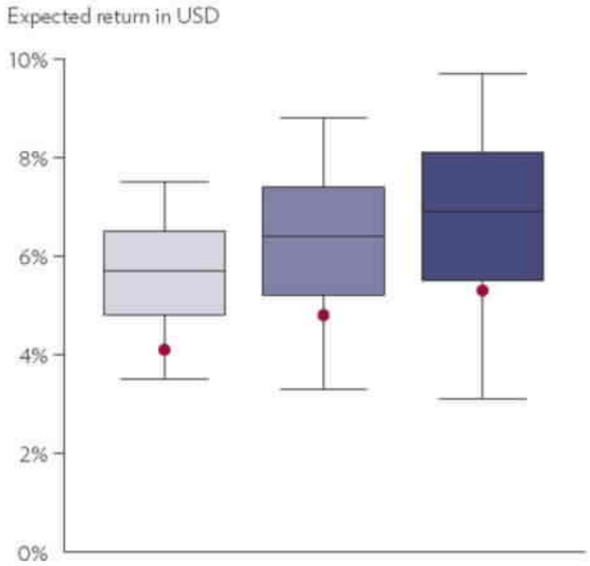
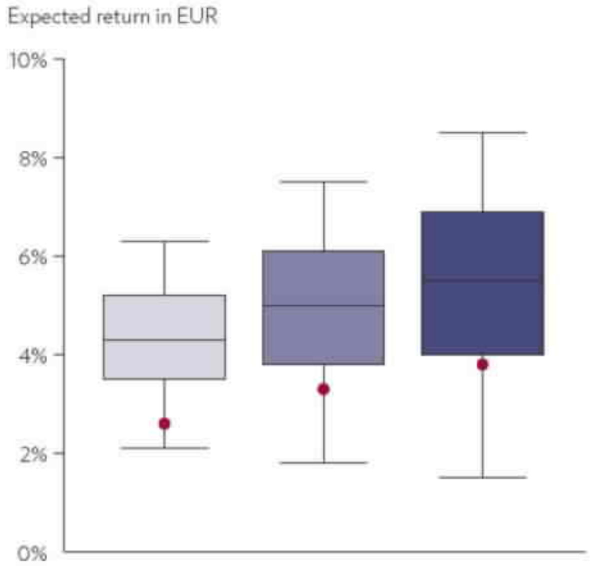
While our expected returns are comfortably higher than last year, many known and unknown 'unknowns' remain along the route to your investment goals. Now, more than ever, flying with an experienced captain is key to ensuring a safe flight in which unexpected clouds with potentially severe consequences can be avoided. Similarly, to steer clear of adverse investment weather or to circumnavigate financial tempests, you can trust that our Investment Committee, research analysts, portfolio managers, and risk managers will scrutinise the horizon and pilot the safest route forward.

Going further: The full view

How did we come up with the expected returns of our SAA? They are based on the asset-class-level returns. To find out more about these and to obtain further information on our new SAA, please consult our 'Capital Market Assumptions 2023' or contact your relationship manager.

Chart 5: Strategic Asset Allocation expected returns – point estimates and probability ranges





Income Balanced Growth • 50th percentile as at 30.04.2022

Source: Julius Baer
Note: In this box-plot representation, the bottom, middle, and top of the boxes show the 25th, 50th, and 75th percentiles, respectively, of the distribution. The bottom whisker shows the 5th percentile of the distribution, and the top whisker shows the 95th percentile. The reference level is based on the yields as at 30.09.2022. Past performance and performance forecasts are not reliable indicators of future results. The return may increase or decrease as a result of currency fluctuations.

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Authors
Yves Bonzon, Group Chief Investment Officer, yves.bonzon@juliusbaer.com*
Jacques Roulet, Head of Portfolio Engineering and Risk Management, jacques.roulet@juliusbaer.com

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JULIUS BAER GROUP

Head Office
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P. O. Box
8010 Zurich
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Telephone +41 (0) 58 888 1111
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Measuring the equity risk premium

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Peter Best*

is a senior portfolio manager at Old Mutual Asset Managers in London, where he manages international equities using quantitative models.

Alistair Byrne

is Head of Investment Strategy at AEGON Asset Management in Edinburgh and is also responsible for the firm's quantitative research team. Peter and Alistair have been working on risk premium analysis since 1995, when they were both at Scottish Equitable.

*Old Mutual Asset Managers Limited, 80 Cheapside, London EC2V 6EE, UK.
Tel: 44 20 7332 7558; e-mail: peter.best@omam.co.uk

Abstract We use surveys of economic forecasts to derive a forward-looking estimate of the US equity risk premium (ERP) relative to government bonds. Our ERP measure helps predict short-term relative returns between stocks and bonds. Over the period we studied, low readings of the ERP tended to adjust back to the mean via a rally in the bond market rather than a fall in stock prices. We do not generalise from this result, however, as our sample period is characterised by strong trends of falling inflation and rising stock prices. Our estimate of the expected ERP — averaging just over 2 per cent — is markedly lower than the premium that historical studies show has been realised. Data from the UK paint a similar picture to the US experience.

Keywords: *equity risk premium; survey data; asset allocation*

Introduction

In this paper, we use surveys of consensus economic forecasts to produce a forward-looking estimate of the equity risk premium (ERP) relative to government bonds for the US market. Using this novel data source, our model provides a more realistic estimate of the *ex ante* ERP than assuming that realised returns accurately indicate what investors expected. Furthermore, the ERP offers the potential to be used as the basis of a tactical asset allocation strategy by active investment managers.

We find that our ERP measure shows a tendency to mean revert and helps predict relative returns between US stocks and bonds; high values of the risk premium are associated with above-average short-term equity–bond return spreads. Also, when the ERP is low, the correction typically takes place via a rally in the bond market rather than a fall in stock prices. We need to be cautious in generalising this result, however, as the period we investigate is characterised by strong trends of falling inflation and rising stock prices.

In the sections that follow, we outline our measure of the ERP and describe the underlying data. We then test the power of the measure in predicting relative returns between stocks and bonds and look in detail at what contributes to this. In particular, we look at the process by which extreme values of the series adjust back towards the mean. We also look briefly at UK data to assess the similarity with the US experience.

The equity risk premium

Finance theory holds that stocks are more 'risky' than government bonds — meaning that equity prices are more volatile than bond prices. Investors require higher expected returns in order to invest in the (volatile) stock market than they do to invest in (more stable) bonds. In simple terms, equity returns must offer a 'risk premium' compared with the returns available on bonds and treasury bills. Welch (1999) notes that this equity risk premium 'is perhaps the single most important number in financial economics', with implications for asset allocation decisions and providing a key input into calculations of the appropriate discount rate for evaluating investments.

It is well documented that US stocks have delivered higher returns, on average, than US Treasury bonds. Returns on the stock market have also been more volatile than those earned from bonds. Figures for the period 1900–1999 are shown in Table 1.

Table 1 US stock and bond returns, 1900–1999 (%)

	Stocks	Government bonds
Arithmetic average annual return	12.2	5.0
Standard deviation	20.0	8.1

Source: Dimson *et al.* (2000).

Welch describes the approach of extrapolating the historically realised equity premium as 'the most popular' method of obtaining an estimate of the required ERP. His survey of the views of 226 financial economists yields an average estimate for the ERP relative to treasury bills of about 7 per cent, not far below the figure derived from historical information. Mehra and Prescott (1985) noted that the realised ERP in the US from 1889 to 1978 (6 per cent) was much larger than could be explained by standard models of risk aversion. Implicitly, they make the assumption that the realised figure they measured is a fair estimate of what investors had required. Their paper sparked a search for a solution to the 'equity premium puzzle'.[1]

The view that the realised ERP is a fair estimate of what investors *required*, or expected, however, needs some quite strong assumptions. We must assume the investors hold 'rational expectations' and that the required risk premium is constant. The growing literature on behavioural finance contains many illustrations of investors making decisions that are inconsistent with the traditional notions of rationality used in finance.[2] Furthermore, Fama and French (1989) present plausible arguments and evidence to suggest risk premiums are not constant, but rather vary through the business cycle. It is also possible to argue that structural factors, such as changing demographics, can cause longer-term shifts in the level of required risk premiums.

Relaxing the rational expectations and constant risk premium assumptions breaks the link between what actually happened — the realised risk premium — and the premium expected by investors when they made their investment. Bernstein (1997), in particular, argues that realised returns on stocks and bonds — and risk premium estimates derived from them — are dominated by unexpected changes in valuations. Siegel (1999) notes the high realised ERP appears to be due more to low returns on bonds than to high returns on stocks. The average real return on fixed income assets this century looks unduly low, and he suggests this may be the result of investors' failure to anticipate higher inflation.[3] If the high realised ERP was not expected by investors, there may not be an 'equity premium puzzle', at least not in the sense used by Mehra and Prescott.

Overall, we think the evidence weighs against the realised ERP being a good measure of the premium investors actually expected. A key motivation of our work is to find a better way of estimating the risk premium expected by investors than the 'extrapolation' approach. As active investors, we also want to assess whether the estimate is a useful predictor of short-term relative returns. The following section outlines the model we use.

Our model

The *ex ante* ERP is simply the difference in expected return between stocks and bonds.

In notation form:

$$ERP = r - y \tag{1}$$

where ERP is the *ex ante* equity risk premium, r is the expected return on the stock market, and y is the expected return on long-term government bonds.

The expected return on the stock market can in turn be expressed in terms of the constant growth dividend discount model developed by Gordon (1962).[4] The model is represented as follows:

$$r = (d/p) + g \tag{2}$$

where d is the expected value of dividends payable in the coming year, p is the price of the stock market index, and g is the expected long-term growth rate of dividends.

Substituting Equation (2) into Equation (1) yields the following expression for the ERP:

$$ERP = (d/p) + g - y \tag{3}$$

The obvious problem with Equation (3) is that only one of the right-hand-side variables, p, the value of the stock market index, is observable. The other variables relate to investors' expectations and are not directly observable. To make our model operational, we need to find proxies for these expectations.

Variable y, the expected return on government bonds, can be dealt with relatively easily. The current redemption yield on a government bond is a reasonable approximation of its longer-term expected return, and this can be observed in the market.[5]

Survey data can be used to provide estimates of d and g. Analysts' forecasts for corporate earnings are readily available through services such as IBES.[6] Each month IBES collate analysts' earnings estimates for each stock and calculate a 'consensus' in the form of the mean forecast. It is then possible to aggregate these forecasts to derive an earnings figure for the market as a whole. By applying a payout ratio to the forecasts of the following year's earnings, we can arrive at an estimate of d, the next period dividends expected by investors. The calculation of the payout ratio is discussed in the next section.

We also need an estimate of expectations of the long-term rate of dividend growth. Over the longer term, we assume that profits, and by implication dividends, will grow at the same pace as nominal gross domestic product. For this assumption to be true, a number of conditions must hold, namely that the stock market index is representative of the economy as a whole, the profit share of GDP is steady, the overseas earnings of US listed companies grow at the same pace as their domestic profits, and the payout ratio is steady. While these conditions may not hold exactly, our analysis will show whether our approach represents a valid proxy for long-term dividend growth expectations.

Long-term 'consensus' forecasts of GDP growth are available from a publication called *Blue Chip Economic Indicators* (various editions). Each month since August 1976, Blue Chip has published a survey of economists' forecasts of key variables for the US economy looking one to two years ahead. The survey takes forecasts from about 50 economists at major financial institutions, industrial corporations and consulting firms. Twice a year since 1979, the survey has been extended to cover the economists' ten-year forecasts. We use the Blue Chip ten-year forecast of nominal GDP growth as our proxy for g — the expected long-term rate of dividend growth.

We are now in a position to estimate the ERP from Equation (3) using observable proxies for the unobservable expectation variables. In the next section, we examine whether our estimate of the ERP is useful as a measure of valuation — specifically, whether it helps predict the short-term return spread between stocks and bonds.

Our measure is closely related to the practice common among market participants of estimating the ERP by comparing the nominal yields available on stocks and bonds — either in ratio form or as a difference. In difference form, this comparison is equivalent to our model with the long-term growth parameter, g, missing. The risk in excluding this parameter is that we may confuse yield shifts that are an appropriate response to changing profit growth expectations with shifts driven by other factors, possibly including 'irrational' misvaluation. In the following section, we test these alternative specifications of the risk premium model. We also test specifications of our model using actual rather than forecast dividends.

Predicting relative returns

In this section, we test whether our estimate of the ERP is useful for predicting the short-term return spread between stocks and bonds. If investors require a risk premium for investing in (volatile) stocks rather than (more stable) bonds, this implies stocks should outperform bonds on average over the long run. However, the degree of outperformance we observe is volatile and, in some shorter periods, bonds return more than stocks. Our ERP measure may offer a more reliable prediction of the return spread in any single period than simply assuming the historical average will hold.

We make the assumption that the equilibrium level of the ERP is relatively stable over time.[7] Our hypothesis is then that unusually high observations of the ERP should be associated with subsequent periods when stocks outperform bonds by more than average and the risk premium reverts towards its mean level. In contrast, unusually low observations should be associated with low, and possibly negative, return spreads between stocks and bonds as the risk premium reverts to the mean.

It is possible for our risk premium series to mean revert without being a useful predictor of relative returns between stocks and bonds. It may be that the expectation variables in our model change in such a way as to generate mean reversion in the risk premium series independent of moves in relative prices. Our tests deal with this

Table 2 Equity risk premium and relative returns, March 1979–March 1999 (%)

	ERP	Subsequent stock return	Subsequent bond return	Stock–bond return spread
Mean	2.06	8.60	4.37	4.23
Standard deviation	1.33	11.68	7.08	12.81
Minimum	0.11	−18.02	−11.03	−33.54
Maximum	6.25	38.85	23.52	39.03

All returns are expressed as semi-annual rates.

by looking directly at whether the ERP predicts relative returns.

The data we require to estimate Equation (3) are obtained from a number of sources. The forecasts of long-run nominal GDP we use to proxy dividend growth are available from the Blue Chip publication in March and October each year from 1979, with the survey being published on the 10th of the month.[8] We match these data with the corresponding level of the S&P500 index and the ten-year Treasury note yield obtained from Datastream. In the latter case, we use the Datastream Ten Year Benchmark index.

IBES data are used to estimate the forward dividend yield on the S&P500 index. We apply an estimated payout ratio of 0.4 to the IBES consensus forecast of the next 12 months' earnings. We estimate the payout ratio by calculating the relationship between IBES earnings forecasts and subsequent dividends over the period for which we have data. On average, subsequent dividends amount to about 40 per cent of the earnings forecast. Varying the payout ratio between 30 per cent and 50 per cent shows the results of our analysis are largely insensitive to the figure used.

We also use Datastream to source total return data for the S&P500 index and the ten-year benchmark bond index. We match each calculation of the risk premium with the total returns on stocks and bonds in the following period, eg we calculate the risk premium on 10th March and match this with returns from 10th March to 10th October. Since the Blue Chip data are published in March and October, our time series consists of five-month and seven-month periods rather than actual half years. We transform the five-month and seven-month returns into the corresponding semi-annual rates. The return spread series is calculated in ratio form rather than as differences.

