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WHEN SELL-SIDE ANALYSTS MEET HIGH-VOLATILITY STOCKS: AN ALTERNATIVE EXPLANATION FOR THE LOW-VOLATILITY PUZZLE

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Using a global equity dataset that includes emerging markets, we confirm that high-volatility stocks tend to deliver low average returns; this effect is robust to adjustments for country and style factors. We also show that sell-side analysts' earnings growth forecasts for high-volatility stocks are more biased. It is well known that sell-side analysts are predictably optimistic; however, the relationship between the degree of optimism and a stock's volatility has not been documented before. We hypothesize that analysts inflate earnings forecasts more aggressively for volatile stocks, in part because the inflation would be more difficult for investors to detect. Because investors are known to overreact to analyst forecasts (under-adjust to analyst bias), this contributes to systematic overvaluation and low returns for high-volatility stocks. Additionally, we find sell-side analysts' research informative despite the biases; stocks that have high forward E/P ratios based on analyst earnings forecasts tend to outperform and produce significantly positive Fama–French alphas. This evidence rejects the cynical view of some in our industry that sell-side analysts are unskilled. More interestingly, we find high forward E/P stocks also exhibit high analyst bias, which supports an interpretation that analysts are more willing to inflate earnings forecasts for stocks that they believe are likely to deliver high returns—or for which their inflated forecasts are likely to do no harm.

1 Introduction

Contrary to naive intuition, empirical research shows that high-volatility stocks tend to deliver lower average returns than low-volatility stocks. Various explanations of this low-volatility puzzle have been advanced, but the topic remains open. This paper primarily aims to document a previously undetected cross-sectional pattern of bias in equity analysts' earnings growth forecasts. We also seek to add to the literature by arguing that analyst behavior may partially explain the low-volatility anomaly.

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After reviewing the literature, we extend the existing research in two ways. First, using a global dataset that includes emerging markets data, we confirm that the low-volatility effect is robust even after controlling for regions, industrial sectors, and various firm characteristics. Second, we explore a possible link between analyst forecasts and the performance of high-volatility stocks. We find that high-volatility stocks tend to reflect high upward bias in analyst earnings growth forecasts, and we argue that sell-side analysts have strategic reasons to prefer to inflate growth forecasts for volatile stocks. Additionally, high bias (optimistic forecasting) generally leads to low stock returns; this observation supports the conclusion that investors underestimate the magnitude of the bias and therefore overreact to analyst growth forecasts.[1] These facts and their interpretations coherently imply a new linkage between analyst behavior and the low-volatility puzzle.

We also find that, despite the upward bias, analyst earnings forecasts are informative for trading. Our evidence indicates that sell-side analysts are likely more skilled than the industry's widespread cynicism would imply, and their behavior is not fully explained by the incentive to maintain positive relationships with banking clients and prospects. Specifically, stocks with a high analyst-forecasted earnings-to-price (forward E/P) ratio tend to deliver significantly higher returns and positive Fama–French alphas—that is, *stocks that analysts find "cheap" based on their forecasts tend to subsequently outperform.*[2]

2 Literature review

2.1 Low-volatility puzzle

The literature on the low-volatility puzzle has typically examined the systematic and idiosyncratic components of total volatility separately. The earlier literature on the validity of the CAPM found that low-beta stocks produce higher risk-adjusted returns than high-beta stocks.[3] These findings are related to the low-volatility effect because low- (high-) beta stocks are likely to exhibit low (high) volatility. The low-beta effect does not, however, subsume the low-volatility effect. More recent literature has generally found that stocks with low idiosyncratic volatility tend to produce higher risk-adjusted returns than stocks with high idiosyncratic volatility.[4] This finding is also related to the low-volatility puzzle since stocks with low idiosyncratic volatility usually exhibit low total volatility. Using developed country equity data from 1985 to 2006, Blitz and van Vliet (2007) reported that low-volatility stocks outperformed high-volatility stocks. Frazzini and Pedersen (2011) also documented similar results using an expanded time horizon (1984–2009).

Baker *et al.* (2010) and Frazzini and Pedersen (2011) provide excellent syntheses of the pertinent theories and related empirical evidence. Baker *et al.* summarized and argued in favor of the behavioral explanation for the low-volatility effect: investors are assumed to have a "preference for lotteries" and view high-volatility stocks as speculation/gambling tools, an approach which inflates the price for high-volatility stocks and depresses their future returns.[5] Rational asset managers are unable to arbitrage away this behavioral anomaly because overweighting low-volatility stocks creates too much tracking error against their benchmarks.[6]

Pedersen and Frazzini (2011) advocated a rational model in which investors are leverage-constrained. In this model, investors use high-beta stocks to improve expected portfolio returns even though leveraging low-volatility stocks would produce better results. The consequent excess demand for high-volatility stocks results in high prices in the present day followed by low future returns for these securities.[7] Because all investors are leverage- and shorting-constrained to varying degrees, the low-volatility premium is not arbitraged away. In the rational model, high-beta stocks would have lower returns than "fair" but they would not be expected to have lower returns than low-beta stocks. Nonetheless, the latter outcome has been documented in a number of empirical studies. In this paper, we offer another explanation for the low-volatility effect based on sell-side analyst behavior and investor reactions to analyst forecasts.

2.2 *Sell-side analyst behavior*

It is well known that sell-side analysts tend to issue upward-biased earnings forecasts; anecdotal evidence and theoretical research suggest that the optimism may be strategic rather than indicative of a lack of skill.[8,9] Interestingly, despite the strong evidence of sell-side analyst optimism, investors do not seem to properly correct for this bias; accordingly, the ability to anticipate analyst bias can be a valuable tool. For stocks that are associated with high analyst optimism, the literature documents initial price overreaction to the rosy forecasts, followed by mean reversion when high growth fails to materialize.[10]

Because investors do not fully adjust for sell-side analyst optimism, the ability to forecast analyst bias for stocks can be a valuable tool for investors. Frankel and Lee (1998) hypothesized that analysts, like naïve investors, can exhibit the behavioral tendency to over-extrapolate recent firm growth in making their own forecasts. They also found that growth-oriented stocks (those with high P/B ratios, high past sales growth, and high long-term earnings and ROE forecasts) tend to experience high analyst optimism. In this paper, we identify two additional stock characteristics—high volatility and high forward E/P—that predict analyst optimism. Our variables, however, are driven by rational and strategic analyst behaviors and not by analysts' mistakes.

