive forecast dispersions appear to be reflected in prices. However, I most certainly concur with their finding " . . . that analysts' earnings forecasts are excessively dispersed in the sense that high forecasts tend to be over-estimates and low forecasts tend to be under-estimates. Indeed despite the substantial dispersion in analysts' forecasts across companies, one cannot reject the hypothesis that they have zero correlation with realised growth." I found no correlation with realized or forecast growth.

The substantial profits I calculate for sub-portfolios A-1 through E-1 (and A-3 through E-3 if shorting) can be considered "economic rents" (Lo, 2005) and theoretically come at the expense of Black's (1986) "noise traders": individuals who trade on what they consider to be information but which is, in fact, merely noise. The outcome of my analysis may be evidence of Andrew Lo's (2005) "Adaptive Markets Hypothesis" (AMH) insofar as it elucidates the behavior of analysts' with respect to consensus EPS revisions and the symbiotic behavior of noise traders and information traders. The latter believe it pays to seek out costly information to use advantageously when trading with noise traders. Note that 21st century high frequency traders (HFT) are notoriously the ultimate gatherers of costly yet "true" information, namely, that you really and truly have entered an order and that trade is coming down the pipe to buy or sell at a certain price that they attempt to front run using faster computers pushing, literally, the boundary that is the speed of light. Black (1986) (because as a prisoner of his time was less informed about speed of light computer trading that would come thirty years in the future) was more nuanced in his definition of noise traders and information traders: the former were deemed to be trading on ill-advised golf course tips and "bad research" and the latter were so-called professionals that spent time and effort researching the "truth" about companies and their stocks.

Earnings revision investment strategies focused on anticipating changes in consensus earnings have the potential to be quite effective and persistently rewarding because they are by their very nature adaptive. As cited previously, Brown and Rozeff (1979) concluded that "[a]daptive expectations are a significant element in security analysts' revision of expectations of future quarterly earnings per share. . . . [A]nalysts responded to earnings forecast error as if they were behaving in an adaptive manner, raising (lowering) their forecasts of future quarterly earnings when they under-predicted (over-predicted) this quarter's earnings per share."

Elton *el al*. (1984) did find that analysts' errors decline monotonically as the end of the fiscal year approaches. In light of Brown and Rozeff's (1979) findings concerning the adaptive behavior of analysts with respect to their forecasts, this is logical. As analysts learn more about a company's performance during the fiscal year and also learn more about their personal errors with respect to their analysis of the company to date, accuracy will tend to increase. Thus, the substantial outperformance of portfolios of stocks that by year-end still exhibit a consensus forecast error despite improved analyst accuracy might offset information traders' gathering costs.

4. Errors across market capitalization and attendant price returns

I now endeavor to answer my fourth question by analyzing sub-portfolios across market capitalization strata, specifically, the S&P 500, S&P Mid Cap 400, and S&P Small Cap 600 indices. Of the 7,731 company fiscal years during the period 1993-2004 for which errors were made in consensus forecast EPS:

- 2,465 (31.88%) were S&P 500 Index constituents
- 2,049 (26.50%) were S&P Mid Cap 400 Index constituents
- 3,217 (41.60%) were S&P Small Cap 600 Index constituents

Of the remaining 39.93% or 5,137 of the 12,868 analyzed company fiscal years in which consensus forecast EPS were on target:

- 2,340 (45.50%) were S&P 500 Index constituents
- 1,345 (26.18%) were S&P Mid Cap 400 Index constituents
- 1,452 (28.26%) were S&P Small Cap 600 Index constituents

S&P 500 member stocks tend to attract the largest analyst following and S&P Small Cap 600 member stocks tend to attract the smallest analyst following (Das, 1998; Bhushan, 1989) because it is more profitable for major brokerage firms and other investment firms to only provide research about the stocks which are most heavily traded by their clients. Such firms are primarily in the business of executing trades for a commission. They provide research to (hopefully) better inform their client-traders prior to trading. They are not publishing houses. Small, virtually unknown publicly traded companies account for very little of the relative daily trading volume compared to the three thousand or so member stocks of the major indices such as the S&P 500, the Wilshire 5000, the Russell 3000 and NASDAQ Composite. There is little demand for research of small, virtually unknown companies; therefore, little research is generated by analysts.