Descriptive statistics for the estimated ERP and the relative return series are shown in Table 2. The ERP measure is graphed in Figure 1. While the sample period is short by comparison with those used in many academic studies, it has to be noted that we are constrained by the availability of the survey data. We have used all of the available data.[9]

Figure 1 shows the ERP started the sample period at a high level of over 5 per cent, perhaps reflecting the uncertain economic environment following the second OPEC oil price 'shock'. The premium declined sharply over the following two years and the range 1–3 per cent is much more typical for the rest of the sample period, with the mean level just over 2 per cent. Most deviations outside this range look to have 'corrected' quite quickly. Interestingly, the range is consistent with the theoretical estimates produced by Mehra and Prescott (1985) using standard models of risk aversion. The low of the series occurs in October 1987, just before the 'crash'. It is notable that the

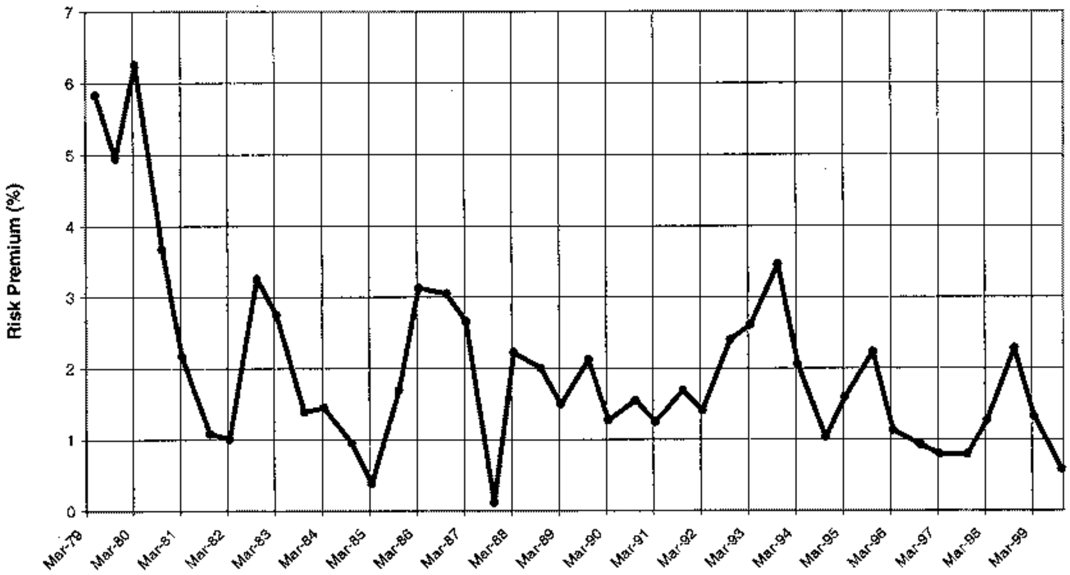

Figure 1 US equity risk premium

last data point from October 1999 is the third-lowest reading in the series, lending support to some commentators' concerns about high valuation levels in the US equity market.

To test whether our ERP measure is a useful predictor of the return spread between stocks and bonds, we estimate an ordinary least squares regression, where the level of the ERP at the end of one period is used to explain the return spread in the following period.

In notation terms:

$$SVB_t = a + b\ ERP_{t-1} + e_t \tag{4}$$

where SVB_t is the log total return on stocks in period t relative to the total return on bonds [=(1 + total return on S&P500 index)/(1 + total return on Datastream 10-Year Treasury Index)], ERP_{t-1} is the estimated ERP at the end of period $t-1$, and e_t is the error term. The results of the regression are shown in Table 3.

The regression equation reveals a positive relationship between our ERP measure and the subsequent return spread between stocks and bonds. The t-statistic of 3.3 indicates the relationship is statistically significant at a 99 per cent confidence level. Our ERP measure explains almost 20 per cent of the variation in relative returns between stocks and bonds over the sample period. Diagnostic tests show no significant econometric problems, although the sample size is relatively small.

Putting our results into more obvious economic terms, on average, stocks outperformed bonds by 4.2 per cent in each semi-annual period in our sample. The average ERP measure over the sample period was 2.1 per cent. For every percentage point increase (decrease) in the ERP, the subsequent semi-annual relative return was increased (decreased) by 4.5 percentage points. Figure 2 shows a scatter diagram of the ERP

Table 3 Regression results, March 1979–March 1999

	SVB_t	$-5.00 + 4.47\ ERP_{t-1}$
t-statistics		(1.50) (3.27)
Adjusted	$R^2 = 19.5\%$	$n = 41$

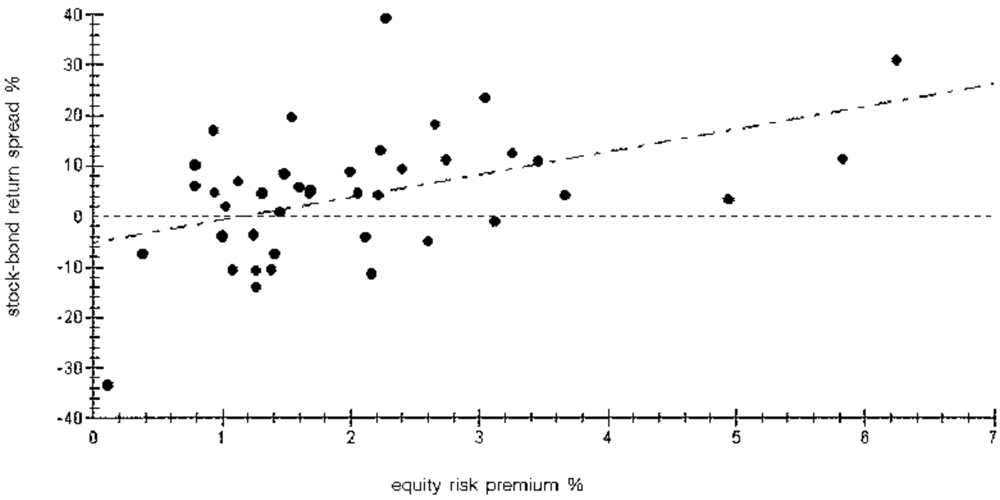

Figure 2 Stocks and bonds return spread against equity risk premium

observations against the subsequent equity–bond return spread. The positive relationship can be seen in the data.

In order to test the robustness of our results, we also tested a number of alternative specifications of the ERP. Using actual dividends rather than the IBES forecasts produces results that are similar, but slightly weaker, than our initial specification. Using the difference between the nominal earnings yield on stocks and the bond yield, ie omitting the long-term growth term, also produces similar results for predicting relative returns. This measure does not show significant mean reversion, however, raising questions about its reliability. Using the ratio between the forecast earnings yield on the stock market and the bond yield produces results similar to but slightly stronger than our chosen specification. Our main concern about this specification is that it is unlikely to be robust to significant changes in long-term dividend growth expectations. Using the Blue Chip forecasts for growth in the national income definition of profits rather than nominal GDP produces similar, but slightly weaker results.

In short, the alternative specifications produce similar, though generally slightly weaker, results. We would argue that the more complete specification of our measure makes it more robust to changes in the environment, especially revised long-term growth expectations.

What really happened

We have established that our risk premium measure is a reliable predictor of the return spread between stocks and bonds. An unusually high risk premium implies stocks will outperform bonds by a wider-than-average margin in the following period. Similarly, a low-risk premium implies the short-term return margin between stocks and bonds will be narrow or even negative.

To investigate what is driving these results, we rank the 41 observations according to the level of the ERP. We then split the data into quartiles — missing out the median observation[10] — and examine the return characteristics of each quartile. The results are shown in Table 4. Note all returns shown are expressed on a semi-annual basis.

Table 4 reveals that in quartiles one

Table 4 Equity risk premium and returns by quartile (%)

	Average ERP	Average relative return	Average stock return	Average bond return
Quartile One	3.90	12.38	11.29	−1.09
Quartile Two	2.18	6.29	8.17	1.88
Quartile Three	1.40	0.81	4.75	5.56
Quartile Four	0.82	0.97	8.24	9.21

All returns are expressed as semi-annual rates.

and two, bond returns are below average, while stock returns are higher than average. It is apparent that the above-average relative returns observed in these quartiles are driven both by below-average bond returns and by above-average stock returns. In quartiles three and four, bonds perform better than stocks on average, which is unsurprising given the econometric results in the previous section. The mechanism for this result is interesting, however. The 'overvaluation' of stocks is usually corrected by a rally in the bond market rather than by stocks falling in price — stock returns are below average, but not generally negative. The most notable exception is the October 1987 data point. The forecast ERP registered just 0.1 per cent on 10th October 1987. Over the following five months, bonds delivered a 15.5 per cent semi-annual return, helping to restore a more normal ERP. Stocks dropped sharply, however, registering a return of −18.0 per cent for the period. As we know, the 22.0 per cent 'crash' on Black Monday, 19th October, caused most of the damage to investors' portfolios.

Our measure appears to have some predictive power over both stocks and bonds individually as well as over relative returns. To confirm these results in econometric terms, Table 5 shows regression equations where we use the ERP measure to predict the return on stocks S_t and the return on bonds B_t.

As expected given the quartile analysis above, there is a negative relationship between the ERP measure and the return on bonds, ie bonds tend to perform poorly in the period following a high ERP. Stocks tend to perform strongly following a high ERP, as shown by the positive regression coefficient. The main caveat is that the regression coefficient for stocks is not statistically significant at conventional confidence levels.

Our results show that over the period for which we have data, overvaluation of the stock market relative to bonds has tended to be corrected by a rally in the bond market, ie a fall in yields. In only seven of the 41 periods was the return on the stock market negative. It would be wrong to generalise from this result, however. Over the period we studied, the average level of inflation dropped sharply, providing a beneficial environment for financial assets. Consumer price inflation averaged 7.9 per cent in the five years leading up to

Table 5 Regression results, March 1979–March 1999

	Stocks
	$S_t = 5.32 + 1.59\ \mathrm{ERP}_{t-1}$
t-statistics	(1.57) (1.15)
Adjusted	$R^2 = 0.8\%$ $n = 41$
	Bonds
	$B_t = 10.33 - 2.89\ \mathrm{ERP}_{t-1}$
t-statistics	(5.89) (−4.03)
Adjusted	$R^2 = 27.5\%$ $n = 41$

Table 6 UK equity risk premium and relative returns, April 1982–April 1999 (%)

	ERP	Subsequent stock return	Subsequent bond return	Stock–bond return spread
Mean	2.07	8.40	5.88	2.52
Standard deviation	1.22	12.01	6.20	11.96
Minimum	0.35	−26.75	−6.66	−38.26
Maximum	5.34	30.00	24.53	24.41

All returns are expressed as semi-annual rates.

our first data point in March 1979. For the five years to October 1999, the comparable figure is 2.4 per cent. The ten-year bond yield has fallen in tandem with the drop in inflation, moving from 9.1 per cent in March 1979 to 6.0 per cent in October 1999. Without this beneficial environment of falling inflation, and rising stock prices, investors buying stocks when the risk premium was low may have faced a harsher experience than they have had.

While many investors and media commentators have been talking about the overvaluation of the US stock market for several years, there has been significant variation in the level of the ERP measure over the recent period. During the third quarter of 1998, stocks fell sharply as investors undertook a 'flight to safety' in the aftermath of the Russian government's decision to introduce a moratorium on debt repayments. Treasury bond yields fell as investors sought secure and liquid instruments in which to hold their capital. The result was to drive the ERP to an above-average level of 2.3 per cent in October 1998. In contrast, the March 1998 reading was only 1.3 per cent. The October 1998 data point stands out as the 'best' buying signal for equities in our series, with the S&P500 index outperforming bonds by 39.0 per cent on a semi-annual basis over the following five months, as fears of deflation and recession abated.

The international evidence

We have focused on the US market due to the ready availability of the survey data we use to proxy expectations. Some data, however, are also available for international markets. In particular, we have been able to assemble a series of ERP estimates for the UK market from April 1982 to April 1999 using IBES earnings forecasts and long-run nominal GDP from Consensus Economics Inc.'s *Consensus Forecasts* (various editions), an international equivalent to *Blue Chip Economic Indicators*.[11] We use the FTSE 100 as our equity index and the Datastream ten-year benchmark gilt index for our bond series. With the exception of the sources of the forecasts, the methodology and data sources are the same as outlined for the US in the section on 'Our model'. Table 6 gives descriptive statistics for our UK ERP measure and the corresponding returns. Figure 3 plots the ERP series.

It is notable that the UK series shares many similarities with our US data. The mean level of the ERP, at 2.1 per cent, is almost identical to the US average. The highs and lows are also broadly similar, and both series typically occupy a range from about 1 per cent to 3 per cent. Unlike the US, October 1987 did not represent the low for the UK, which in fact occurred in April 1991. The last data point in the sample, 1.7 per cent in October 1999, is much closer to the mean than the comparable US observation.

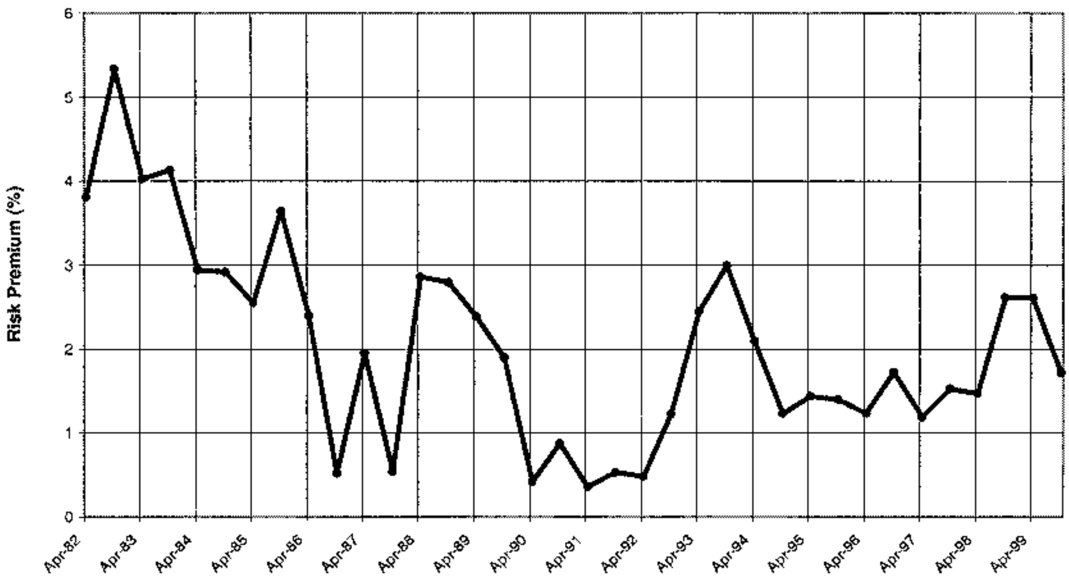

Figure 3 UK equity risk premium

Following the US analysis, we also test whether the UK ERP series helps predict the short-term stock–bond return spread. The regression yields a slope coefficient of 3.72 with a t-statistic of 2.35 — similar to the US equation. The adjusted R-square statistic at 12 per cent is lower than in the US model. Overall, the results are qualitatively similar.