Although analysts are encouraged to produce auspicious forecasts, they are also incentivized to provide high-quality research and profitable stock recommendations. Research finds that analyst reputation drives brokerage order flows.[11] Research also supports the supposition that analyst promotions are related to their relative forecast accuracy and the profitability of their stock picks.[12] This finding, according to Francis and Philbrick (1993), suggests a complex optimization problem for sell-side analysts. Jackson (2005) claimed that an equilibrium can exist in which sell-side analysts inflate earnings growth forecasts, but these forecasts are still informative. Empirical evidence seems to substantiate the informational content of analyst research in spite of the observed bias: Kim *et al.* (1997) and Green (2006) found that early access to sell-side analyst stock picks leads to abnormal profits.

It is an interesting question to explore whether sell-side analyst stock recommendations are valuable when investors do not have privileged early access. In the present paper, we are able to extract information by examining the forward E/P for stocks based on the sell-side analyst earnings forecast. We found that stocks with high forward E/P ratios based on publicly available I/B/E/S analyst 12-month earnings forecasts produced higher subsequent 12-month returns. This conclusion, a new finding in the sell-side analyst literature, is consistent with earlier results supporting market under-reaction to analyst recommendations.[13]

3 A model of analyst behavior and an explanation for the low-volatility puzzle

We propose a simple model to reconcile the empirical observation that sell-side analyst earnings forecasts are upward biased and unreliable on the one hand, yet are informative in producing abnormal profits for investors on the other. Although sell-side analysts have been shown to display overoptimism regarding firm earnings growth, it is hard to believe that analyst forecasts are arbitrarily positive. Analysts are presumably skilled and rational economic agents who optimize their behavior to satisfy competing objectives.[14] Sell-side research, considered by some to be valuable, can drive significant brokerage trade flows.[15] Thus, because sell-side research can influence client investment activities, analysts are rated and the rankings are publicized. Presumably, research quality rankings matter to the analysts' employers. Theoretical and empirical research support the thesis that forecast accuracy and stock recommendations are linked with analysts' promotions and turnover.[16]

Correlatively, theories and empirical evidence also suggest that relationships with investment banking clients and prospects could influence analysts to bias their earnings growth forecasts upward and to set target stock prices higher than they otherwise would.[17] So, how might a skilled sell-side analyst achieve the complex objective of producing favorable earnings growth forecasts without appearing obviously biased and, at the same time, providing profitable trading recommendations to clients?

We propose a simple model of analyst behavior that produces both (1) the observed cross-sectional pattern in which high-volatility stocks experience high analyst forecast bias and (2) forecasts that are informative for trading. Imagine that analysts are skilled at ascertaining the mean and standard deviation of earnings growth for the stocks they cover. These analysts need to produce quality research and profitable recommendations to further their careers and reputations, while at the same time remaining sensitive to senior management's desire to maintain profitable investment banking relationships. We posit that there is an equilibrium behavior such that all analysts inflate their reported growth estimates upward by, say, half a standard deviation in order to (1) be investment banking business friendly[18] and (2) avoid detection for inflating growth forecasts in certain situations.

This equilibrium behavior would predict higher growth forecast bias for firms with higher earnings growth variability and would, in turn, predict higher return volatility for these firms. This prediction is consistent with our empirical finding that high-volatility stocks are associated with high analyst forecast bias. Further, because evidence suggests that investors do not fully appreciate the upward bias, and thus overreact to analyst optimism in the short run, volatile stocks tend to be overvalued and experience low subsequent returns. This could then explain, in part, the documented underperformance of high-volatility stocks.

Our simple model also posits that analysts express valuable information in their forecasts in order to signal their skill to clients and management, but they strategically mask the information in an attempt to provide client-friendly inflated forecasts. If true, this suggests that profitable trading information can potentially be backed out of biased analyst forecasts; investors simply need to decode the analyst signal more effectively. We know that analysts overwhelmingly prefer to communicate equity attractiveness using E/P ratios,[19] so we can interpret the forward E/P ratio as a proxy for the analyst's private information on the outlook for a stock.

4 Data

Our global equity dataset is broader than those used in previous research on the low-volatility premium puzzle. Specifically, we expand the global dataset to include emerging markets. We use the I/B/E/S database to gather consensus analyst earnings forecasts. For each stock in the

Table 1 I/B/E/S consensus forecast for company A.

Date	Previous fiscal year end (FY0)	Current fiscal year end (FY1)	Next fiscal year end (FY2)	FYO realized EPS	FY1 consensus EPS forecast	FY2 consensus EPS forecast
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Jun-2000	Sep-1999	Sep-2000	Sep-2001	1.35	193	2.18
Jul-2000	Sep-1999	Sep-2000	Sep-2001	135	1.95	2.25
Aug-2000	Sep-1999	Sep-2000	Sep-2001	1.35	1.95	2.25
Sep-2000	Sep-1999	Sep-2000	Sep-2001	1.35	1.95	2.25
Oct-2000	Sep-2000	Sep-2001	Sep-2002	1.76	1.21	1.39
Nov-2000	Sep-2000	Sep-2001	Sep-2002	1.76	1.19	1.39

I/B/E/S database, the consensus earnings forecast is generally provided for at least the next two fiscal years. At the start of each fiscal year, the database memorializes the reported earnings per share (EPS) for the previous fiscal year as well as the consensus year-end EPS forecast for the current and the following fiscal years. Table 1 shows the I/B/E/S monthly data structure for Company A, whose fiscal year ends in September. At month-end October 2000, the database records realized EPS for the prior fiscal year (1999) as well as the consensus forecast for the current fiscal year (2000), which ends in September 2001, and the next fiscal year (2001), which ends in September 2002. We denote the prior fiscal year as FY0, the current fiscal year as FY1, and the next fiscal year as FY2.