Chen *et al*. (1997) found that when stocks are followed by many financial analysts a greater volume of high quality information is available to investors resulting in smaller earnings surprises. Roulstone (2003) found that analyst following had a positive association with liquidity. Accordingly, given their extensive analyst coverage, one would expect fewer forecast EPS errors among S&P 500 constituents and more forecast EPS errors among S&P Mid Cap 400 constituents. One might expect the most forecast EPS errors to occur among S&P Small Cap 600 constituents if for no other reason than the paucity of information. Therefore, in a list of stocks ranked by analyst forecast EPS errors (such as Portfolios A,B,C,D,E) I expected to see lists of stocks ranked by largest errors (whether due to underestimation or overestimation—sub-portfolios A1, A3, B1, B3, C1, C3, D1, D3, E1, E3) to be predominantly S&P Small Cap 600 stocks with a few S&P Mid Cap 400 stocks and very few, if any, S&P 500 stocks. I further expected the lists of on target stocks displaying little if any analyst forecast EPS error (-10 to +10% of actual EPS—sub-portfolios A2, B2, C2, D2, E2) to be dominated by the S&P 500 stocks. The data do not support my expectations or the conclusion of Chen *et al*. (1997).

Stocks in the S&P 500 Index accounted for about one-third of all forecast EPS errors in every fiscal year from 1993-2004—even more than S&P Mid Cap 400 constituents. I confirmed that many more analysts covered S&P 500 constituents than Mid Cap 400 constituents that, in turn, received more coverage than Small Cap 600. Yet, contrary to Chen *et al*. (1997), depending upon the level of analysis (A,B,C,D,E portfolios or A-1 through E-3 sub-portfolios), I find that S&P 500 constituents generate earnings surprises (forecast errors) equal (and often greater) in magnitude to those of S&P Mid Cap 400 or S&P Small Cap 600 constituents.

Diether *et al*. (2002) found evidence that stocks with higher dispersion in analysts' earnings forecasts earn lower future returns than otherwise similar stocks and the effect is most pronounced in small stocks and stocks that have performed poorly over the past year. I find no relation between returns and analysts' earnings forecasts from fiscal year to fiscal year. Price performance each fiscal year appears to be independent (as predicted by EMH). Furthermore, I find some evidence to support their pronounced lower return effect in small stocks, but as I further detail below returns can also be profoundly higher. I calculated the following dispersion of errors in the data:

Index	Mean	Median	Std. Dev.	Mean Abs. Dev.
S&P 500	-33.27%	0.35%	265.57%	66.20%
S&P 400	-52.96%	0.00	456.97%	104.97%
S&P 600	-88.78%	-4.05%	509.56%	148.66%

I compared the price performance of each sub-portfolio within each sub-index with the magnitude of the original EPS growth forecast and the magnitude of the error. Just as was reported earlier at the global level, the A-2 through E-2 sub-portfolios with on-target forecast errors (-10 to +10%) all performed about the same as or even a little worse than their respective indices in every year with the exception of years when the indices produced negative returns. In those years (2002, 2001, 2000, and 1994) sub-portfolios A-2, B-2, C-2, D-2 and E-2 tended to outperform, but occasionally the latter two underperformed.

Most significantly, even across market capitalization, sub-portfolios of companies with consensus forecasts that underestimated EPS growth by at least 10% (Portfolios A-1, B-1, C-1, D-1 and E-1) all substantially outperformed their respective indices every year. With the exceptions again of years with negative index returns, sub-portfolios A-3, B-3, C-3, D-3, and E-3 (the sub-portfolios of companies with consensus forecasts that underestimated EPS growth by at least 10%) all substantially underperformed their respective indices. Anticipating changes in consensus forecasts appears to be a key determinant of abnormal portfolio returns even across market capitalization; accuracy is not enough.

Das *et al*. (1998) concluded that analysts issue more optimistic forecasts (and, therefore, generate more negative errors) for low predictability firms (which tend to be S&P Small Cap 600 constituents) than for high predictability firms (which tend to be S&P 500 constituents). I find more errors in small cap stocks than large cap stocks, but large cap stocks have more errors than mid cap stocks. Das *et al*. (1998) focused only on predictability while specifically controlling for size.