Regression of the ERP series on stock and bond returns separately produces a contrast to the US results. In our results (not shown), we find the ERP series is more predictive of stock returns than bond returns. The slope coefficient of the bond equation is statistically insignificant, though it has the expected negative sign.

In general, the UK results and their similarity to the US experience give us confidence in the validity of our approach. The techniques are also applicable for other international markets, but data availability is a problem. For many European and Asian markets, comprehensive surveys of economic forecasts have only become available in the past decade. This will, however, provide a useful 'out-of-sample' test of our analysis once the data histories are longer.

Table 7 Regression results, April 1982–April 1999

	Stocks	
	SVB_t	$-5.19 + 3.72\ \mathrm{ERP}_{t-1}$
t-statistics		(−1.37) (2.35)
Adjusted	$R^2 = 11.7\%$	$n = 35$

Conclusions

Our work represents an attempt to produce a well-specified *ex ante* measure of the ERP expected by investors. We use surveys of economic forecasts as a novel way to solve the problem that many of the variables in the risk premium calculation are unobservable. We focus on the US experience, but also present results for the UK which are similar.

The results show that the ERP measure helps predict the short-term relative return between stocks and bonds. When the premium is higher than average, the stock–bond return spread in the coming period also tends to be above average. When the risk premium measure is below average, the subsequent return spread tends to be low or even negative. The measure therefore offers scope to be the basis of a tactical asset allocation strategy.[12]

It is not clear why our measure, which uses widely available data, should offer potential for generating excess returns. It may be the model captures inefficiency in the relative pricing of stocks and bonds, but other, more 'rational', explanations are possible. Fama and French (1989) find that US stock and bond returns between 1926 and 1987 were predictable using the market dividend yield; the 'default' spread between the average corporate bond yield and the yield on AAA-rated bonds; and the term premium of AAA-rated corporate bonds over Treasury bills. They argue the explanatory variables are related to the business cycle and that predictable variation in expected returns reflects a rational response to economic conditions. For example, when business conditions are poor, income is low and expected returns from bonds and stocks must be high to induce substitution from consumption to investment. In the case of our analysis, it may be that the business cycle leads to short-term fluctuations in the compensation investors require for equity risk. Similarly, the actual or perceived level of risk in stocks and bonds may vary through the business cycle, leading to variations in expected returns that have rational foundations. Our tests do not offer any way to decide between these different explanations.

Our analysis also suggests, in recent years at least, the risk premium expected by equity investors has been significantly less than the levels (7 per cent or so) that historical studies show have been realised. The most recent US data we have show stocks priced to deliver only about 1 per cent more than bonds over the longer term, if our model specification is correct. Our concluding message has to be to caution against using a measure of the realised ERP as an indication of what can be expected in future.

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Notes

1 A review of some of the initial solutions proposed can be found in Kocherlakota (1996).
2 See Shefrin (1999) for a comprehensive review of this field.
3 Best *et al.* (1998) show that investors in the US bond market in recent years appear to have made large and persistent errors in forecasting inflation. As a result the realised real returns earned by these investors seem to have been very different from what they expected at the outset. It is not apparent in the data that these forecast errors average out to zero over time.
4 The Gordon model is a simple valuation model, which necessarily rests on a number of strong assumptions. The firm is assumed to be debt free and to finance its investments through retaining a constant portion of its earnings. The investments have infinite lives and earn a constant return on capital. A full critique of the model and the assumptions is outwith the scope of our paper.
5 This approximation involves a number of assumptions, such as a flat and unchanging yield curve and the ability to reinvest coupon payments at the same rate as the yield. The effect of these assumptions is likely to be small.
6 IBES is a data vendor specialising in the systematic collection of earnings estimates from 'sell-side' investment analysts.
7 It is possible to argue the risk premium will shift over time, eg as a result of changing demographics. Such changes by their nature, however, are likely to be very gradual. Tests on the ERP series indicate it is stationary over the sample period. The augmented Dickey–Fuller statistic for the series is −5.99, which is significant at a 95% confidence level.
8 Prior to 1983, some of the data points relate to May and November. After 1983, the series becomes more regular.
9 To avoid the need for survey data, some analysts assume investors have had perfect (or at least unbiased) foresight. They argue that what happened, for example in terms of dividend growth, was what

investors had expected and thus historical out-turn data can proxy for prior expectations. While this can yield longer data histories, to us the assumption is too strong.

10 The median observation is from October 1985 and is characterised by: *ERP*   1.69 per cent; stock return   28.01 per cent; bond return   23.52 per cent; relative return = 4.49 per cent.

11 UK data from IBES and Consensus Economics is only available from 1987 and 1989 respectively. We create our own comparable series for the early periods by combining the relevant forecasts of leading economic forecasting institutions.

12 Best and Byrne (1997) present the results of a simulated tactical asset allocation strategy based on this measure.

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Richard A. Michelfelder *is Clinical Associate Professor of Finance at Rutgers University, School of Business, Camden, New Jersey. He earlier held a number of entrepreneurial and executive positions in the public utility industry, some of them involving the application of renewable and energy efficiency resources in utility planning and regulation. He was CEO and chairperson of the board of Quantum Consulting, Inc., a national energy efficiency and utility consulting firm, and Quantum Energy Services and Technologies, LLC, an energy services company that he co-founded. He also helped to co-found and build Comverge, Inc., currently one of the largest demand-response firms in the world, which went public in 2006 on the NASDAQ exchange. He was also an executive at Atlantic Energy, Inc. and Chief Economist at Associated Utilities Services, where he testified on the cost of capital for public utilities in a number of state jurisdictions and before the Federal Energy Regulatory Commission. He holds a Ph.D. in Economics from Fordham University.*

Panayiotis Theodossiou *is Professor and Dean of Faculty of Management at the Cyprus University of Technology. Previously he was Professor of Finance at Rutgers University, School of Business, Camden. Dr. Thedossiou has also held a number of other faculty positions in finance at Catholic University and Clarkson University. He has also provided consulting advice to national governments. He holds a Ph.D. in Finance from the City University of New York.*

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Public Utility Beta Adjustment and Biased Costs of Capital in Public Utility Rate Proceedings

The Capital Asset Pricing Model (CAPM) is commonly used in public utility rate proceedings to estimate the cost of capital and allowed rate of return. The beta in the CAPM associates risk with estimated return. However, an empirical analysis suggests that the commonly used Blume CAPM beta adjustment is not appropriate for electric and electric and gas public utility betas, and may bias the cost of common equity capital in public utility rate proceedings.

Richard A. Michelfelder and Panayiotis Theodossiou

I. Introduction

Regulators, public utilities, and other financial practitioners of utility rate setting in the United States and other countries often use the Capital Asset Pricing Model (CAPM) to estimate the rate of return on common equity (cost of common equity).[1] Typically, the ordinary least squares method (OLS) is the preferred estimation method for the CAPM betas of public utilities. Although the CAPM model has been widely criticized regarding its validity and predictability in the literature, as summarized by Professors Fama and French in 2005,[2] many firms and practitioners extensively use it to obtain cost of common equity estimates; e.g., such as shown by Bruser et al. in 1998, Graham and Harvey in 2001, and Gray, et al. in 2005.[3] Michelfelder, et al. in 2013[4] in this

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journal presents a new model, i.e., the Predictive Risk Premium Model, to estimate the cost of common equity capital and compare and contrast the poor results of the CAPM to that model and the discounted cash flow model.

Major vendors of betas include, but are not limited to, Merrill Lynch, Value Line Investment Services (Value Line), and Bloomberg. These companies use Blume's 1971 and 1975[5] beta adjustment equation to adjust OLS betas to be used in the estimation of the cost of common equity for public utilities and other companies.

The premise behind the Blume adjustment is that estimated betas exhibit mean reversion toward one over time; that is, betas greater or less than 1 are expected to revert to 1. There are various explanations for the phenomenon first discussed in Blume's pioneering papers. One explanation is that the tendency of betas toward one is a by-product of management's efforts to keep the level of firm's systematic risk close to that of the market. Another explanation relates to the diversification effect of projects undertaken by a firm.[6]

While this may be the case for non-regulated stocks, regulation affects the risk of public utility stocks and therefore the risk reflected in beta may not follow a time path toward one as suggested by Peltzman in 1976, Binder and Norton in 1999, Kolbe and Tye in 1990, Davidson, Rangan, and Rosenstein in 1997, and Nwaeze in 2000.[7] Being natural monopolies in their own geographic areas, public utilities have more influence on the prices of their product (gas and electricity) than other firms. The rate setting process provides public utilities with the opportunity to adjust prices of gas and electricity to recover the rising costs of fuel and other materials used in the transmission and distribution of electricity and gas. Companies operating in competitive markets do not have this ability. In this respect, the perceived systematic risk associated with the common stock of a public utility may be lower than that of a non-public utility. Therefore, forcing the beta of a utility stock toward one may not be appropriate, at least on a conceptual basis.

The premise behind the Blume adjustment is that estimated betas exhibit mean reversion toward one over time.

The explanations provided by Blume and others to justify the latter tendency are hardly applicable to public utilities. Unlike other companies, utilities can and do possess monopolistic power over the markets for their products. This power impacts the "negotiation process" for setting electric and gas prices. Furthermore, it provides them with the opportunity to raise prices to recover increases in operating costs without regard to competitive market pressure. Such price influence is rarely available to companies operating in competitive market environments for their products. In that respect, macroeconomic factors will have a greater impact on the earnings and stock prices of the non-utility companies resulting in larger systematic risk or betas.

The application of Blume's equation to public utility stocks generally results in larger betas, since most raw utility betas are less than 1. Therefore, applications of these betas to estimate the cost of capital and an allowed rate of return on common equity possibly biases the required rate of return or cost of common equity, leading to an over-investment of capital as predicted by Averch and Johnson in 1962,[8] which preceded the trend in prudency reviews that began to occur in the 1980s. Although reported public utility betas may have been biased upward by the vendors of beta that applied Blume's adjustment to public utility betas, ex post prudency reviews of "used and useful" assets defined and supported by the Duquesne 1989 US Supreme Court decision[9] resulted in an underinvestment of capital in generation and transmission assets, leading to electric brownouts and blackouts. This article examines the behavior of the betas of the population of publicly traded U.S. energy utilities. In

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addition to evaluating the stability of these betas over the period from the January 1962 to December 2007, we also test whether or not public utility betas are stationary or mean reverting toward 1 or perhaps a different level.

II. Background

Investor-owned public utility regulatory proceedings to change rates for service almost always involve contentious litigation on the fair rate of return or cost of common equity. Since the cost of common equity is not observable, it must be inferred from market valuation models of common equity. The differences in the recommended allowed rates of return resulting from necessary subjective judgments in the application of cost of common equity models can easily mean 500 basis points or more in the estimate. Therefore, both the impact on customer rates for utility service and the profits of the utilities are very sensitive to the methods used to estimate the cost of common equity and allowed rate of return. The two most commonly used models are the Dividend Discount Model (DDM) and the CAPM. We discuss the use of CAPM for estimating the cost of common equity for public utilities. Our focus is on the use of market-influential betas from the major vendors of betas: Merrill Lynch, Value Line, and Bloomberg. These vendors apply Blume's adjustment to raw betas to estimate forward-looking betas. Blume[10] performed an empirical investigation, finding that beta is non-stationary and has a tendency to converge to 1. Bey in 1983 and Gombola and Kahl in 1990[11] found that utility betas are non-stationary and concluded that each utility beta's non-stationarity must be viewed on an individual stock basis, unlike the recommendation of Blume which adjusts all betas for their tendency to approach 1. Similarly with Gombola and Kahl, we find that public utility betas have a tendency to be less than 1. They investigated the time series properties of public utility betas for their ability to be forecasted whereas we are concerned with the institutional reasons for the trends in beta, the bias instilled in cost of capital estimates assuming that utility betas converge to one and the widespread use and applicability of the Blume adjustment to public utility betas. McDonald, Michelfelder and Theodossiou in 2010[12] show that use of OLS is problematic itself for estimating betas as the nonnormal nature of stock returns result in beta estimates that are statistically inefficient and possibly biased.

Investor-owned public utility regulatory proceedings to change rates for service almost always involve contentious litigation on the fair rate of return or cost of common equity.

Blume's equation is:

$$\beta_{t+1} = 0.343 + 0.677\beta_t \qquad (1)$$

where β_{t+1} is the foreasted or projected beta for stock i based on the most recent OLS estimate of firm's beta β_t. For example if β_t is estimated using historical returns from the most recent five years, then the projected β_{t+1} may be viewed as a forecast of the beta to prevail during the next five years. As mentioned earlier, Blume's equation implies a long-run mean reversion of betas toward 1. The long-run tendency of betas implied by Blume's equation can be computed using the equation:

$$\overline{\beta} = \frac{0.343}{1 - 0.677} = 1.0619 \approx 1 \qquad (2)$$

The same result can be obtained by recursively predicting beta until it converges to a final value. This can only be appropriate for stocks with average betas, as a group, close to one. This is, however, hardly the case for public utility betas that are generally less than 1 (as discussed in detail below).

The magnitude of adjustment for Blume's beta equation is initially large and declines dramatically as the adjusted beta approaches 1 either from below (for betas lower than 1) or from above (for betas greater than 1). In this respect, the beta adjustment step (size) will be larger for betas further away from 1.

As we will see in the next section, the median beta of the public utilities studied ranges between 0.08 and 0.74 over time,

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depending upon the period used. Under the assumption that betas for public utilities are consistent with Blume's equation, the next period beta for a stock with a current beta of 0.5, will be $\beta_{t+1} = 0.343 + 0.677\ (0.5) = 0.6815$, implying a 36.3 percent (0.6815/ 0.5) upward adjustment. On the other hand a beta of 0.4 will be adjusted to $\beta_{t+1} = 0.343 + 0.677\ (0.4) = 0.6138$ which constitutes a 53.5 percent upward adjustment and a beta of 0.3 will be adjusted to 0.5461 or by 82.0 percent.

The beta adjustment method most widely disseminated by the major beta vendors is the Blume adjustment. Therefore, our focus is on the Blume adjustment for public utility betas and the public utility cost of common equity capital. Occasionally, an expert witness in a public utility rate case estimates their own betas, but they are quickly repudiated in rate proceedings since these betas are not disseminated by influential stock analysts and presumed not to be reflected in the stock price. Section III discusses the data and empirical analysis of the Blume adjustment and its impact on the cost of common equity for public utilities.