A key variable of interest is the analyst forecast bias for current fiscal-year EPS. Analyst forecast bias is simply the average of the forecast errors or the differences between the consensus EPS estimates and the subsequently realized EPS numbers. Operationally, we define the forecast error for Company A associated with the month of October 2000 as the 12-Month-Forward Realized EPS minus the 12-Month-Forward Consensus EPS Forecast.[20] The forward consensus EPS is the time-weighted average of the current and next year's consensus EPS, and the forward realized EPS is also the time-weighted average. Because EPS_t is neither standardized (EPS_t gives no information for making cross-sectional comparisons) nor stationary (EPS_t generally grows over time and is unbounded), we elect to work with a transformed variable, EPS_t/BPS_{t-1}. Dividing earnings per share by book value per share creates a stationary variable that is standardized across stocks.

EPS_t/BPS_{t-1} is also referred to as the return on shareholder equity, or ROE_t.[21] However, we do not have an explicit interest in ROE; we are merely interested in standardizing the EPS variable so that it can be more meaningfully compared on a cross-sectional and intertemporal basis. Other transformations, such as EPS/Assets or EPS/Sales, would accomplish the same goal and produce similar analyses.

Corporate accounting data are sourced from Worldscope, and total return data come from IDC Exshares. The sample period for our study ranges from January 1987 through December 2011 for developed countries and from December 1994 through December 2011 for emerging countries.[22,23] All return-related statistics are computed using excess returns, calculated as the net return in excess of local three-month interest rates. Our universe of stocks draws from the union of the MSCI and FTSE index memberships across all developed and emerging market countries.[24]

Because we use I/B/E/S consensus and reported EPS in our study, our universe is restricted to stocks for which both variables are available. The average number of stocks in the unrestricted universe is 3,308 and 910 for the developed and emerging markets, respectively. Eliminating stocks without consensus EPS reduces the universe to 2,846 for the developed markets[25] and 537 for the emerging markets. We examined the effect of the sample selection rules and concluded that they do not adversely influence our results. For robustness, we also repeated the tests with winsorized observations and determined that our research appears to be unaffected by outliers. We do not report these results in the interest of brevity.

5 Portfolios sorted on volatility

5.1 *Low-volatility premium in developed and emerging markets*

We begin our analysis by examining the pattern of returns in the cross-section of global stocks, sorted by volatility. At the end of each month, we rank stocks based on their volatility using the past five years of monthly data. We then report the annualized buy-and-hold return for each decile portfolio. We note, however, that in a simple global sort, the constituents for each volatility decile could be dominated by a particular country or global sector whose constituent stocks might share a similar level of volatility. As a result, country and/or sector effects can become indistinguishable from the volatility effect. Additionally, we observe that small-capitalization stocks tend to be more volatile than average. To adjust for the impact of country, sector, and firm characteristics, we perform a global volatility portfolio sort neutralizing these effects. Specifically, we sort on adjusted volatility using the following equation:

$$\begin{aligned}\log(Vol_i) = \beta_1 \cdot Size_i + \beta_2 \cdot BP_i \\ + \sum_j \gamma_j \cdot SD_{i,j} \\ + \sum_k \delta_k \cdot Ctry_{i,k} + \varepsilon_i, \quad (1)\end{aligned}$$

where Vol_i is the total volatility of stock i measured from the previous 60 months, $Size_i$ is the market capitalization at the end of the preceding month, $SD_{i,j}$ is a dummy variable for industrial sector j (as classified by the ten GICS® sectors), $Ctry_{i,k}$ is a dummy for country k, and ε_i is the adjusted volatility residual net of the influences of country, sector, and firm characteristics. Using Equation (1), we computed the adjusted volatility for each stock in our global universe and then sorted stocks into decile portfolios based on this adjusted measure.

We report the returns and characteristics of the adjusted volatility portfolios in Table 2. The decile portfolios D1 and D10, in the top panel, contain firms with the lowest and highest adjusted volatilities, respectively, for the developed markets. The quintile portfolios report results for the emerging markets in the same format.

For the developed markets, the returns of the low-volatility portfolios are higher than those of the high-volatility portfolios, and the pattern is nearly monotonic. For the emerging markets, the low-volatility effect is not present when we only examine the quintile returns. When we include the Sharpe ratio term, however, the low-volatility puzzle is strong for both the developed and emerging market countries. We also note that when we eliminate the 1994–1998 sample period, which was characterized by unprecedented EM currency fluctuations, the low-volatility effects are statistically stronger. This pattern holds true for the global portfolios sorted using raw (unadjusted) volatilities, which we do not separately report.

Table 2 Adjusted volatility decile portfolios.

Developed markets	Low D1	D2	D3	D4	Volatility D5	D6	D7	D8	D9	High D10
Arithmetic mean %	6.7	6.2	6.7	6.1	5.3	6.6	6.1	6.2	5.5	4.3
Volatility (portfolio) %	11.7	13.3	14.3	15.4	16.5	17.7	18.6	19.7	21.7	24.2
Volatility (constituent stock)	21.8	26.0	28.7	31.0	33.6	36.2	39.7	43.8	50.4	65.3
Sharpe ratio	0.58	0.47	0.47	0.40	0.32	0.38	0.33	0.32	0.26	0.18
Portfolio B/P	47.0	45.3	47.0	46.6	46.8	48.9	44.6	45.1	44.2	36.7
Portfolio avg. market cap	4,944	5,166	5,096	5,049	4,952	4,619	4,243	4,450	4,448	5,402
Portfolio market beta	0.71	0.82	0.89	0.97	1.03	1.10	1.15	1.21	1.33	1.44

*January 1987 to December 2011 for Developed Market equities. Returns are reported as: local return – local 3M interest rate.