Others (Barber *et al*., 2001; Womack, 1996; Shleifer and Vishny (1997), and Pontiff, 1996) state explicitly or imply that the investment performance of analysts' consensus recommendations is greater for smaller firms to the extent that there is less information publicly available. Womack (1996) showed that the price reaction to individual analyst upgrades and downgrades, as well as the post-recommendation price drift, was more pronounced for small stocks. Diether *et al*. (2002) found a pronounced lower return effect among small stocks with high analyst forecast dispersion.

My general findings are as follows with respect to market capitalization and return:

- When the forecast error is greater than ten percent and the overall market has a positive return, returns of small cap stocks are higher than mid cap stocks that are higher than large cap stocks but all outperform their respective index.

- When the forecast error is greater than ten percent and the overall market has a negative return, large cap and mid cap stocks have better (whether a lower negative or a positive) return than small cap stocks but all still outperform their respective index.

- When the forecast error is lower than negative ten percent and the overall market has a positive return, small cap stocks are essentially punished—the sub-portfolio A-3 through E-3 returns are much lower (more negative) than the large cap and mid cap A-3 through E-3 sub-portfolio returns but all underperform their respective index—the small caps more so.

- When the forecast error is lower than negative ten percent and the overall market has a negative return, small cap stocks are punished even more—the sub-portfolio A-3 through E-3 returns are even lower than above with otherwise similar results.

- In some years mid cap stocks have larger errors than either large cap or small cap stocks and also quite often have much larger positive returns in portfolios A-1 through E-11 and much larger negative returns in portfolios A-3 through E-3.

- Mid cap stocks display characteristics distinctly independent of large cap or small cap and as an asset class merit serious analysis and consideration.

- During 1993-2004, the average number of analysts covering:
  - S&P 500 Index constituents was 17
  - S&P Mid Cap 400 Index constituents was 8
  - &P Small Cap 600 constituents was 5

5. Results of an investment strategy

Wiedman (1987) found that analyst forecast errors have a higher association with excess returns than random walk forecast errors and that the higher association is positively related to firm size and negatively related to dispersion in analysts' forecasts. Brown and Rozeff (1979) showed that analysts employ an adaptive expectations model when revising their EPS forecasts throughout the year. Bulkley and Harris

(1997) concluded that **as analysts' forecast errors become apparent, stock prices adjust accordingly** and so excess returns accrue. Elton *et al*. (1981) specifically examined how expectations concerning EPS affect share price. They first concluded that knowledge concerning analysts' forecasts of EPS cannot by itself lead to excess returns, a conclusion my analysis supports, because EMH states any information contained in the consensus EPS estimate is already included in the share price.

Accordingly, Elton *et al*. (1981) posit that investors who buy stocks with high consensus EPS growth estimates should not earn an excess return. My finding that portfolios A, B, C, D, and E have returns in any given year unrelated to consensus EPS growth forecasts—even across market capitalization—is supportive. Elton *et al*. (1981) conclude that much larger excess returns can be earned if one is able to determine those stocks for which analysts most underestimate return (make the largest forecast errors). Ergo, the largest returns can be earned by knowing the stocks for which analysts will make the greatest revision in their estimates, a result my analysis confirms and quantifies for years 1993-2004 even across market capitalization. Their final finding is that the pattern of results suggests that share price is affected by expectations about EPS and best results can be obtained by acting on the differences between their individual forecasts and consensus forecasts, i.e., the errors.

The above-cited authors, as well as Barber *et al*. (2001), Brown and Jeong (1998), Abarbanell and Bernard (1992), La Porta (1996), Jennings (1987), Imhoff and Lobo (1984) (documented positive correlation between the magnitudes of forecast EPS revisions and abnormal returns), inter alia, all hint at the major components of a successful investment strategy. I leave it to the reader to use the above-referenced cookbooks to bake the cake.

6. Intellectual access to information

In 1968, Roy Radner's Econometrica paper formalized the conditions under which a set of prices each greater than zero can be guaranteed to be found—general equilibrium—when both the future exists and agents hold different views about the future. The key point of his proof is that each agent is required to have access to an infinite amount of computing power. Agents carry out rational maximization with full information. If there are constraints on the cognitive abilities of agents, then general equilibrium theory breaks down. Thus, can market participants truly process all the information EMH requires?