III. Data and Empirical Analysis

The data include monthly holding period total returns for 57 publicly traded U.S. public utilities for the period from January 1962 to December 2007 obtained from the University of Chicago's Center for Research in Security Prices (CRSP) database. The sample includes all publicly traded electric and electric and gas combination public utilities with SIC codes 4911 and 4931 listed in the CRSP database. All non-U.S. public utilities traded in the U.S. and non-utility stocks were not included in the dataset. The monthly holding period total returns for each stock as calculated in the CRSP database were used for estimating betas of varying periods. The monthly market total return is the CRSP value-weighted total return.

Occasionally, an expert witness in a public utility rate case estimates their own betas, but they are quickly repudiated in rate proceedings.

The computation of the betas is based on the single index model, also used in Blume:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + e_{i,t}, \tag{3}$$

where $R_{i,t}$ and $R_{m,t}$ are total returns for stock i and the market during month t, α_i, and β_i are the intercept and beta for stock i and $e_{i,t}$ is a regression error term for stock i. As previously mentioned, OLS is the typical estimation method used by many vendors of beta and is used in this investigation.

Table 1 presents the mean and median OLS beta estimates for the 57 utilities using 60, 84, 96, and 108 monthly returns respectively over five different non-lapping periods between December 1962 and December 2007. We also performed the same empirical analysis for periods of 4, 6, 10, 11, 12 and 13 years and the results were similar; the results are not shown for brevity but available upon request. We used non-overlapping periods to avoid serial correlation and unit roots. If we take, for example, 360 months of time series of returns for a stock and estimate 60-month rolling betas moving one month forward for each beta, this would result in 300 betas. Since only two of 60 observations would be unique due to overlapping periods, the error term would be highly serially correlated. A Blume-type regression of these betas would have a unit root, a coefficient of one and an intercept near 0, and therefore appear to follow a random walk. Therefore, the empirical nature of beta requires that lags in the Blume equation involve no overlapping time periods.

The mean and median betas in Table 1 not only do not rise toward 1 as the time period moves forward; the betas generally decline. **Table 2** includes OLS regressions of the Blume equation for the 5-, 7-, 8-, and 9-year betas. We estimated five sets of 4- through 13-year betas inclusively for each public utility then

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Table 1: Mean and Median Betas for Varying Time Periods.

9-Year Periods	12/62–12/71	12/71–12/80	12/80–12/89	12/89–12/98	12/98–12/07
Mean	0.69	0.60	0.41	0.40	0.27
Median	0.68	0.57	0.40	0.36	0.22
8-Year Periods	**12/67–12/75**	**12/75–12/83**	**12/83–12/91**	**12/91–12/99**	**12/99–12/07**
Mean	0.76	0.39	0.45	0.27	0.33
Median	0.74	0.37	0.43	0.23	0.27
7-Year Periods	**12/72–12/79**	**12/79–12/86**	**12/86–12/93**	**12/93–12/00**	**12/00–12/07**
Mean	0.68	0.40	0.40	0.09	0.50
Median	0.65	0.39	0.38	0.06	0.47
5-Year Periods	**12/77–12/82**	**12/82–12/87**	**12/87–12/92**	**12/92–12/97**	**12/97–12/02**
Mean	0.36	0.38	0.53	0.49	0.12
Median	0.35	0.38	0.50	0.45	0.08

The following model was estimated for the sample of public utility stocks for five 60-, 84-, 96-, and 108-month non-overlapping periods. The ordinary least squares method was used to estimate the parameters of the single index model: $R_{i,t} = \alpha_i + \beta_i R_{m,t} + e_{i,t}$
where $R_{i,t}$ and $R_{m,t}$ are total returns for stock i and the market during month t, α_i and β_i is the intercept and capital asset pricing model beta for stock i, respectively, and $e_{i,t}$ is a regression error term for stock i. The entire data series ranges from December 1962 to December 2007. The stock returns are the monthly holding period total returns from the CRSP database. The market returns are the CRSP market value-weighted total returns.

regressed the latter beta on the previous period betas. The 5-, 7-, 8-, and 9-year equations are shown for brevity. The diagnostic statistics strongly refute the validity of the Blume equation for public utility stocks. Most of the R^2's are equal to or close to 0.00 and the largest is 0.09. Only one F-statistic (tests the significance of the equation estimation) is significant and all but two slopes are insignificant. Also shown is the long-run beta implied from each Blume model as shown in equation (2). They range from 0.08 to 0.59. Only one estimate, the first-period 9-year Blume equation, includes a positive and statistically significant slope and intercept. The implied long-term beta of that equation is 0.59, which is substantially below one and the largest value of all estimates. As a final and visual review of the trends in betas, we developed and plotted probability distribution box plots developed by Tukey in 1977[13] for the 4- through 13-year public utility betas. We have shown only the 4- and 5-year beta box plots as shown in Figures 1 and 2 for brevity (the 6- to 13-year plots are available upon request). Tukey box plots show the 25th and 75th percentiles (the box height), the 10th and 90th percentiles (the whiskers), the median (the line inside the box), and the dispersion of the outlying betas. The box plots should be viewed as looking down on the distributions of the betas. We developed 4- through 13-year beta box plots to review the trend in shorter-term versus longer-term betas. None of the 51 beta probability distributions display any tendency for betas to drift toward one. The 5-, 6- and 7-year betas have higher variances in the last period relative to all other periods. A few outlying betas are greater than 2.0. This pattern is consistent with the notion that utility holding companies are investing in risky ventures of affiliates that can retain excess returns should they be realized. Note that the mean beta in Figures 1 and 2 show the cyclical nature of short-term utility betas with a severe downturn in the late 1990s and a severe upswing in the early 2000s. Generally, the box plots show a long-term downward trend in public utility betas.

It is interesting to note that the drop in beta occurred just after

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Table 2: Public Utility Blume Equation Estimates.

9-Year Betas	$\beta_2 = f(\beta_1)$	$\beta_3 = f(\beta_2)$	$\beta_4 = f(\beta_3)$	$\beta_5 = f(\beta_4)$
γ_0	0.463***	0.318***	0.480***	0.235***
	(0.074)	(0.062)	(0.096)	(0.080)
γ_1	0.214**	0.153	−0.186	0.800
	(0.102)	(0.099)	(0.227)	(0.179)
Long Run β	0.59	0.38	0.41	0.26
R^2	0.09	0.04	0.01	0.00
F-Statistic	4.43**	2.36	0.67	0.20
p-Value	0.04	0.13	0.42	0.65
8-Year Betas	$\beta_2 = f(\beta_1)$	$\beta_3 = f(\beta_2)$	$\beta_4 = f(\beta_3)$	$\beta_5 = f(\beta_4)$
γ_0	0.341***	0.464***	0.184**	0.321***
	(0.083)	(0.047)	(0.088)	(0.070)
γ_1	0.058	−0.034	0.193	0.035
	(0.106)	(0.115)	(0.189)	(0.220)
Long Run β	0.36	0.45	0.23	0.33
R^2	0.01	0.00	0.02	0.00
F-Statistic	0.30	0.09	1.04	0.02
p-Value	0.58	0.76	0.31	0.88
7-Year Betas	$\beta_2 = f(\beta_1)$	$\beta_3 = f(\beta_2)$	$\beta_4 = f(\beta_3)$	$\beta_5 = f(\beta_4)$
γ_0	0.370***	0.375***	0.074	0.491***
	(0.081)	(0.052)	(0.075)	(0.049)
γ_1	0.048	0.059	0.036	0.128
	(0.115)	(0.122)	(0.179)	(0.259)
Long Run β	0.39	0.40	0.08	0.56
R^2	0.00	0.00	0.00	0.00
F-Statistic	0.17	0.23	0.04	0.24
p-Value	0.68	0.63	0.84	0.62
5-Year Betas	$\beta_2 = f(\beta_1)$	$\beta_3 = f(\beta_2)$	$\beta_4 = f(\beta_3)$	$\beta_5 = f(\beta_4)$
γ_0	0.329***	0.474***	0.321***	0.106*
	(0.047)	(0.086)	(0.088)	(0.061)
γ_1	0.151	0.137	0.316**	0.019
	(0.119)	(0.213)	(0.157)	(0.111)
Long Run β	0.39	0.55	0.47	0.11
R^2	0.03	0.01	0.07	0.00
F-Statistic				
p-Value	1.62	0.41	4.07	0.03
	0.21	0.52	0.05	0.87

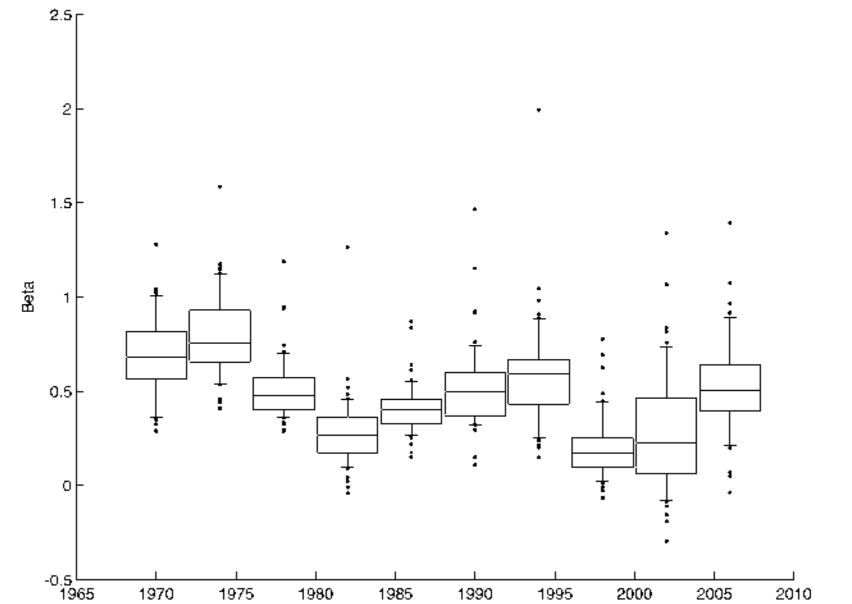
The following Blume equation was estimated using the betas of public utility stocks for five 60-, 84-, 96-, and 108-month non-overlapping periods. The ordinary least squares method was used to estimate the parameters of the following model: $\beta_{i,t-1} = \gamma_0 + \gamma_1\beta_{i,t} + \varepsilon_{i,t}$,
where $\beta_{i,t+1}$ is the OLS estimated CAPM beta for stock i, $\beta_{i,t}$ is the previous period beta for stock i, γ_0 and γ_1 are the intercept and slope of the Blume equation, and ε_t is the regression error term. The time subscripts on the betas refer to the time periods of estimation from Table 1. For example, β_5 in the 9 year panel refers to the beta estimated for each stock using the returns data from December 1998 to December 2007. The long-run $\beta = \gamma_0/(1 - \gamma_1)$; it can also be found by solving recursively for the next period beta until it converges on a final value. Newey-West autocorrelation and heteroskedasticity consistent standard errors are in parentheses.

* Significance at 0.10 level.

** Significance at 0.05 level.

*** Significance at 0.01 level.

deregulation of the wholesale electricity market in April 1996. This is inconsistent with the buffering theory of Peltzman and Binder and Norton[14] who found that regulation buffers the volatility of cash flows of public utilities from the vicissitudes of competition and business cycles and therefore reduces their systematic risk. However, this is consistent with Koble and Tye's 1990[15] theory of asymmetric regulation and the empirical findings of Michelfelder and Theodossiou in 2008,[16] who found that asymmetric regulation is associated with down-market public utility betas greater than their up-market betas. Adverse asymmetric regulation began in the 1980s and resulted in an upper boundary for public utilities' allowed rates of return equal to the cost of capital. If public utilities were granted an opportunity to earn their cost of common equity, regulators frequently would disallow specific investments *ex post* from earning the allowed rate of return if they were deemed "not used and useful," even though they were deemed to be prudent when the decision was made to make these investments. The result was that utilities were not truly granted the opportunity to earn their allowed rate of return. If they happened to over-earn their allowed rate of return due to higher than anticipated demand forecasts, "excess" returns were taken away. This became known as regulatory risk, quantified as a risk premium in the cost of



Boxes give the 25th and 75th percentiles; line in the boxes is for the median; whiskers give the 10th and 90th Percentiles

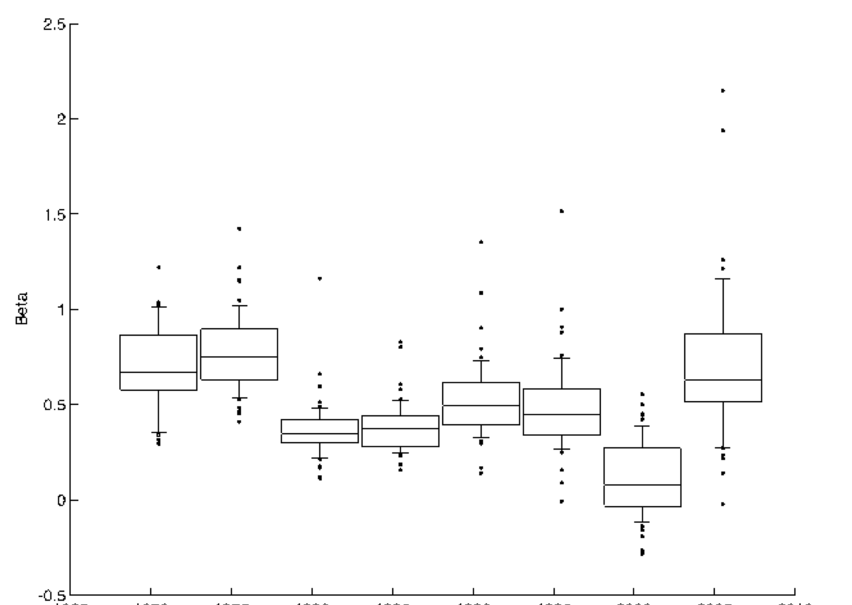
Figure 1: Boxplots of Utility Stock Betas Using 4 Year Periods Data

common equity. Michelfelder and Theodossiou in 2008[17] also concluded that public utility stocks are no longer defensive stocks dampening the downward behavior of otherwise less diversified portfolio returns in down markets.

Therefore, some suggest that *de*regulation may have "buffered" utility cash flows from regulatory risk, i.e., the chance that regulation would impose disappointing allowed rates of return in the manner described above. The advent of generation deregulation caused electric utilities with generating plants to no longer face regulatory risk on over 50 percent of their asset base. This is consistent with falling betas after deregulation of electric generation. The Brattle Group in 2004[18] found the same result in a research project for the Edison Electric Institute, an electric utility trade and lobbying organization. They found that electric utility betas fell after deregulation.

We suggest that it may be due to the relief of deregulation from asymmetric regulation. In any case, we find that the Blume adjustment toward 1 is not supported by our empirical results. This adjustment suggests that in the long run, all public utilities (and all firms) would gravitate toward the same risk and return. Our results herein suggest that the Blume adjustment is inappropriate for public utilities as it assumes that public utility betas are moving toward one in the long run as are non-utility company betas.