Emerging markets	Low Q1	Q2	Volatility Q3	Q4	High Q5
Arithmetic mean %	7.0	7.8	11.4	8.1	7.1
Volatility (portfolio) %	15.9	18.8	23.3	22.4	25.1
Volatility (constituent stock)	33.8	41.4	46.7	52.9	68.9
Sharpe ratio	0.44	0.41	0.49	0.36	0.28
Portfolio B/P	63.3	92.2	61.7	65.6	53.2
Portfolio avg. market cap	2,786	2,852	2,369	2,394	2,697
Portfolio market beta	0.72	0.86	0.92	1.02	1.11

*December 1994 to December 2011 for Emerging Market equities. Returns are reported as: local return – local 3M interest rate.

These results are consistent with those reported by Blitz and van Vliet (2007) and Frazinni and Pedersen (2011). They confirm that the low-volatility effect is robust globally and is neither subsumed by the standard size and value anomalies nor driven by country or industry differences.

5.2 Analyst forecast bias and stock volatility

In this section, we examine the portfolio characteristics associated with the various volatility decile portfolios. Table 3 reports the descriptive statistics such as book-to-price (B/P), earnings growth variability, average market capitalization, and so forth for the stocks in the decile portfolios. In addition, we report statistics on analyst earnings growth forecasts, subsequent realized growth, and analyst forecast bias. Again, we only report the statistics of portfolios formed on adjusted volatility, noting that the results are similar using raw volatilities.

Because the influences from countries, sectors, and firm characteristics are neutralized in the portfolio construction process, it is not surprising that the average market-cap and B/P characteristics are similar across the decile portfolios. The country and industry allocations are similar as well, but are omitted from Table 3 for brevity.

Several facts are salient. First, we observe that the earnings growth forecast biases, as measured by ($\text{EPS}_{\text{12-months-forward forecast}}$ – $\text{EPS}_{\text{12-months-forward realized}}$)/BPS, are positive on

Table 3 Volatility-sorted portfolios and their characteristics.

Developed markets	Low D1	D2	D3	D4	Volatility D5	D6	D7	D8	D9	High D10
Portfolio (aggregation)										
Return volatility	11.9	13.3	14.2	15.4	16.3	17.6	18.3	19.7	21.5	24.0
Market beta	0.72	0.82	0.88	0.97	1.01	1.09	1.14	1.20	1.32	1.42
For constituent stocks										
Average market cap	5,027	5,335	5,266	5,186	5,081	4,846	4,554	4,673	4,843	5,355
Average B/P	66.7	61.7	61.2	61.6	62.5	65.6	67.3	67.1	67.0	65.0
Average ROE variability	4.4	5.5	5.3	5.7	6.2	7.7	8.4	13.0	14.2	32.7
Forecasted earnings growth	2.53	2.83	3.12	3.18	3.51	4.01	4.49	5.03	6.12	8.03
Ex-post reported earnings growth	0.42	0.50	0.50	0.82	0.49	0.57	0.57	1.04	0.91	1.17
Growth forecast bias	2.11	2.33	2.62	2.35	3.02	3.44	3.91	3.99	5.22	6.86
Trailing 12 mo E/P	7.4	6.9	6.7	6.3	6.1	6.0	5.2	4.9	3.9	2.0
Forward 12 mo E/P	7.7	7.6	7.5	7.4	7.6	7.6	6.9	7.1	6.6	5.9

January 1987 to December 2009. Returns and growth rates are reported in percentages.

Emerging markets	Low Q1	Q2	Volatility Q3	Q4	High Q5
Portfolio (aggregation)					
Return volatility	16.9	19.2	21.2	21.9	24.8
Market beta	0.75	0.87	0.96	0.98	1.10
For constituent stocks					
Average market cap	3,118	3,137	2,551	2,678	2,982
Average B/P	70.9	78.2	75.5	75.2	71.2
Average ROE variability	6.3	6.5	7.5	8.9	15.3
Forecasted earnings growth	4.50	4.65	4.80	5.41	6.50
Ex-post reported earnings growth	1.27	1.62	1.33	1.16	1.73
Growth forecast bias	3.23	3.03	3.47	4.24	4.78
Trailing 12-mo E/P	8.7	10.3	8.8	7.9	7.4
Forward 12-mo E/P	10.6	10.7	11.5	11.5	11.8

December 1994 to December 2009. Returns and growth rates are reported in percentages.

average for stocks, meaning that analysts are systematically over-optimistic regarding future corporate earnings growth. This is consistent with the literature on upward bias in sell-side analyst forecasts. Additionally, we observe that the low-volatility portfolios generally have lower forecasted earnings growth, as measured by $(\text{EPS}_{\text{12-months-forward forecast}} - \text{EPS}_{\text{past-12-months realized}})/\text{BPS}$, but do not generally display lower realized earnings growth as measured by $(\text{EPS}_{\text{12-months-forward realized}} - \text{EPS}_{\text{past-12-months realized}})/\text{BPS}$. This observation suggests an interesting pattern of analyst bias in the cross-section—analysts seem to be more optimistic about the more volatile stocks! In the Appendix, we show that the analyst bias pattern is similar for U.S. companies, developed x-U.S. companies, and emerging market companies. This suggests that the pattern we observe is not driven by a particular region but is systematic for all stocks across all geographies.

5.3 *A model of sell-side analyst behavior*

The insight that return volatility is cross-sectionally correlated with analyst bias in earnings growth forecasts is a new empirical finding which contributes to the literature on analyst forecast bias as well as that on the low-volatility premium. Because this paper is empirical in nature, we put forward a plausible story to explain this finding, but do not propose testable implications of the story to ascertain its validity against competing hypotheses. Our "story" is consistent with anecdotal evidence cited in the literature on analyst behaviors and with our own conversations with research analysts and investment bankers from global investment banks.[26]

As we discussed earlier, sell-side analysts' behaviors are thought to be influenced by their desire: (1) to maintain good relationships with investment banking clients and prospects, (2) to avoid damaging their reputation with brokerage clients who subscribe to analyst research reports, and (3) to achieve high published quality rankings against other analysts.