Infinite processing power is required of all agents for there to be an equal playing field. Sonnenschein (1972) demonstrated we can only guarantee that the overall demand schedule is well-behaved when each of the individuals has identical tastes and preferences, i.e., whenever the price changes, each individual reacts in exactly the same way. But what if they do not? By extension, what if each individual can only process information according to one's own uniquely personal cognitive ability? Enter George Akerlof, Joseph Stiglitz, Herbert Simon and the concept of bounded rationality—maximizing under incomplete or asymmetric information—which expanded the practical domain over which economic theory offers a reasonable approximation of reality. They realized the key assumption concerning the unlimited cognitive ability of agents to gather information had to be relaxed. We know there are limits to the ability of agents to process information and learn because of the degree of interest and natural ability. Agents quickly learn just enough to avoid catastrophic mistakes and assure survival (physical and financial). With respect to less critical decisions, they learn only enough to make an optimal decision under the circumstances. Yet, such researchers have proven repeatedly that the result is usually sub-optimal even if they know the right answer!

If humans cannot process all of the obviously available public/private information EMH requires, then prices cannot fully reflect the same. Therefore, in light of the obvious constraints on the cognitive abilities of agents, was a self-serving operational meaning of "information" employed as early as Samuelson (1965) and Mandelbrot (1966)? If as humans we are left with merely a "satisficing" level of cognitive processing power, then the playing field is decidedly not level. Each individual will have different interpretations of information and its importance—even different intellectual access to the same information! Francis and Soffer (1997), Hong *et al.* (2000), Piotroski (2004), inter alia, find that information is absorbed slowly by the market, market participants overreact (underreact) to positive (negative) information, and some even ignore certain public information altogether.

Thus are created Black's (1986) information gathering opportunities: "Unanticipated shifts in tastes and technology within and across sectors is what we call information in discussing financial markets." In the same way that light cannot escape a black hole due to its enormous gravitational pull, is there perhaps some "information" that cannot—for lack of a better word—escape share prices (Black, 1986; unnamed research in the area of complex adaptive systems)) in such a way as to be readily available, and, therefore, useful to market participants when making investment decisions? I mean something unanticipated that at least some investors cannot extract—something beyond noise since noise is known and, therefore, readily available and already fully reflected in prices. For example, no one really knows the motivation for the timing and size of a corporate insider's 10b5-1 selling programs (and this is an admittedly weak example of my own nebulous assertion since the very existence of the 10b5-1 selling program is at least known to market participants).

Consider the concepts of materiality and access as contemplated by the United States securities laws. In TSC Industries, Inc. v. Northway, Inc., 426 U.S. 438 (1976), the United States Supreme Court articulated a legal standard for materiality: there must be "a substantial likelihood that the disclosure of the omitted fact would have been viewed by the reasonable investor as having significantly altered the 'total mix' of information made available." In Basic Inc. v. Levinson, 485 U.S. 224 (1988), the Court adopted this standard for SEC Rule 10b-5 (the famous insider trading prohibition if one is in possession of material, non-public information). The U.S. securities laws (as interpreted by various courts) are intended to protect not only investors that do not possess physical access to material information, but also those who do not possess intellectual access, i.e., the unsophisticated. An investor not only has to be in physical possession of material information to make a reasonable decision, but must also be sophisticated enough to intellectually grasp the information. In Halliburton Co. v. Erica P. John Fund, Inc., 2014 BL 172975 (U.S. June 23, 2014), the Supreme Court revisited Basic Inc. v. Levinson in the context class action lawsuits. The issue of proof boiled down to whether efficient markets quickly (almost instantly) reflect corporate misstatements in stock prices that drop causing investor losses, as the plaintiffs argued, or whether maybe, just maybe, markets aren't that efficient and maybe even the bad information that might cause a stock price to drop instantly really takes a while for the market to digest and the drop in the stock price wasn't really caused by the corporate misstatement, as the defendants argued. In siding with the defendants in this case, the U.S. Supreme Court relied more upon 2013 Nobel Laureate Robert Shiller's version of "less-than-efficient markets" than 2013 Nobel Laureate Eugene Fama's version of "pure efficient markets" but did not go so far as to deny that at some point prices reflect all available information whether truthful or fraudulent. Clearly, this is a legal opinion that was more "satisficing" than satisfying for either side.