We perform a simple calculation to show the impact of a biased beta on public utility revenues. We calculate the common equity risk premium on the market as the annual total return for the CRSP market return from 1926 to 2007 to be approximately 12 percent and the average return on a three-month T-Bill to be about 4 percent. The long-term common equity risk premium is 8 percent. The difference between a beta of 0.50 and a Blume adjusted beta of .67 would result in a difference in cost of common equity



Boxes give the 25th and 75th percentiles; line in the boxes is for the median; whiskers give the 10th and 90th Percentiles.

Figure 2: Boxplots of Utility Stock Betas Using 5 Year Periods Data

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of 136 basis points. Using a common equity ratio of 0.50, this would impact the weighted average rate of return by 68 points. Assuming a rate base of $5 billion (the level for a moderately large electric utility), the difference in "allowed" net income would be 0.0068 × $5 billion, or, $34 million. Assuming a 37.5 percent income tax rate, the increase in revenues required to earn the additional $34 million would be $54 million. This is obviously a substantial difference. It is important for us to stress in this example that we do not necessarily advocate these inputs for the recommended cost of common equity for a utility with a raw beta of 0.50. The deliberation in recommending the cost of common equity is performed with a careful and detailed analysis of the company and stock, referral to more than one valuation model of the cost of common equity estimation and expert judgment.

IV. Conclusion

Major vendors of CAPM betas such as Merrill Lynch, Value Line, and Bloomberg distribute Blume-adjusted betas to investors. We have shown empirically that public utility betas do not have a tendency to converge to 1. Short-term betas of public utilities follow a cyclical pattern with recent downward trends, then upward structural breaks with long-term betas following a downward trend. We estimate the Blume equation for electric and gas public utilities, finding that all but one equation is statistically insignificant. The single significant equation implies a long-term convergence of beta to approximately 0.59. During our nearly 45-year study period, the median beta ranged from 0.08 to 0.74. Therefore the Blume equation overpredicts utility betas and Blume-adjustments

of utility betas are not appropriate.

We are not suggesting that betas should not be adjusted for prediction. Rather, the measurement period and subjective adjustment to beta should be based upon the likely future trend in peer group or *public utility betas*, or the specific utility's beta, not the trend in betas for all stocks in general. The time pattern of utility betas is obviously more complex than a smooth curvilinear adjustment, or for that matter, any adjustment toward one. Nor do we suggest as an alternative the use of raw or unadjusted betas in an application of the CAPM to estimate a public utility's cost of common equity.■

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Who benefits from Analyst "Top Picks"?

Justin Birru[a], Sinan Gokkaya[b], Xi Liu[c], and René M. Stulz[d]*

October 2020

Abstract

Following the Global Settlement, analysts extensively use a top pick designation to highlight their highest conviction best ideas. Such a designation enables analysts to provide greater granularity of information, but it can potentially be influenced by conflicts of interest. Examining a comprehensive sample of top picks, we find, even though top picks are more likely to be investment banking clients, they have greater investment value, attract greater media and investor attention, and lead to more trading. Top picks with poor ex post investment value are more likely to be influenced by strategic objectives and have adverse consequences for analysts. Institutions, but not retail investors, discern between top picks with good and poor ex post investment value.

[a] Fisher College of Business, The Ohio State University.
[b] Ohio University and a Visiting Scholar at Fisher College of Business.
[c] Farmer School of Business, Miami University.
[d] Fisher College of Business, The Ohio State University, NBER, and ECGI.

* We are grateful to Leandro Sanz for comments.
René Stulz consults and provides expert testimony on issues involving financial institutions that may employ analysts. None of his current or recent consulting concerns analysts.

1. Introduction

In the early 2000s, concerns about conflicts of interest of sell-side analysts led to new regulations and eventually to the Global Analyst Research Settlement. As discussed in Kadan, Madureira, Wang, and Zach (2009), one important byproduct of these regulations is the adoption of a new stock rating system by most leading investment banks. Before the Global Settlement, 85% of analyst recommendations are issued using a traditional five-tier rating system, but only less than 20% are afterwards.

Though a coarser three-tier rating system has the potential to reduce gains to analysts from engaging in strategic behavior, such a system also reduces the information available to investors. That is, sell-side analysts cannot fully discriminate among stocks whose performance they expect to be superior. To mitigate the costs of a coarser three-tier stock rating system, we would expect brokerage houses to attempt to increase the granularity of information available to financial market participants by devising new ways to draw attention to their best stocks. Consistently, we show that a new stock designation, "top picks," emerges following the Global Analyst Research Settlement and its use becomes widespread mostly among three-tier brokers. A top pick is typically the stock for which the analyst has the strongest conviction of superior performance compared to other buy recommendations. Notwithstanding the disproportionate amount of attention top picks receive from investors, media, and regulatory agencies, there exists no academic research on top picks we are aware of. A possible reason for this lack of research is that top picks are not identified on traditional databases academics rely upon (e.g., IBES). As a result, little is known about even basic details of top picks and whether analysts use top pick designations to give their best investment advice to investors, or are tempted to use these important designations to pursue strategic objectives that are not in the interest of investors.

Exploiting a novel and comprehensive sample of 3,563 top picks by 113 unique brokerage houses over 1999-2016, we find that top picks attract more retail, institutional and financial press attention and affect the trading of both institutional and retail investors more compared to buy recommendations. We investigate whether potential conflicts of interest affect the choice of top pick stocks and whether the market and investors can see through designations potentially tainted by conflicts of interest. Although investment banking clients are more likely to be selected as top picks, top pick designations, on average, have superior investment value for investors. Top picks with poor ex post investment performance are more likely to be investment banking clients. Though top pick designation announcements have a strong positive stock price reaction, the stock price reaction for top picks that have poor ex post performance is neither statistically nor economically significant, which suggests that the market does not credit poor top picks when they are announced. Top picks that have poor ex post performance are costly for analysts in that they worsen their career prospects and hurt their credibility with investors.

Top picks differ from stock recommendations in a number of ways.[1] First, a top pick is not a recommendation but an optional designation that represents an analyst's highest conviction "single best" idea within her coverage universe. In contrast, a buy recommendation typically means a stock is expected to outperform its industry peers. Hence, there can be at most only one top pick selection while there are multiple buy rated stocks outstanding by the same analyst at a given point in time. Second, unlike stock recommendations, "top pick" designations are assigned to a stock only for the upcoming one-year investment horizon (typically at the end or beginning of the year, with December, January, and February accounting for 66% of top pick announcements) and almost always expire on December 31st. Third, though analysts select their top pick stock from their buy recommendations, only 19% of top pick announcements coincide with a recommendation initiation, reiteration, or revision. In other words, the top pick designation represents a stand-alone analyst research output and we can directly assess its impact on financial markets. Fourth, top picks appear to be intentionally used as a marketing tool for brokerage houses. Indeed, a primary reason for the clustering of top picks in December – February is so that brokers can advertise stocks as top picks for the upcoming calendar year. In addition, brokers frequently organize best idea conferences to which they invite institutional clients and

[1] Throughout the paper, we use "buy rating" to also include "strong buy rating" when such a rating is employed by a brokerage firm. Occasionally, when the distinction is important, we refer to "strong buy" and "buy" ratings separately. Three-tier brokerages do not use the strong buy rating.

showcase their top pick selections, and product marketing teams periodically update investors about the performance of top pick selections through regular publications.

To further highlight the distinction between top picks and typical analyst recommendations, consider the following example. On December 17, 2012, an analyst from Barclays announced Penn National Gaming (henceforth, Penn) as her top pick for 2013 without changing or reiterating her recommendation, target price or EPS forecasts. The main investment thesis behind her top pick designation included Penn's conversion into a REIT structure to result in a higher trading multiple and Penn's robust dividend payout policy to attract both REIT and gaming operator investors. At the time of this top pick announcement, the analyst's coverage portfolio consisted of eight firms, including Boyd Gaming, Las Vegas Sands, Pinnacle Entertainment, Caesars Entertainment, MGM resorts, International Game Technology, Wynn Resorts and Penn, with five out of the eight coverage stocks holding a buy rating. According to Barclays, a top pick represents "the single best alpha-generating investment idea within each industry and is taken from among the Overweight-rated stocks within that industry". IBES does not record this top pick designation, or any others.

We start by documenting a number of facts regarding top picks. To begin with, top picks are increasingly common in the period following the regulatory changes of 2002. In 2000, before the reforms, only 5 firms are designated as top picks. In the year after the Global Analyst Research Settlement, there are 49 top picks. The number of top pick stocks continues to exhibit a steep upward trend in the years immediately following the Settlement. On average, from 2005 to 2016, there are 267 top picks every year. When we differentiate brokers based on their stock rating scales, we find that the vast majority of top picks are generated by brokers that switched from a five-tier to a coarser three-tier rating system following the new regulations.[2] Given that more than 50% of coverage stocks continue to be assigned a buy rating by sell-side analysts in the post-Global

[2]An important motivation behind the change in rating scales is Rule 2711 that requires brokers to disclose the percentage of stocks assigned buy, hold/neutral and sell recommendations in their coverage in each report (Kadan et al., 2009). Rule 2711 intends to help investors make better assessments of a broker's research and also curb analysts' strategic forecasting behavior.

Settlement period, we interpret these results as brokers attempting to increase information granularity and, potentially, strategic discretion, under a three-tier coarser rating system.

We find strong evidence that the top pick designation draws significant attention to a stock. We measure the attention of retail (institutional) investors by the Google Search Volume Index (Bloomberg search activity) and document that both retail and institutional investors devote more attention to announcements of top picks relative to that of buy recommendations in the same industry or in the same analyst's coverage universe. We next examine whether increased investor attention extends to the financial press and find more pronounced press coverage of top picks. In economic terms, 48% of top picks receive media coverage during the [0, +5] event window surrounding their announcements compared to only 25% (30%) for industry-year (analyst-year) matched buy recommendations. Furthermore, top picks are discussed in about three times as many financial news articles relative to buy recommendations.

Given the investor and media attention captured by top picks, we next seek to understand the potential motives underlying analysts' choice of top picks. The analyst could simply select a top pick with the intent of giving her best investment advice to investors. If this were the case, we expect top picks to be credible to investors if they believe that the analyst is skilled, so that they act on the recommendation and it has investment value. However, the exceptional stock distinction and greater attention-grabbing nature of top picks may potentially tempt an analyst to use the designation to pursue strategic objectives such as selecting a current or potential investment banking client as her top pick. This could potentially explain why we find that an investment bank affiliated stock, defined as the stock of a firm which used the investment bank for an IPO or a common stock issued over the last two years, is almost twice as likely to be designated as a top pick compared to unaffiliated stocks. If a stock is designated as a top pick for strategic reasons, the choice could have low investment value.

Diminishing potential concerns about strategic motives for top pick designations, we find strong evidence that these designations have investment value on average. For instance, a calendar-time portfolio comprised only of analysts' top picks earns roughly 1.33% characteristic-adjusted monthly returns (17.18% in annual terms) compared to only about 0.51% (6.29% in annual terms) for buy recommendations of the same analyst in a given year. In addition, the top picks' outperformance extends to buy recommendations issued in the same industry by other analysts. The evidence suggests that analysts exhibit skill in identifying their highest conviction best ideas and that strategic motives are unlikely to be important for an average top pick in that investors gain from following the investment advice. Conversely, consistent with Barber, Lehavy, McNichols, and Trueman (2001) and Altinkilic, Hansen, and Ye (2016), there is only weak evidence that buy recommendations have investment value for investors who take a position shortly after the announcement. Therefore, unlike their stock recommendations, sell-side analysts exhibit consistent long-term stock picking ability with their top picks, on average.

The investment value results show that analysts, on average, exhibit skill in designating top picks. However, not surprisingly, there is cross-sectional variation in the investment performance of top picks. In principle, the ex post poor performance of a top pick should be a surprise to investors if analysts are skilled and designate a stock as their top pick with high conviction. Hence, if poor performing top picks can be discerned when the designation is announced, it reflects either that the analyst making the designation lacks skill and is perceived as such by investors or that the analyst has skill on average but the designation is influenced by conflicts of interest. To identify top picks most (least) likely to reflect genuine best investment ideas, we separately focus on top picks in the top (bottom) quartile of ex post investment performance. We call top picks in the top (bottom) quartile good (bad) top picks. We find that bad top picks are more likely to be investment bank affiliated stocks. For these top picks, analysts do not expect significantly greater EPS and target price implied future stock returns. Therefore, the evidence is consistent with strategic objectives playing a role for a subset of top picks. However, if bad stock picks are designated to provide booster shots to investment banking clients, they do not appear to be helpful to these companies as the market is not fooled by such behavior. Specifically, we find that bad top picks are not associated with a significant positive stock price reaction. In sharp contrast, investment banking affiliation is not a significant predictor for good top picks but higher EPS forecasts and target price implied stock returns are. Moreover, good top picks are associated with significant positive stock price reactions.

We next turn our attention to trading behavior of financial market participants and examine whether institutional and retail investors value top picks and discern among bad and good top pick designations when they are announced. Examining institutional trading imbalances in the days around the top pick announcements with 286 million daily equity transactions obtained from *Ancerno Ltd.*, we find that institutional investors trade top picks at a greater intensity relative to stock recommendations, and seem to be able to discern whether a top pick is good or bad when it is announced. In economic terms, the average institutional buy-sell trading imbalance is 2.99% to 5.04% *higher* over the two-day event window surrounding the announcement of good top picks. In contrast, the average institutional trading imbalance is 3.5% to 4.7% *lower* over the same event window for bad top picks. Focusing on daily retail trading activity using Trade and Quote (TAQ), we document that retail trading imbalance is likewise greater for top picks relative to recommendations. However, unlike institutional investors, retail investors do not seem to distinguish among good and bad top picks.

Finally, we consider reputational and potential career implications of top picks for sell-side analysts. We uncover evidence suggesting that analysts pay a reputational cost for bad top picks. We find that the stock-price reaction to recommendation upgrades/downgrades by an analyst is lower in the year after the same analyst makes a bad top pick selection, consistent with the marketplace disciplining bad top pick selections. We also find that analysts that make bad top pick recommendations are more likely to be demoted to lower ranked brokerage houses. Further, analysts that make good top picks are more likely to be subsequently selected to the all-American team.

Our paper makes contributions to multiple segments of the literature focused on sell-side analysts and their outputs. First, we contribute to the vast body of analyst literature attempting to identify the most influential stock recommendations and sell-side analysts' stock picking skill based on a set of individual analyst or brokerage house characteristics (see, for instance, Stickel, 1992, Clement, 1999, Asquith, Mikhail, and Au, 2005, and Bae, Stulz, and Tan, 2008), stock-level abnormal returns, or the state of the economy (Loh and Stulz, 2018). In this paper, we take a novel approach and identify the most influential recommendations from the *analysts'* point of view. Our results suggest that top pick designations have to be considered when evaluating the role of analysts and their performance.