Empirical evidence supports the fact that sell-side analysts have superior abilities to analyze public information and are adept at producing valuable private information on companies. It is not unreasonable to model analysts as skilled at estimating the distribution of next-period earnings growth, $\tilde{g}_t$, for firms they cover. Note that realized earnings growth, $\tilde{g}_t$, is a random variable drawn from a distribution with mean g_t and standard deviation σ_t. More formally, each analyst i produces a forecast of $\hat{g}_{t,i}$ and $\hat{\sigma}_{t,i}$. The true skill of an analyst is determined by the deviation over time between $\hat{g}_{t,i}$ and the unobserved true mean $g_{t,i}$. Since $g_{t,i}$ cannot be observed, the skill of analyst i can only be estimated by the average difference between his forecast $\hat{g}_{t,i}$ and the realized $\tilde{g}_{t,i}$ over time.[27] Finally, we posit that analysts report a biased forecast, $G_{t,i}$, instead of their true private information, $\hat{g}_{t,i}$.

We assume that the utility function of the analysts is: (1) increasing in the "optimism of the reported growth forecast", or $G_{t,i} - \hat{g}_{t,i}$; (2) decreasing in the "detectability of the forecast bias," or $(G_{t,i} - \hat{g}_{t,i})/\hat{\sigma}_{t,i}$; and (3) decreasing in distortion in valuation accuracy of the forecast, or $|EPS(G_{t,i})/P_t - EPS(\hat{g}_{t,i})/P_t|$, where $EPS(G_{t,i})/P_t$ is the forward E/P based on the reported forecast $G_{t,i}$, and $EPS(\hat{g}_{t,i})/P_t$ is the forward E/P based on the true forecast $\hat{g}_{t,i}$. Although these assumptions are naïve and incomplete as descriptions of reality, they are consistent with the empirical evidence on analysts' behaviors and motivations.

If the variability of earnings growth, σ_t, for firm i is extremely low, then large bias, $G_{t,i} - \hat{g}_{t,i}$, would be easy for brokerage clients to detect. An econometrically savvy investor can detect whether an analyst has been "pumping" stock prices through highly inflated forecasts (over the last T periods) by testing if $\frac{1}{T}\sum(G_{t,i} - \tilde{g}_t)/\tilde{\sigma}_T$ is significantly larger than zero, where $\tilde{g}_t$ and $\tilde{\sigma}_T$ are the realized earnings growth and variability. Analyst stock recommendations are usually justified by valuation multiples based on forward earnings. As a result, analysts would not want to inflate $G_{t,i}$ and next year's earnings $EPS(G_{t,i})$ so significantly that an unattractive stock (with low $EPS(\hat{g}_{t,i})/P_t$ based on the analyst's true forecast) appears attractive.

Without writing a formal mathematical model, we simply state that a repeated game equilibrium exists whereby all analysts inflate their reported earnings growth forecasts relative to their private unbiased growth estimates by k times earnings growth variability. The scalar k is determined by: (1) the benefit to the analyst from maintaining or improving relationships with investment banking clients and prospects through "friendly" outlooks, (2) the risk of being accused of materially overstating expected growth, and (3) the benefit from providing quality stock recommendations to brokerage clients. Intuitively, in this equilibrium, analysts inflate growth forecasts by a judicious amount to avoid losing credibility outright and to ensure that their forecasts can still result in forward E/P ratios leading to favorable buy/hold/sell recommendations.[28]

Theoretically, return volatility has a positive relationship with earnings growth variability, as we confirm empirically in Table 3. This then suggests that more volatile stocks are more likely to receive greater analyst inflation in earnings growth forecasts. Since investors are known to overreact to analyst growth forecasts, our model predicts (and accounts for) low returns for high-volatility stocks.

6 Forward *E/P* and stock returns

6.1 High forward E/P = high returns

Another prediction of our simple model is that stocks with analyst-forecasted high forward E/P ratios will outperform stocks with low forward E/P ratios. In Table 4a, we show that developed market stocks in the top decile, as sorted by analyst-forecasted forward E/P ratios, produce a 6% higher annualized return than those in the bottom decile. The Sharpe ratios for the top and bottom deciles are 0.48 and 0.19, respectively. Similarly, for emerging market stocks, the top quintile stocks outperform the bottom quintile by nearly 10% per annum (a Sharpe ratio of 0.73 versus 0.35).[29]

Table 4a Forward E/P sorted portfolios (developed markets).

			Low		Forecast E/P		High			
Developed markets	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Arithmetic mean % p.a.	4.87	1.99	1.98	3.27	5.44	5.77	7.70	8.53	9.93	10.82
Volatility (portfolio) % p.a.	25.71	18.58	17.73	15.97	15.31	15.13	15.69	16.62	17.86	22.49
Sharpe ratio p.a.	0.19	0.11	0.11	0.20	0.36	0.38	0.49	0.51	0.56	0.48
Forecast bias (constituent)	1.59	1.55	1.40	1.14	1.52	1.53	2.20	3.18	3.95	7.02
			Low		Forecast E/P		High			
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
FF3 Alpha % p.m.	−0.15	−0.20	−0.19	−0.10	0.04	0.06	0.17	0.21	0.28	0.25
t-Stat	−0.69	−1.67	−1.64	−1.21	0.52	0.78	2.18	2.20	2.58	1.39
bMKT	1.40	1.06	1.02	0.96	0.94	0.93	0.95	1.00	1.06	1.25
bSMB	0.88	0.80	0.73	0.62	0.55	0.51	0.50	0.48	0.51	0.66
bHML	0.19	−0.05	−0.02	0.12	0.26	0.30	0.39	0.44	0.48	0.57

January 1987 to December 2009. Returns and growth rates are reported in percentages.

Table 4b Forward E/P sorted portfolios (emerging markets).