Paradoxically, Samuelson (1965), Mandelbrot (1966), Fama *et al*. (1970) are undoubtedly correct in asserting that prices fully reflect all available information whether obviously public and/or private—it's just that prices contain more "total mix" of information than is observable. Not all market participants have the same intellectual access to or ability to extract all of the existing information at the same time so prices only fully reflect all intellectually available information to you the individual investor assessing prices at that moment. Prices do not fully reflect the intellectually unavailable information that exists nonetheless and is discoverable by the intrepid and persistent and, quite simply, more intelligent. For example, constantly gyrating market prices are a result of Black's (1986) noise traders and information traders constantly re-assessing "available" (both intellectual and physical) "information" (including noise) and discovering new "information" (including noise) which EMH contends was right under their nose the whole time but which I further contend was intellectually unavailable to them part of the time. At the moment such information "suddenly" becomes intellectually available (they wake up and "smell the coffee" or simply run to line up with a herd the leader(s) of which "smelled the coffee") then the likelihood of a demand shock is high.

7. Conclusion

Market efficiency does not imply perfect foresight, so it is reasonable to expect analyst forecasts and market prices to be wrong ex post (Hirshleifer and Teoh, 2003). Perhaps prices contain but do not fully reflect economically advantageous information with respect to future earnings prospects that is not intellectually available to all market participants at any given time. To the astute, analyst errors in consensus EPS forecasts is just one form of said information. As stated earlier, the author has identified five other forms of earnings-related data of statistical significance. To wit:

> "The price of a stock will be a noisy estimate of its value. The earnings of a firm (multiplied by a suitable price-earnings ratio) will give another estimate of the value of the firm's stock. This estimate will be noisy too. So long as noise traders do not always look at earnings in deciding how to trade [other research has shown they do not], *the estimate from earnings will give information that is not already in the estimate from price* [emphasis added]."
>
> Fisher Black, *Noise* (1986), p. 534

The financial markets exhibit all of the characteristics of complex adaptive systems. Research along this line of inquiry suggests that there exists a "weaker form" of the weak EMH (Fama, 1991) according to which market prices contain, in addition to the information generally available to all, subtle information formed by the global market that most or all individuals have not yet learned to decipher and use—emergent intelligence at a macroscopic scale the existence of which individuals at the microscopic scale are unaware. The usual EMH will be recovered in this context when market participants learn how to extract and act upon this novel collective information.

Until such time, an investment strategy dedicated to identifying this information before it becomes intellectually available to "the crowd" holds promise for achieving abnormal returns even if only moderately successful in uncovering said information. John Maynard Keynes (1964) likened professional investing to participating in a newspaper contest to predict the winner of a beauty contest where ". . . each competitor has to pick, not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of other competitors, all of whom are looking at the contest from the same point of view." To win, one need only to ascertain the information the crowd will use to make its decision—one example being consensus EPS forecasts and revisions—and then predict better than the crowd how the crowd will behave once that information becomes intellectually available to it.

While this paper was concerned with EPS forecast errors and changes in consensus estimates, another body of research where it has been demonstrated beyond any doubt that information (available or unavailable?) exists leading to persistent excess returns is the so-called "momentum effect" or anomaly. This author has conducted research and will continue to conduct research in the area of momentum, especially that of "managed momentum." The seminal work on momentum is, of course, Jegadeesh and Titman (1993). Among others, Fama and French (2008) are still confounded by momentum to this day. Yet, it exists, persists and continues to generate excess returns despite its "discovery" over twenty years ago. Stivers and Sun (2010); Han and Zhou (2014); Cooper, Gutierrez and Hameed (2004); and, Daniel and Moskowitz (2013), among others but most notably in this author's opinion, have done very interesting work on the concept of "tweaking" or managing the pure momentum of Jegadeesh and Titman (1993) for practical implementation in a daily portfolio management system. The best overview of the current state of momentum research and investing is Asness *et al*. (2014) and well-constructed "pure momentum" indices tracking that version first elucidated by Jegadeesh and Titman (1993) are free at www.puremomentuminvesting.com.

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