Second, we add to the literature that seeks to understand the implications of the regulatory environment on sell-side research and potential conflicts of interest emanating from investment banking business. Buy (hold/sell) stock recommendations have become less (more) common following the Global Analyst Research Settlement (e.g., Barber, Lehavy, McNichols, and Trueman, 2006, and Clarke, Khorana, Patel, and Rau, 2011) and there is evidence of a reduction in investment banking related strategic behavior (Corwin, Larocque and Stegemoller, 2017). Kadan et al., (2009) also show that most investment banks transition from a traditional five-tier rating system to a coarser three-tier rating system in the post-Settlement period. We add to this literature by documenting that regulations have been followed by a new "top pick" designation adopted by brokers transitioning to a coarser three-tier rating system. While this designation is valuable to investors on average, we cannot exclude that strategic concerns at times play a role in top pick designations in that top picks with poor investment value are more likely to be firms that are investment banking clients.

Third, we contribute to the literature that examines whether institutional investors can sort through Wall-Street research and discern among good and bad stock recommendations. For example, Malmendier and Shanthikumar (2007), Mikhail, Walther and Willis (2007) and others show institutions trade only good stock recommendations. In contrast, Busse, Green, and Jegadeesh (2012) fail to uncover empirical evidence that institutions can differentiate among analyst recommendations. Exploiting the unique and important laboratory provided by analyst' top picks, we revisit this important research question and document that institutions can distinguish between good and bad top picks when they are announced and trade more (less) actively when they believe that a top pick represents a good (bad) stock selection.

Fourth, we add to the literature pioneered by Hong, Kubik and Solomon (2000) and Hong and Kubik (2003) that examines the role of career concerns for analysts, how analysts are rewarded by investors and employers for their performance, and how their actions affect the credibility of recommendations and formation of their reputations. We use a novel setting that purportedly represents analyst's highest conviction best ideas. We find that analysts benefit from making good top pick choices, but they get punished in the labor market and suffer reputational consequences for making bad ones.

The paper proceeds as follows. Section 2 provides institutional background on top picks and describes our sample. Section 3 assesses the attention paid to top picks. Section 4 examines the characteristics of top pick selections. Section 5 measures the investment value of top picks. Section 6 sheds light on top pick motives and whether financial market participants can discern among good and bad top picks. Section 7 explores the career and reputational consequences of good and bad top pick designations for analysts. Section 8 concludes.

2. Institutional Background, Sample, and Summary Statistics

In 2002, the NYSE adopted Rule 472, NASD adopted Rule 2711, and ten of the largest US investment firms entered an enforcement agreement with the SEC, the NASD, and the NYSE to address investment banking related potential conflicts of interest concerning stock recommendations by sell-side analysts. Regulators believed that these conflicts of interest led analysts to make too optimistic stock recommendation decisions for strategic reasons, such as helping their firm's investment banking arm. Before these regulatory changes and enforcement actions, it was typical for analysts to use a five-tier system for their recommendations, where they had both buy and strong buy recommendations. After 2002, all sanctioned investment firms and most other brokerage houses transition to a three-tier system and investors lose the benefit of a more granular rating system (e.g., Kadan et al., 2009). Absent strategic forecasting behavior emanating from conflicts of interest, investors benefit more from a more granular stock rating system, at least up to a point. With a finer gradation, analysts can distinguish among stocks that they expect to perform well and stocks whose performance they expect to be even better. However, potential conflicts of interest may lead to situations where analysts issue strong buys for strategic reasons such as increasing the likelihood of their firms being hired as underwriters or providing booster shots to investment banking clients (see Mehran and Stulz, 2007, for a review of this literature). A three-tier rating system reduces the benefit to analysts from acting strategically.

After the Global Settlement, brokerage houses extensively use a top pick designation to distinguish their top stocks. A top pick is not a stock rating, but an optional designation and is distinct from buy recommendations along various dimensions. First, a top pick represents an analyst's "highest conviction best idea" among her coverage portfolio of stocks while a buy recommendation means, on average, a stock is expected to outperform its industry peers. In other words, although an analyst may have multiple buy recommended stocks, there can be at most only *one* top pick in an analyst's coverage portfolio in a given year. Further, while the vast majority of analysts have at least one buy recommended stock in their coverage universe, they issue top pick designations much less frequently. Second, a stock can typically have a top pick designation only for the upcoming one-year investment horizon and it typically expires on December 31st of the year a stock is given a top pick status for (unless reiterated or removed before its expiration). In contrast, buy recommendations extend over an unspecified investment horizon, and don't expire at the end of a calendar year with a sizable fraction being neglected (i.e., not dropped, revised or reiterated) by the analyst (e.g., Boulland, Ornthanalai, and Womack, 2017). Third, analysts generally announce top pick status for a coverage stock between November and February while buy recommendation announcements do not exhibit such time clustering across months. Our conversations with current sell-side equity analysts also indicate that analysts take the top pick selection process very seriously — they say that they commit a significant amount of time identifying top picks, the investment thesis, and the conviction behind the choice underlying their top picks. Further, analysts publicize top picks within their brokerage houses, present them to and interact with institutional investors during broker-sponsored "best idea" conferences, and draw attention to them with media appearances. Lastly, product marketing and equity research teams at brokerage houses periodically update investors about top pick stocks' performance with monthly/quarterly publications.

Traditional databases academics rely on (i.e., IBES) do not carry information about the top pick status of stocks covered by analysts. Therefore, following conversations with sell-side analysts currently employed at bulge bracket investment banks, we manually construct a comprehensive sample of top picks from Thomson *Reuters Investext* and *Thomson Reuters Eikon* by searching each full-text analyst report for discussions on the variants of "top pick & best idea."[3] Overall, we have a comprehensive sample of 3,563 top picks identified by 113 unique brokers over 1999-2016.

Table 1 provides yearly descriptive statistics for our sample. Corroborating Kadan et al., (2009), we find that there is a widespread transition to three-tier scale rating systems among brokerage houses after 2002. In 2001, 31.60% of brokers use a three-tier system and 14.60% of stocks are covered by three-tier brokers. These figures sharply increase to greater than 60% in 2003 and further exceed 70% from 2004 on. All ten original investment banks that signed the Global Settlement in 2002 (joined by Deutsche Bank and Thomas Weisel in 2004) transitioned to a coarser three-tier rating system shortly after.

Following the transition from a five-tier to a three-tier rating system, the potential gains to analysts from engaging in strategic behavior are sharply lower because receiving a "buy" recommendation is not in any way receiving an exceptional distinction. However, investors lose the benefit from finer gradation in ratings due to the removal of strong buy ratings. While the distribution of buy rated stocks becomes more balanced after 2002, more than 50% of coverage stocks continue to be assigned a "buy" recommendation by three-tier brokers. If these gradations were valuable to investors or enabled analysts to act strategically, we expect them to resurface. Consistently, Panel B shows that the Global Analyst Research Settlement is followed by the emergence of, and the steady increase in the new top pick designation. The first column shows that there are only 17 top pick firms in total between the years 1999 and 2001. The number of top pick stocks, however, exhibits a steep upward trend in the years following the regulations enacted in 2002. In 2003, there are 49 top pick firms and this figure increases to 128 in 2004, and 200 in 2005. In the last six years of our sample period, there are at least 300 top picks identified by analysts each year.

[3] To finalize our list of bigram word combinations, we download and read 100 randomly identified analyst reports and summarize the way analysts discuss their top pick stocks. Our complete keyword list is (Top or Best) AND (idea or pick). Next, we download and manually verify each observation by reading the title, table of contents and full body of the report to ascertain a firm is explicitly assigned a top pick status. For the sake of being conservative, we purge any observation for which there is ambiguity on the top pick designation of a coverage firm. We collect information on the name of coverage firm designated as top pick, sell-side analyst and brokerage house authoring the report, date of the report, investment horizon (i.e., calendar year a stock is designated as top pick for) and expiration date of top pick status.

We distinguish brokerage houses by rating scales and find that the vast majority of top picks are generated by three-tier brokers following the market regulations aimed at curbing investment banking-related conflicts of interest. This is potentially consistent with three-tier brokers attempting to increase rating granularity or strategic discretion. Since each analyst can at most have one top pick (if any) in a given year, it is not surprising that top pick firms represent only 0.16% of buy rated stocks by three-tier brokers in 2003, reaching a peak of 1.86% in 2008. In contrast to a buy recommendation, a top pick designation is an exceptional distinction for a coverage stock.

Panel C examines how frequently top pick announcements overlap with announcements of stock recommendations in IBES. Only 7% of top picks are announced jointly with a recommendation change or a reiteration and 14.7% overlap with recommendation initiations. This lack of overlap suggests that we can directly isolate the association between top picks and financial market attention, investment value of analyst research, market reaction, and institutional/retail investors' trading behavior. In the remainder of our paper, we focus on top pick designations that do not overlap with stock recommendations.

In Panel D, we report the distribution of top pick announcements across months and find that more than two-thirds of top picks are announced in December, January, or February, and nearly 80% of top picks are issued between November and March. In untabulated analyses, we document that 81.21% of stocks keep their top pick designation only for one investment year or less while the remaining top picks (roughly 18%) keep their designations for another year or more.

3. Top Picks and Financial Market Attention

The clustering of top pick announcements around the turn of the year enables brokerages to implement top pick marketing strategies where they can publicize these top picks collectively. Brokerages devote considerable attention to publicizing their top pick selections. They do so through broker hosted investor conferences devoted to top picks as well as through media appearances. In this section, we investigate whether top picks capture the attention of investors and whether the attention to top picks by retail investors differs from that of institutional investors. We then show the extent to which the financial press covers top picks relative to buy recommendations.

3.1. Retail and Institutional Investor Attention.

To measure the attention of retail investors to top picks, we follow related work and focus on the average Google Search Volume Index (GSVI) (see, e.g., Da, Engelberg, and Gao, 2011, and Focke, Ruenzi and Ungeheuer, 2020) over the (0,+5) event window surrounding the announcement of analyst research outputs. We input each stock ticker in Google Trends and download daily GSVI from 2004 to 2016. As indicated by Da, Engelberg, and Gao (2011), this methodology follows the logic that people searching financial information in Google with a stock ticker are more likely to represent retail investors as opposed to institutional investors since the latter group of investors typically use Bloomberg terminals for financial research purposes. In an attempt to make the data collection and screening process more manageable, we restrict our analysis to S&P 500 firms. We further measure the surge in retail investor attention with normalized GSVI. To do so, we calculate an abnormal retail attention (AGSVI) measure that subtracts the median value of GSVI over the eight weeks preceding the announcement of a corresponding analyst research output from the raw level of GSVI.

To measure institutional investors' attention, we measure their search activity on Bloomberg terminals. This approach is originally introduced by Ben-Rephael, Da, and Israelsen (2017) and is employed by a growing strand of academic literature (e.g., Focke, Ruenzi and Ungeheuer, 2020, and Gibbon, Illiev and Kalodimos, 2020). Bloomberg records the number of times users actively search for and read news articles on a specific stock and assigns a score of 1, 2, 3 or 4 if the average is between the 80th and 90th percentile, the 90th and 94th percentile, the 94th and 96th percentile, or exceeding the 96th percentile of the rolling average over the previous 30 days, respectively. Bloomberg also assigns a score of 0 if the average is less than the 80th percentile of the past 30 days' hourly counts. Consistent with Ben-Rephael, Da, and Israelsen (2017), we transform Bloomberg's score to continuous values with Bloomberg search scores taking the value of -0.350, 1.045, 1.409, 1.647 and

2.154, respectively. Similar to our retail attention measures, we restrict the institutional attention analysis to S&P 500 firms and calculate the average Bloomberg scores over [0,+5] relative to the announcement of analyst research.

As a starting point for our analysis, we compare the univariate differences of retail and institutional investor attention across top picks and buy recommendations issued for stocks within the same industry in the same year. Industries are classified using 4-digit Global Industry Classification Standard (GICS) codes. Boni and Womack (2006) indicate that GICS industry codes match well with sell-side industry research practice. Comparison of top picks to buy recommendations issued in the same industry in the same year further ensures that any difference in the attention to top picks and buy recommendations is unlikely to be driven by economic conditions specific to a given industry in a given year.

Panel A of Table 2 presents the univariate analyses. We find that retail and institutional investors appear to devote more attention to the announcement of top pick designations relative to that of buy recommendations. A plausible concern with these univariate comparisons is that market participants may focus on a subset of analysts and devote more attention to their research irrespective of its content. If top picks are more likely to be generated by attention-grabbing analysts, then our univariate inferences may potentially be biased. Therefore, Panel B of Table 2 compares investor attention devoted to analysts' top picks to the *same* analyst's buy recommendations in the *same* year. Our inferences remain similar.

In Panel C of Table 2, we employ panel regressions that regress GSVI, AGSVI, and Bloomberg search measures on a battery of analyst and firm specific covariates. We include a broad set of firm, analyst, and forecast-level characteristics that may also be correlated with retail and institutional attention. Our independent covariates include proxies for analyst forecasting ability including firm-specific and general forecasting experience, portfolio size and complexity, All-star status (*Fexp, Gexp, Portsize, Port Gics, All-Star*), forecast specific variables, including analyst effort (*Drop Coverage*), optimistic EPS forecasts relative to consensus estimates (*Relative EPS Optimism*), investment banking affiliation based on initial public/seasoned equity offerings (IPO or SEO) by coverage firm *i* in the past 24 months (*Investment Bank Affiliation*), and a binary indicator variable which equals one if the recommendation is rated a strong buy (*Strong Buy*). Moreover, we isolate brokerage house characteristics with the broker size and industry specialization (*Top 10, Broker ind specialization*). In terms of firm characteristics, we control for firm size (*Size*), book-to-market (*BM*), stock turnover (*Turnover*), institutional ownership (*Institutional holding*), number of analysts following the stock (*SSA coverage*), idiosyncratic volatility (*Idiosyncratic volatility*), earnings forecast dispersion (*Dispersion*), and past 12-month abnormal stock returns (*Past 12 m return*). Appendix A provides detailed information on the construction of variables. Finally, we include industry-year (or analyst-year) paired fixed effects and report heteroskedastic consistent standard errors clustered at the analyst and firm level. Formally, our model is as follows (we omit the time and stock subscripts):

$$\begin{aligned}&\textit{GSVI/AGVI/Bloomberg Search} - \beta_1 \textit{Top Pick} + \beta_2 \textit{Strong Buy} + \beta_3 \textit{Size} - \beta_4 \textit{BM} + \beta_5 \textit{Institutional Holding} \\ &+ \beta_6 \textit{Turnover} \quad \beta_7 \textit{SSA Coverage} \quad \beta_8 \textit{Idiosyncratic Volatility} + \beta_9 \textit{Dispersion} \quad \beta_{10} \textit{Past 12-m return} \quad \beta_{11} \\ &\textit{Fexp} \quad \beta_{12} \textit{Gexp} + \beta_{13} \textit{Portfolio Size} \quad \beta_{14} \textit{Portfolio GICS} \quad \beta_{15} \textit{Relative EPS Optimism} + \beta_{16} \textit{All-star} + \beta_{17} \\ &\textit{Drop Coverage} + \beta_{18} \textit{Top 10 Broker} - \beta_{19} \textit{Investment Bank Affiliation} - \beta_{20} \textit{Broker Industry Specialization} + \\ &\textit{Industry*Year Fixed Effects/Analyst*Year Fixed Effects} + \varepsilon \qquad (1)\end{aligned}$$

Models 1 and 2 of Panel C in Table 2 show that a top pick designation draws significantly higher raw and abnormal retail investor attention relative to buy recommendations in the same industry and year over [0,+5] days surrounding the announcement of analyst research. In Model 3, we repeat analogous analyses for institutional investors and find that analysts' top picks also attract higher abnormal attention from institutional investors. In the last three columns, we benchmark top picks against buy recommendations generated by the same analyst at the same point in time and continue to illustrate the relatively higher attention-grabbing nature of top picks. It is noteworthy that these regressions show that investors pay less attention to recommendations of analysts for coverage firms with which their investment bank arm has an affiliation. This suggests that both retail and institutional investors distinguish between stocks where there is a potential conflict of interest and others. Such a result suggests that strategic recommendations may face investor skepticism.