Emerging markets	Low Q1	Q2	Forecast E/P Q3	Q4	High Q5
Arithmetic mean % p.a.	9.06	0.94	4.46	7.48	18.63
Volatility (portfolio) % p.a.	26.26	18.31	18.89	20.63	25.66
Sharpe ratio p.a.	0.35	0.05	0.24	0.36	0.73
Forecast bias (constituent)	1.28	1.03	3.11	3.06	6.23

	Low Q1	Q2	Forecast E/P Q3	Q4	High Q5
FF3 Alpha % p.m.	0.23	−0.34	−0.15	−0.02	0.57
t-Stat	0.70	−2.78	−1.35	−0.14	2.56
bMKT	1.09	0.89	0.91	0.98	1.12
bSMB	0.78	0.43	0.48	0.61	0.86
bHML	0.01	0.08	0.20	0.29	0.52

December 1994 to December 2009. Returns and growth rates are reported in percentages.

The forward E/P ratio can be interpreted as a tool for analysts to communicate the attractiveness of stocks.[30] In the bottom panel of Tables 4a and 4b, we show that the information contained in an analyst's forward E/P is not subsumed by the Fama–French return model; specifically, stocks that analysts find attractive (those in three of the top four deciles for developed markets and in the top quintiles for emerging markets) display significant Fama–French alphas. Moreover, brokerage clients with advanced access to analyst research and recommendations appear to achieve better investment performance.

Tables 4a and 4b reveals another novel empirical fact: the analyst-earnings-growth-forecast bias is increasing in the forward E/P. New to the literature, this observation suggests that analysts inflate the earnings growth forecasts more aggressively for stocks that they find attractive from a forward E/P perspective, and, conversely, they do not tend to inflate the earnings as aggressively for stocks they find to be less attractive. On average, for stocks that analysts find most attractive in the developed markets (the top decile stocks by forward E/P), the upward growth bias is 7%, and in the emerging markets (top quintile), the bias is 6%. This behavior is consistent with our simple model in which the analyst prefers to inflate earnings as much as possible without losing credibility with clients. For stocks that analysts believe are likely to produce great returns, inflating earnings aggressively is less likely to create a poor experience for clients who trade on analyst forecasts.

6.2 *Volatility and forward E/P double-sorted portfolios*

To identify any potential interactions, we perform an unconditional double sort on volatility and forward E/P. We report the portfolio statistics in Table 5a for developed markets and Table 5b for emerging markets. This brings a new finding to light: the low-volatility effect is much more pronounced for the low forward E/P stocks. In the developed markets, for low forward E/P stocks, the lowest volatility portfolio has a Sharpe

Table 5a Forward E/P and volatility double-sorted portfolios (developed markets).

Volatility (High–Low)			Q1	Low Q2	Forecast E/P Q3	High Q4	Q5
Low	Q1	Arithmetic mean % p.a.	5.2	4.0	5.8	7.3	8.3
		Volatility (portfolio) % p.a.	12.4	11.2	11.5	11.7	13.1
		Sharpe ratio p.a.	0.42	0.36	0.50	0.63	0.63
		Forecast bias (constituent)	0.7	0.7	0.8	1.7	4.2
		Number of observations	76	129	168	167	121
	Q2	Arithmetic mean % p.a.	4.2	1.6	5.3	6.9	9.2
		Volatility (portfolio) % p.a.	15.5	14.6	14.2	15.5	16.8
		Sharpe ratio p.a.	0.27	0.11	0.37	0.45	0.55
		Forecast bias (constituent)	1.1	0.9	1.4	2.9	6.3
		Number of observations	89	137	149	152	134
	Q3	Arithmetic mean % p.a.	3.9	1.7	5.1	8.2	10.9
		Volatility (portfolio) % p.a.	18.1	17.3	16.3	17.0	19.6
		Sharpe ratio p.a.	0.21	0.10	0.31	0.48	0.56
		Forecast bias (constituent)	1.6	2.1	2.4	3.2	5.1
		Number of observations	110	139	136	139	138
	Q4	Arithmetic mean % p.a.	1.5	2.3	4.7	8.5	9.2
		Volatility (portfolio) % p.a.	21.5	20.6	18.8	19.5	22.1
		Sharpe ratio p.a.	0.07	0.11	0.25	0.44	0.42
		Forecast bias (constituent)	2.1	1.8	3.0	3.8	5.8
		Number of observations	146	142	119	119	135
High	Q5	Arithmetic mean % p.a.	3.6	4.4	8.9	11.4	13.0
		Volatility (portfolio) % p.a.	31.4	25.5	23.5	24.7	29.1
		Sharpe ratio p.a.	0.11	0.17	0.38	0.46	0.45
		Forecast bias (constituent)	1.9	3.2	4.0	5.7	8.6
		Number of observations	241	114	89	85	131

ratio of 0.42 and the highest volatility portfolio has a Sharpe ratio of 0.11, a difference of 74%. For high forward E/P stocks, the Sharpe ratios for the lowest and highest volatility portfolios are 0.63 and 0.45, respectively, a difference of 28%. In the emerging markets, we observe the same pattern. For low forward E/P stocks, the low-volatility portfolio has a Sharpe ratio of 0.39 compared with a Sharpe ratio of 0.26 for the high-volatility portfolio, which is a 33% difference, and for high forward E/P stocks, the corresponding Sharpe ratios are 0.61 and 0.55, respectively, a 9% difference.

Table 6 displays the corresponding Fama–French alphas for the double-sorted portfolios. The results show a general pattern in which alphas are large for high forward E/P stocks and low-volatility stocks, and small for low forward E/P stocks and high-volatility stocks. In our view, the cross-sectional pattern of Fama–French alphas shown in Table 6 succinctly captures the degree

Table 5b Forward E/P and volatility double-sorted portfolios (emerging markets).