3.2. Financial Press Coverage

The results thus far show that financial market participants devote more attention to analysts' top picks than to their buy recommendations. We next examine whether increased attention extends to the financial press coverage.

To test this conjecture, we construct our sample of financial media coverage data from *RavenPack's Dow Jones Edition* that includes news articles from *Dow Jones Newswire* and *The Wall Street Journal*.[4] Our data screening process includes matching each top pick and recommendation announcement to a financial news piece and then manually checking each article's headline (using the information on the brokerage house's name and direction of research) to ascertain we have the correct news article. We focus on financial media articles published on days [0, +5] relative to the announcement of analyst research.[5]

Table 3 presents results for media attention to top picks. The first column of Panel A shows that roughly 48% of top picks receive media coverage during the [0, +5] event window surrounding top pick announcements. In contrast, the next column documents that approximately only one-fourth of buy recommendations sharing the same industry and year are covered by the financial press, a figure consistent with past studies (e.g., Ahn, Drake, Kyung and Stice, 2019). The difference is not only statistically significant but also economically meaningful (last column). More striking is the difference in the intensity of media coverage. The bottom row of Panel A shows that top picks are discussed in about three times as many news articles as buy recommendations (1.95 vs 0.66).

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[4] Dow Jones News and Ravenpack have been extensively employed in numerous finance studies such as, Barber and Odean (2007); Tetlock (2010); Ben-Rephael, Da and Israelsen (2017)

[5] Results are similar when we consider financial press coverage over shorter event windows (i.e., [0, +2]; [0, +3]; [0, +4]) or longer event windows (i.e., [0, +10]) surrounding the announcement of top picks. Results are available from authors upon request.

An important concern with our univariate analysis in Panel A is that the financial press tends to focus on a subset of "celebrity" analysts and devotes more news articles to such analysts' research in their news pieces (e.g., Bonner, Hugo and Walther, 2007). If top picks are issued by such celebrity analysts, then our univariate inferences may potentially be misleading. To alleviate this concern, Panel B compares financial press coverage devoted to top picks with that of buy recommendations by the same top pick issuing analyst at the same point in time. Our evidence supports a positive association between a stock's top pick status and coverage by the financial press.

In Panel C, we employ multivariate OLS regressions to test the hypothesis that top picks attract more media attention than buy recommendations. Our dependent variable is equal to the number of news articles devoted to a top pick designation or buy recommendation by analyst *i* at time *t*. Once again, since these characteristics may also be correlated with the intensity of financial press coverage, we include controls for the battery of firm- and analyst-level characteristics introduced in Section 3.1. Finally, we include industry-year or analyst-year paired fixed effects and report heteroskedastic consistent standard errors clustered at the analyst and firm level.

In Panel C of Table 3, the coefficient estimate on *Top Pick* is positive and statistically significant in Model 1 (*t*-statistic of 25.88). In economic terms, the announcement of analysts' top picks are associated with 1.14 more news articles by the financial press relative to that of buy recommendations. To put this result in perspective, All-star ranked analysts generate 0.13 more news pieces by the financial media. Other control variables also have expected signs. For instance, the financial media devotes more attention to research by sell-side analysts possessing longer firm-specific and general forecasting experience. In Model 2, we re-estimate our econometric specifications by focusing only on top pick issuing analysts with the inclusion of analyst-year paired fixed effects. Essentially, this setting compares press coverage on each analyst's top pick relative to buy recommendations in the same analyst's coverage portfolio within the same point in time. This methodology has the added benefit of isolating the time-varying analyst specific characteristics that may be also potentially correlated with financial media attention (including her celebrity status). The evidence again indicates top picks receive considerably higher media attention when compared to buy recommendations issued by the same analyst at the same year. While investors pay less attention to stock recommendations for affiliated stocks, there is no significant evidence that the media pays less attention to analyst research on such stocks.

Taken as a whole, the empirical evidence presented in Section 3 lends support to the notion that the top pick designation generates more pronounced attention by retail and institutional investors as well as the financial press. While these results may be a manifestation of the top pick designation being assigned non-strategically to represent analysts' genuine best ideas, and therefore perceived to convey more information than a buy recommendation, it is also plausible that analysts strategically assign top pick status to seek increased exposure and visibility for investment banking clients. Hence, in Section 4, we turn to examining the characteristics of top picks relative to buy recommendations.

4. Characteristics of Top Picks

To understand the potential underlying motives driving analysts' choice of top pick firms, we next examine how firm and forecasting characteristics differ between top picks and stocks with buy ratings. We estimate logistic regression models where the dependent variable is a binary indicator that equals one if stock *j* is assigned a top pick designation by analyst *i* for year *t*, and zero if a stock operates in the same industry, is rated buy in year *t*, and does not carry a top pick status. In addition to the host of firm specific characteristics introduced in Section 3.1, we further consider the forecasted stock return implied by analyst *i*'s target price (*%Target price implied return*) on stock *j*. Our logistic regressions include industry-year (or analyst-year) paired fixed effects and continues to report standard errors that are heteroskedastic consistent and double clustered at the analyst and firm level. Formally, our model is as follows (we omit the time and stock subscripts):

$$(\textit{Top Pick}=1) = \beta_1\,\textit{Size} + \beta_2\,\textit{BM} + \beta_3\,\textit{Institutional Holding} + \beta_4\,\textit{Turnover} + \beta_5\,\textit{SSA Coverage} + \beta_6\,\textit{Idiosyncratic Volatility} + \beta_7\textit{Dispersion} + \beta_8\textit{Past 12-m return} + \beta_9\textit{Investment Banking Affiliation} + \beta_{10}\,\textit{Relative EPS Optimism} + \beta_{11}\,\textit{Target Price Implied Return (\%)} + \beta_{12}\,\textit{Target Price Implied Return Rank \#1/\#2/\#3/\#4/\#5} + \textit{Industry*Year Fixed Effects/Analyst*Year Fixed Effects} + \varepsilon \qquad (2)$$

Model 1 of Table 4 compares top picks with buy recommendations and illustrates that top pick stocks tend to be relatively larger and are also more likely to be growth and momentum stocks as measured by the book-to-market ratio and the past 12-month returns. We further discover that top pick stocks are more visible to the investment community as evidenced by higher institutional ownership and more intense sell-side analyst coverage. Additional results indicate that the likelihood of a stock being identified as top pick is negatively associated with the level of uncertainty and diversity of opinion surrounding a stock as evidenced by lower idiosyncratic volatility and earnings forecast dispersion.

Focusing on analyst forecasts, the positive coefficient estimates on relative EPS optimism and target price implied returns are consistent with analysts expecting higher EPS and stock return performance from top picks compared to buy recommendations. For example, a one standard deviation increase in relative EPS optimism (%target price implied returns) increases the odds of a stock being designated top pick by 12.74% (21.63%) relative to buy recommended stocks without a top pick designation. Interestingly, we also uncover empirical evidence pointing to potential investment banking related "strategic bias" underlying the selection of top pick stocks — analysts are more likely to select investment banking clients as their top picks and the economic significance of investment banking affiliation on top pick selection is substantial. Specifically, investment bank affiliated stocks are associated with 97.56% higher likelihood of being designated as top picks relative to unaffiliated stocks. In unreported analyses, we consider alternative definitions of investment banking affiliation and continue to find similar results.[6]

In Models 2 and 3, we focus only on analysts issuing at least one top pick and re-estimate logistic regressions with the inclusion of analyst-year paired fixed effects. That is, we compare the attributes of top pick

[6] Untabulated analyses consider alternative definitions of investment banking affiliation by focusing on IPOs or SEOs underwritten by analyst's investment banking units six or twelve months preceding the announcement of analyst research. The results are similar and available upon request.

stocks to buy recommendations generated by the same analyst in the same year. Again, our main inferences remain unchanged — top picks look different from buy recommendations within an analyst's portfolio.

A top pick designation would be uninformative if all that an analyst does is select the stock with the highest expected price appreciation as her top pick. To examine this possibility, Model 3 includes a binary indicator variable for the ranking of the stock's target price implied percentage return (i.e., highest rank of 1, 2, 3, 4, and 5) relative to other buy-rated stocks in the same analyst's coverage universe in the same year. While stocks with the highest target price implied returns are more likely to be selected as top picks relative to other buy rated stocks in an analyst's portfolios, the coefficient estimate for stocks with the highest target price implied returns (i.e., rank 1) is not significantly larger than for stocks ranked 2, 3, and 4 This is consistent with the interpretation that analysts do not simply follow a mechanical rule of selecting stocks with the highest target price implied stock returns as their top picks, but instead, take into account other considerations when identifying their highest conviction best ideas. These other considerations may be influenced by potential conflicts of interest, and if they are, we would expect top picks to have poor investment value. We investigate investment value next.

5. Investment Value of Top Picks

If stocks are given a top pick status for strategic reasons such as providing a booster shot to investment banking clients, or helping the investment banking arm win future mandates, or capturing financial market attention and publicity for a favored firm, then we would not expect stocks with top pick status to outperform buy recommended stocks. On the other hand, if analysts confer top pick status on stocks for which they have the highest conviction with regards to superior future performance and analysts possess stock picking skills in identifying top picks, then we expect top pick status to be informative for future returns.

As a first step towards providing answers to this question, we employ an investor-oriented calendar-time portfolio approach. We follow Barber, Lehavy, McNichols and Trueman (2006) and construct a portfolio comprised of top picks and a portfolio comprised of industry-year matched buy/strong buy recommendations, but without a top pick designation. For the investment portfolio of top picks, we start by identifying the announcement date of a top pick designation and then skip a trading day before inclusion into the portfolio to ensure the information on top picks is publicly available to all market participants. For instance, if a stock is announced as a 2016 top pick on January 3rd of 2016, the stock enters the top pick portfolio on January 4th and exits the calendar-time portfolio on December 31st of 2016 (unless reiterated for the next year or the analyst removes the top pick designation before December 31st of 2016). We rebalance top pick portfolios on a daily basis when a new top pick is announced or current top pick designation expires, is reiterated, or removed before its expiration. For the portfolios of buy recommendations, we follow an analogous methodology with the exception of expiration dates. As indicated earlier, stock recommendations do not expire at the end of a calendar year nor do they have an investment horizon. To understand the investment value of top picks relative to buy recommendations, we calculate portfolio excess stock returns with a multitude of characteristic and risk adjustments, including Daniel, Grinblatt, Titman and Wermers (1997)'s (henceforth DGTW) characteristic-adjusted returns, risk-adjusted portfolio returns from the Fama and French (1993) three-factor model (*3-Factor alpha*), the Carhart (1997) momentum factor model (*4-Factor alpha)*, the Pastor and Stambaugh (2003) liquidity factor model (*5-Factor alpha)* as well as Fama-French's short-term and long-term reversal factor models (*6-* and *7-Factor alpha)*.

Panel A of Table 5 presents the results. Comparing excess stock returns accrued to top picks with those to buy stock recommendations generated by the *same* analyst during the *same* year, we find that a calendar-time investment portfolio comprised only of analysts' top picks generates DGTW-adjusted monthly returns of 1.33% (17.18% in annual terms). Buy recommendations, on the other hand, yield only about 0.51% DGTW-adjusted returns on a monthly basis (6.29% in annual terms). The difference is not only statistically significant at conventional levels (*t*-statistic for the difference is 3.25), but also economically important. These results are likewise robust to measuring excess stock returns using the factor models listed in the previous paragraph. Therefore, it appears that analysts' top picks carry significantly greater investment value for financial market participants than buy stock recommendations issued by the same analysts.

In Panel B, we investigate whether top picks' outperformance extends to stock recommendations outstanding in the same industry during the same calendar year (excluding recommendations of top pick analyst). As discussed earlier, analysts characterize top picks as representing their highest conviction "best idea" among the stocks they cover. We expect top picks to outperform same industry-year buy/strong buy recommendations issued by *other* analysts only if top picks also represent the best ideas in a given industry. If so, one should consider a stock's top pick designation when analyzing the information content of *all* stock recommendations, not just the recommendations generated by the top pick analysts. Panel B presents the results. Consistent with top picks representing the best stock investment ideas in an industry, the last column shows that DGTW-adjusted monthly returns accrued to top pick stocks are 90 basis points higher relative to that of positive recommendations in the same industry and year (t-statistic for the difference is 4.17). The remaining rows show that the magnitude of differences between top picks and same industry-year buy/strong buy recommendations is even larger, ranging between 110 and 120 basis points when using risk adjustments of the Fama and French (1993) three-factor model (*3-Factor alpha)* and when we add to that model, in succession, the Carhart (1997) momentum factor (*4-Factor alpha)*, the Pastor and Stambaugh (2003) liquidity factor (*5-Factor alpha)*, the Fama-French short-term reversal factor (*6-Factor alpha)*, and the long-term reversal factor (*7-Factor alpha).* In untabulated analyses, we further stratify buy stock recommendations into strong buys and buys and document results with comparable economic magnitudes to those in Panel B.

A logical concern with the analyses in Panel B of Table 5 is that analysts identifying top picks may possess superior stock picking skills relative to analysts not issuing top picks so that our results may be biased by the differences across analysts' forecasting ability. To alleviate this concern, Appendix Table A1 compares buy recommendations of analysts who use the top pick designation with industry-year matched buy recommendations of analysts who do not use the designation. The return differences range between 8 and 24 basis points per month depending on characteristic and risk adjustments – however, none of the differences are statistically significant at conventional levels.