			Low T1	Forecast E/P T2	High T3
High Volatility Low	T1	Arithmetic mean % p.a.	5.8	5.6	10.2
		Volatility (portfolio) % p.a.	15.0	14.6	16.8
		Sharpe ratio p.a.	0.39	0.38	0.61
		Forecast bias (constituent)	1.0	2.5	4.6
		Number of observations	93	125	86
	T2	Arithmetic mean % p.a.	1.3	3.8	14.1
		Volatility (portfolio) % p.a.	20.7	20.4	22.9
		Sharpe ratio p.a.	0.06	0.19	0.61
		Forecast bias (constituent)	1.5	2.9	4.6
		Number of observations	98	97	109
	T3	Arithmetic mean % p.a.	9.0	3.7	16.7
		Volatility (portfolio) % p.a.	34.6	27.0	30.6
		Sharpe ratio p.a.	0.26	0.14	0.55
		Forecast bias (constituent)	0.7	4.6	4.2
		Number of observations	113	81	109

to which investors over- or underreact to different aspects of the analyst research report. We believe this particular finding is novel and contributes to the empirical literature on investor over-/under-reaction to the release of analyst research. It also supports our inference that forward E/P is a proxy for analysts' valuable private information, which is communicated only to their

Table 6 Forward E/P and volatility double-sorted portfolios Fama–French alphas (developed markets).

			Q1	Low Q2	Forecast E/P Q3	High Q4	Q5
High Volatility Low	Q1	Alpha	0.10	0.06	0.17	0.26	0.31
		t-Stat	0.85	0.61	1.80	2.70	2.75
	Q2	Alpha	−0.05	−0.23	0.02	0.11	0.25
		t-Stat	−0.44	−2.19	0.29	1.12	2.20
	Q3	Alpha	−0.09	−0.24	−0.04	0.16	0.30
		t-Stat	−0.74	−1.86	−0.46	1.70	2.46
	Q4	Alpha	−0.41	−0.24	−0.12	0.13	0.11
		t-Stat	−2.70	−1.65	−1.15	1.18	0.72
	Q5	Alpha	−0.20	−0.05	0.24	0.34	0.32
		t-Stat	−0.70	−0.32	1.55	1.83	1.20

Table 6 (*Continued*)
Fama–French alphas (emerging markets).

			Low T1	Forecast E/P T2	High T3
High Volatility Low	T1	Alpha	0.20	0.11	0.33
		t-Stat	1.23	0.89	1.93
	T2	Alpha	−0.31	−0.22	0.38
		t-Stat	−1.88	−1.52	2.17
	T3	Alpha	0.03	−0.47	0.27
		t-Stat	0.05	−2.28	1.01

brokerage firm's clients. The forward E/P information from the I/B/E/S database is, therefore, potentially valuable for creating outperformance.

7 Conclusions

The findings reported in this paper are mainly empirical; we do not wish to overstate the significance of our theoretical contribution in the form of plausible explanations for the low-volatility puzzle and sell-side analyst behavior.

Our empirical results corroborate and extend the work of other researchers. We confirm the findings of low-volatility returns in global developed and emerging markets, and, in exploring possible linkages between low-volatility returns and analyst forecasts, we find several interesting results. There is evidence that sell-side analysts are strategic in how they inflate earnings growth forecasts for stocks, and their positive bias has a very specific cross-sectional pattern. First, they tend to inflate earnings growth forecasts for more volatile stocks. We hypothesize that this is because it is harder for clients to detect inflation in growth forecasts for stocks that have highly volatile growth. Second, analysts tend to inflate growth forecasts more aggressively for stocks about which they have strong positive information. We surmise that this is because clients are less likely to complain about overly optimistic growth forecasts for stock recommendations that prove to be profitable.

Indeed, we find that analyst forecasts, while biased upward, do result on average in the correct stock picks for their clients. Specifically, stocks with forecasted high forward E/P ratios tend to outperform stocks with forecasted low forward E/P ratios. The high E/P stocks also produce sizeable positive Fama–French alphas. Finally, we establish that the low-volatility effect is significantly stronger for low forward E/P stocks than for high forward E/P stocks.

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Appendix

We provide additional insights into as well as robustness check on the analyst bias pattern documented in this paper. In Table 7a, using data covering 1987–2009, we disaggregate our

Table 7a Analyst forecast biases: U.S. versus x-U.S. (1987 Jan–2009 Dec).

	Low Q1	Q2	Volatility Q3	Q4	High Q5
USA					
Portfolio (aggregation)					
Return volatility	14.8	16.8	18.6	21.6	26.1
For constituent stocks					
Forecasted earnings growth (%)	2.79	3.27	3.70	5.50	7.42
Ex-post reported earnings growth (%)	0.68	0.94	0.96	1.39	1.73
Growth forecast bias (%)	2.11	2.33	2.74	4.11	5.69
DMxUSA					
Portfolio (aggregation)					
Return volatility	12.7	15.6	17.4	19.0	22.2
For constituent stocks					
Forecasted earnings growth (%)	2.63	2.99	3.72	4.48	6.92
Ex-post reported earnings growth (%)	0.35	0.50	0.43	0.37	0.85
Growth forecast bias (%)	2.28	2.49	3.29	4.11	6.07
UK					
Portfolio (aggregation)					
Return volatility	17.0	18.2	19.8	21.6	26.1
For constituent stocks					
Forecasted earnings growth (%)	2.99	3.43	3.84	4.87	6.87
Ex-post reported earnings growth (%)	0.91	0.74	0.71	0.80	0.76
Growth forecast bias (%)	2.08	2.69	3.13	4.07	6.11
Japan					
Portfolio (aggregation)					
Return volatility	17.6	20.9	23.0	25.0	28.1
For constituent stocks					
Forecasted earnings growth (%)	2.04	2.16	2.73	3.28	4.34
Ex-post reported earnings growth (%)	0.16	0.17	0.21	0.25	−0.33
Growth forecast bias (%)	1.88	1.99	2.52	3.03	4.67

data into U.S. versus developed market x-U.S., and in Table 7b, using a shorter time period (1994–2009), we included comparison of analyst biases for developed market versus emerging market companies. In each case, we dissect the data into quintiles to check for monotonicity in forecast bias as a function of stock volatility. From Tables 7a and 7b we find that analyst bias is persistent for stocks across different markets as is the positive relationship between bias and stock volatility. However, while the magnitude of analyst bias is large for stocks across

Table 7b Analyst forecast biases: DM versus EM (1994 Jan–2009 Dec).

	Low Q1	Q2	Volatility Q3	Q4	High Q5
USA					
Portfolio (aggregation)					
Return volatility	15.3	17.8	19.8	23.3	28.8
For constituent stocks					
Forecasted earnings growth (%)	2.52	2.97	3.40	5.00	6.83
Ex-post reported earnings growth (%)	1.03	0.99	0.97	0.98	1.00
Growth forecast bias (%)	1.49	1.98	2.43	4.02	5.83
DMxUSA					
Portfolio (aggregation)					
Return volatility	11.6	14.5	16.7	19.1	23.4
For constituent stocks					
Forecasted earnings growth (%)	2.19	2.55	3.28	4.35	7.32
Ex-post reported earnings growth (%)	0.58	0.60	0.61	0.47	0.78
Growth forecast bias (%)	1.61	1.95	2.67	3.88	6.54
EM					
Portfolio (aggregation)					
Return volatility	16.9	19.2	21.2	21.9	24.8
For constituent stocks					
Forecasted earnings growth (%)	4.50	4.65	4.80	5.41	6.50
Ex-post reported earnings growth (%)	1.27	1.62	1.33	1.16	1.73
Growth forecast bias (%)	3.23	3.03	3.47	4.24	4.78

all markets, the relationship between bias and stock price volatility seems to be the weakest for emerging market stocks. We have not performed additional empirical testing to determine whether the weaker relationship is statistically meaningful, nor do we provide a rationale for this result. This is an interesting avenue for additional research.

Notes

1 See La Porta (1996), Dechow and Sloan (1997), Rajan and Servaes (1997), Dechow *et al.* (1999), and Hayes and Levine (2000) for evidence on and interpretation of investor overreaction to analyst growth forecasts.

2 Although secondary to the primary focus of our paper, our new findings suggest that not only do sell-side analysts convey valuable information in their earnings forecasts, but that investors underreact to the information long (i.e., months) after the forecasts become available, allowing profitable trading strategies to be constructed based on intelligent manipulation of I/B/E/S data. This evidence is consistent with the findings of Womack (1996), Barber *et al.* (2001), Mikhail *et al.* (2004), and Li (2005) on investor underreaction to analyst recommendations.

3 See Black *et al.* (1972), Miller and Scholes (1972), and Haugen and Heins (1975).

4 See Malkiel and Xu (2002), Spiegel and Wang (2006), Ang *et al.* (2006, 2009), and Bali and Cakici (2008).

5 See Mitton and Vorkink (2007), Barberis and Huang (2008), and Kumar (2009) for more detailed discussions

regarding the investor preference for lottery-like payoffs and for high-volatility stocks.

[6] See Brennan and Chrodia (1993) and Brennan *et al.* (2012) for more detailed discussions of the theoretical motivation for and the empirical evidence that supports why benchmark-sensitive institutional equity managers are unwilling to take advantage of the low-volatility premium.

[7] The original insight into the effect of leverage constraints was provided by Black (1972).

[8] See Ramnath *et al.* (2008) for a comprehensive review of the analyst forecast literature as well as a suggested list of the unexplored questions in the literature.

[9] See Francis and Philbrick (1993), Kang *et al.* (1994), Dugar and Nathan (1995), Lin and McNichols (1998), Michaely and Womack (1999), and Dechow *et al.* (2000).

[10] See Dechow and Sloan (1997), Rajan and Servaes (1997), Dechow *et al.* (1999), and Purnanandam and Swaminathan (2004).

[11] See Irvine (2004), Jackson (2005), and Cheng *et al.* (2006).

[12] See Dechow *et al.* (1999) and Hong *et al.* (2000).

[13] Frankel and Lee (1998), using an accounting valuation method (the residual income model) based on analyst forecasts, found that analyst forecasts are informative for predicting long-term returns. Barber *et al.* (2001) and Loh and Mian (2006) formed trading portfolios based on published analyst recommendations and produced abnormal profits.

[14] See Francis and Philbrick (1993).

[15] See Brennan and Chordia (1993), Hayes (1998), Conrad *et al.* (2001), and Irvine (2000).

[16] See Mikhail *et al.* (1999), Hong *et al.* (2000), and Clarke and Subramanian (2006).

[17] See Dugar and Nathan (1995), Lin and McNichols (1998), and Clarke *et al.* (2004).

[18] The literature primarily focuses on the relationship between analyst earnings forecast inflation and the investment banking client relationship. Evidence also exists, however, that investment banks use inflated earnings growth to justify high price targets and strong buy recommendations in order to encourage more trading for their brokerage businesses (see Irvine (2000)).

[19] See Block (1999), Bradshaw (2004), and Demirakos *et al.* (2004).

[20] We do not use the traditional definition of earnings growth, EPS_{12} months forward/$\text{EPS}_{\text{past 12 months}}$, because EPS can often be negative and can switch signs from year to year, so that the resulting growth rate measurement can become difficult to interpret. In rare situations, book value per share can also be negative. We discard data points with negative book value per share.

[21] Here and hereafter, all subindex t are unnecessary because the context makes the interpretation obvious. Incidentally, $t - 1$ means the prior fiscal year, not the previous month.

[22] Before January 1987 and December 1994, the numbers of stocks are too small.

[23] For the study of analyst forecast biases, however, we need the next fiscal year realized earnings. This would reduce the sample range up to December 2009.

[24] We follow the definition of countries used by the MSCI World (Developed Countries) Index and Emerging Markets Index.

[25] The mean numbers of stocks are 1,138 for North America; 898 for Europe; 596 for Japan; and 214 for Asia Pacific ex-Japan.

[26] We have spoken with professionals from Credit Suisse, Nomura, Citigroup, JP Morgan, China Development Bank, and UBS.

[27] For simplicity, we assume that each analyst covers only one firm.

[28] By proposing this strategic model we do not intend to ascribe ethically dubious conduct to sell-side analysts as a class. Individual analysts may settle into the equilibrium solution more or less unconsciously.

[29] The emerging markets data are likely significantly more noisy than the developed markets data. This might contribute to the lack of monotonicity in the returns and the Sharpe ratios of the sorted portfolios.

[30] See Demirakos *et al.* (2004).

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