Another concern with analyses in Panels A and B is that elevated financial market attention accompanying the announcement of top pick stocks may prompt investors to buy such stocks at a greater propensity relative to recommendations (see Barber and Odean, 2008, for evidence that elevated financial market attention leads to more trading). If so, temporary short-term buying pressure may potentially bias our estimates (especially in the short-term). To address this concern, Appendix Table A2 skips five trading days after the announcement of analyst research and buys the stock at day t+6 relative to the announcement date as opposed to day t+1. Excluding the days immediately after the announcement of a top pick does not change our inferences about the investment value of top pick designations compared to buy recommendations. For instance, characteristic-adjusted (*7-factor alpha*) monthly returns to top picks are roughly 106 (104) basis points after excluding [0, +5] event window surrounding the announcement of analyst research. Top picks also continue to outperform buy/strong buy recommendations issued in the same industry and year by between 80 and 114 basis points, depending on risk-adjustment. Though top picks have significant investment performance irrespective of how we measure excess stock returns, buy recommendations have significant investment performance only with the DGTW approach. This evidence suggests that if an investor starts investing in a top pick stock or a buy recommended stock five trading days after the announcement, there is strong evidence of investment performance for the top pick designation but almost no evidence of investment performance for buy recommendations, highlighting the importance of investors acting quickly to generate returns on analyst buy recommendations as suggested by Barber, Lehavy, McNichols and Trueman (2001) and Altinkilic, Hansen and Ye (2016).

In Table 6, we consider the panel regression methodology adopted by past related work (e.g., Cohen, Frazzini, and Malloy, 2010) to ensure our results are not driven by uncontrolled firm, analyst, and broker specific characteristics. While the dependent variable is the daily abnormal DGTW-adjusted return, we convert coefficient estimates into monthly returns for ease of interpretation. Analogous to the calendar-time portfolio methodology, we exclude the trading day of the top pick or buy recommendation announcement. Our key independent variable of interest is "Top Pick", which is an indicator variable equal to one if a stock j is given top pick status by analyst i for year t. Regressions include combinations of year-month, industry-year, and analyst-year fixed effects. The full regression specification (omitting time and firm subscript) is:

$$\begin{aligned}
&\textit{DGTW adjusted return} = \beta_1 \textit{Top Pick} + \beta_2 \textit{Strong Buy} + \beta_3 \textit{Size} + \beta_4 \textit{BM} + \beta_5 \textit{Institutional Holding} + \\
&\beta_6 \textit{Turnover} + \beta_7 \textit{SSA Coverage} + \beta_8 \textit{Idiosyncratic Volatility} + \beta_9 \textit{Dispersion} + \beta_{10} \textit{Past 12- m return} + \\
&\beta_{11} \textit{Fexp} + \beta_{12} \textit{Gexp} + \beta_{13} \textit{Portfolio Size} + \beta_{14} \textit{Portfolio GICS} + \beta_{15} \textit{Relative EPS Optimism} + \beta_{16} \textit{All-} \\
&\textit{star} + \beta_{17} \textit{Drop Coverage} + \beta_{18} \textit{Top 10 Broker} + \beta_{19} \textit{Investment Banking Affiliation} + \beta_{20} \textit{Broker Ind} \\
&\textit{Specialization} + \textit{Year-Month Fixed Effects} + \textit{Analyst*Year Fixed Effects/Industry*Year Fixed Effects} \\
&+ \varepsilon \qquad (3)
\end{aligned}$$

Model 1 of Table 6 reports regression results with analyst-year fixed effects. The coefficient estimate on *Top pick* is positive and significant, suggesting that top picks outperform buy recommendations issued by the same analyst during the same year. In Model 2, we include industry-year paired fixed effects to investigate whether top pick stocks' outperformance extends to industry-year matched buy/strong buy recommendations generated by *other* analysts. The positive coefficient estimate on *Top Pick* corroborates the earlier results. In economic terms, top pick stocks yield a higher monthly abnormal DGTW-adjusted return of 0.84 percentage points compared to industry-year matched stock recommendations of other analysts. Models 3 and 4 exclude stock returns between day t+1 and t+5 to mitigate the potential influence of heightened market attention on our coefficient estimates and re-estimates equation (3). Our results continue to be robust.

Overall, the empirical evidence from this section suggests that top pick stocks not only generate economically important and statistically significant abnormal returns, but they also outperform buy stock recommendations. Therefore, these findings are consistent with top picks, on average, reflecting analysts' genuinely best ideas and analysts possessing skill in identifying top picks.

6. Heterogeneity among Top Picks: Good and Bad Top Picks

Though top picks, on average, do not appear to be a manifestation of investment-banking related strategic forecasting behavior in the post-regulatory period, we examine in this section the heterogeneity in top pick stocks to better understand the motives underlying analysts' selection of top pick firms.

6.1 Characteristics of Good and Bad Top Pick Selections

To shed further light on whether some top picks are influenced by potential conflicts of interest, we identify best and worst top picks based on their ex post stock performance and examine how firm and forecasting characteristics vary across good and bad top pick selections. The fact that a top pick has poor investment performance could obviously be due to bad luck. Bad developments could occur at the top pick firm that the analyst could not possibly anticipate. However, if top picks are influenced by potential conflicts of interest, then the top picks with poor ex post investment performance, on average, should be more likely to be affected than the ones with good investment performance.

Specifically, we first rank each top pick annually based on its investment value relative to buy recommendations. Analyst *i's Top Pick j* is classified as a "*Good Top Pick*" in year *t* if the abnormal stock performance of *Top Pick j* (relative to buy rated stocks in analyst *i*'s portfolio in year *t*) falls under the highest quartile over its investment horizon compared to that of top picks by all analysts in year *t* for the same industry *j*. Abnormal stock outperformance accrued to a top pick designations and buy recommendations is measured with characteristics adjusted returns based on the calendar-time portfolio methodology used earlier. "*Bad Top Picks*" are identified analogously with the exception of having the lowest quartile ranking.[7]

To understand the characteristics of good and bad top picks, we re-estimate the logistic regressions introduced in Section 4, but now the dependent variable is a binary indicator that equals one if a stock is

[7] We also consider whether our results hold with alternative definitions of good and bad top picks including using top/bottom terciles and deciles (as opposed to quartiles) to identify good/bad top picks as well as using raw and risk-adjusted stock returns to measure stock outperformance (underperformance) of top picks (as opposed to DGTW) relative to buy recommendations. In each case, our inferences remain unchanged. Results are available from authors upon request.

designated as a *Good (*or *Bad) Top Pick* in year *t*. Model 1 of Table 7 in Panel A (B) compares the characteristics of good (bad) top picks to buy recommendations in the same industry-year, while Model 2 focuses on the differences between good/bad top picks and stocks with buy ratings by the same analyst in the same year.

Model 1 of Panel A finds that analysts expect higher EPS and target price implied stock returns for good top picks. In economic terms, a one standard deviation increase in relative EPS optimism (target price implied returns) increases the likelihood of a stock being classified as a *Good Top Pick* by 15.4% (14.94%) relative to buy recommendations. Contrary to the findings presented in Table 4, Model 1 of Panel A fails to find a statistically or economically important association between good top picks and investment banking affiliation. In Model 2, we compare good top picks to buy recommendations generated by the same analyst in the same year with the inclusion of analyst-year paired fixed effects and continue to find similar results. Other controls generally behave as in Table 4 — good top picks are more likely to be issued on larger firms with higher institutional ownership and lower uncertainty.

Panel B of Table 7 examines determinants of bad top picks. In sharp contrast to the results presented in Panel A, we find that underperforming top pick stocks are more likely to be affiliated with the investment banking arm of the top pick issuing analyst's brokerage house. Furthermore, analysts do not expect significantly higher EPS forecasts or target price implied returns for bad top pick selections relative to buy recommendations.

In sum, our results in this section help reconcile the evidence presented in Table 4 showing that top pick status is on average more likely to be designated on investment banking clients, potentially indicative of strategic forecasting behavior, and also more likely to be on stocks for which analysts anticipate higher EPS and target price implied stock performance, suggesting that on average top pick stocks are expected to perform well by analysts. The evidence in Table 7 illustrates that the subset of top picks that exhibit greatest outperformance are stocks that analysts are genuinely most optimistic about. In contrast, the subset of top picks exhibiting the worst future performance are stocks that are more likely to be investment banking affiliated stocks. We interpret these results as evidence that a subset of top picks might be more likely to perform poorly because they are chosen to further investment banking arms' interests rather than genuinely representing analysts' best ideas among their coverage universe. We therefore turn now to an investigation of whether the market and investors can distinguish between good and bad top picks to some extent.

6.2. Do Investors Distinguish between Good and Bad Top Picks?

In this section, we assess whether the financial markets can identify good and bad top picks when they are announced and whether investors trade good (bad) top picks more (less) actively.

6.2.1. Market Reaction

Our evidence up to this point suggests that top picks, on average, outperform buy recommendations; however, there exists a subset of underperforming top picks that are more likely to be generated on the basis of strategic considerations. Top pick implications for investors at least partly hinge on their ability to discern top picks reflecting strategic considerations from genuine best ideas of skilled analysts. In this section, we shift our attention to how the market and investors react to top picks and whether they distinguish between good and bad top picks.

As a starting point, we investigate whether the stock price reaction to the announcement of top picks differs between good and bad top picks. Towards this end, we distinguish between good and bad top picks where best (worst) top picks are, as before, those that exhibit the best (worst) ex post investment performance *excluding* the [0,+1] event window. We then compare cumulative CRSP VW-Index adjusted returns (i.e., CAR) over the [0,+1] event window surrounding the announcement of good and bad top picks. In untabulated analyses, we find that the [0,+1] event window CARs for good top picks is 2.37% with a t-statistic of 6.69. In contrast, the CAR for bad top picks is 0.55% with a t-statistic of 1.13 over the same event window. It follows from this that good top picks have a strong positive stock-price reaction while bad top picks have an insignificant stock price reaction. Not surprisingly, the difference between the abnormal announcement returns of good and bad top picks is significant at the 1% level. Consequently, the market appears capable of distinguishing between top picks when they are announced in such a way that the top picks that generate insignificant market reactions are the ones that subsequently have poor investment performance.

Next, we compare the market reaction to the announcement of good and bad top picks to that of buy recommendations in a multivariate setting. Towards this end, Table 8 re-estimates equation (3) using the cumulative abnormal CRSP VW-Index adjusted returns for the [0, +1] event window surrounding top pick and recommendation announcements as our dependent variable. Model 1 documents that market reactions to top picks are higher than market reactions to buy recommendations. This means that the announcement of top pick designations has an economically important and incremental price impact on stocks that already have a buy recommendation. Economically, top picks announcements generate 0.31% (0.21%) higher CARs over the two days surrounding the announcement window relative to buy recommendations announced in the same industry (by the same analyst) during the same year. To put this result in perspective, the market reaction to the announcement of buy recommendations by All-star analysts (analysts from Top 10 brokers) is 0.20% (0.32%) higher than the reaction to buy recommendations by non-stars (analysts from non-top 10 brokers). Therefore, the financial markets seem to place greater emphasis on top picks when they are announced and this association is economically important.

In Models 3 to 6, we distinguish between good and bad top picks. Our results from Models 3 and 4 suggest that market reactions to good top picks are higher relative to buy recommendations. More importantly, the market reaction to good top picks in Model 3 is higher than the market reaction to top picks in general in Model 1 by 0.63 percentage points. When we focus on bad top picks, however, we find that the market reaction to bad top pick announcements is *lower* compared to buy recommendations. For instance, Model 5 (6) indicates that the market reaction to a bad top pick announcement is roughly 1.20% (0.66%) lower compared to buy recommendations in the same industry-year (by the same analyst-year). Other control variables generally behave as expected. For instance, recommendations by analysts with higher general and firm specific forecasting experience, All-star status and those working at top 10 brokers generate higher market reactions.

Overall, the evidence from this section is consistent with the logic that financial market participants, on average, react more strongly to the announcement of top picks compared to stock recommendations and are also able to distinguish between good and bad top picks.

6.2.2. Institutional vs. Retail Trading Behavior

In light of the evidence provided in section 6.2.1, we next distinguish among financial market participants and investigate whether the trading behavior of institutional and retail investors exhibits asymmetries with respect to top picks as well as good versus bad top picks

Institutional investors represent the most important constituency for analyst research. The academic literature examines whether institutions can sort through Wall-Street research and discern good and bad stock recommendations; however, the evidence is mixed at best. For example, Malmendier and Shanthikumar (2007), Mikhail, Walther and Willis (2007) and others suggest institutions only act upon good stock recommendations and ignore uninformative ones. Conversely, Busse, Green, and Jegadeesh (2012) fail to find evidence of these investors possessing superior skills to analyze and discern among stock recommendations.

Analysts' top picks provide a unique and important laboratory to isolate institutional investors' ability to distinguish among analyst research outputs at least for three reasons: i) top picks capture substantial attention from institutions relative to stock recommendations, ii) analysts typically present top picks to institutional investors and interact with them at broker-hosted "best idea" conferences in an attempt to further discuss and clarify the investment theses and conviction behind their calls so that institutions potentially devote more time to understand sell-side analysts' top picks relative to stock recommendations, iii) while top picks, on average, have the potential to generate significant abnormal stock returns, we show that top pick selections with ex post poor performance are forecastable. Given the efforts made by analysts and brokerage houses to communicate and explain their top picks to institutional investors, we expect institutional investors to trade actively when stocks are designated as top picks. Furthermore, if institutional investors can distinguish between good and bap top picks when they are announced, they are likely to trade more (less) actively when they believe that a top pick is a good (bad) top pick. To test this conjecture, we rely on 286 million daily equity transactions executed by 886 unique funds over 2000 to 2014 period obtained from *Ancerno Ltd.* We calculate total institutional trading imbalance (i.e., institutional buy trading volume minus sell trading volume) over the [0, +1] event window surrounding the announcement date of top picks and buy recommendations.[8] Next, we repeat equation (3) but with the total institutional trading imbalance serving as our dependent variable.

Models 1 and 2 of Table 9 show the institutional buy-sell trading imbalance is significantly higher for top picks relative to buy recommendations. Model 1 (2) shows top picks are associated with 1.13% (1.27%) higher institutional trading imbalance compared to buy recommendations generated in the same industry (by the same analyst) for the same year. Given the average outperformance of top picks shown in Section 5, evidence is suggestive of top picks being beneficial to institutional investors.

Next, we distinguish between good and bad top picks. In Model 3 and 4, we find that the institutional trading imbalance is significantly higher for good top picks relative to buy recommendations. The positive coefficient on *Good Top Pick* in Model 3 (4) suggests that the institutional buy-sell trading imbalance is roughly 2.99% (5.04%) higher over the two days surrounding the announcement of good top picks. These coefficient estimates are roughly 2.5 to 4 times higher in economic terms relative to those obtained on the full sample of top picks (Models 1 and 2). Therefore, institutional investors appear to be able to discern best top picks and trade them at a higher intensity relative to not only buy recommendations but also an average top pick.

Model 5 (6) shows bad top picks are associated with significantly lower institutional trading imbalance compared to buy recommendations. For instance, the negative coefficient on bad top picks in Models 5 and 6 suggest that institutional trading imbalance is 3.5% to 4.7% lower over the two-day event window around the announcement of bad top picks. These results are economically important given the mean value of institutional trading imbalance in our sample is 1.08%. Overall, the results from Section 6.2.2 provide strong empirical

[8] Untabulated analyses consider trading imbalance over the alternative windows [0, +2], [0, +3], [0, +4], and [0, +5]. Our inferences from Tables 9 and 10 remain similar. These results are available from authors based on request.

support for the notion that institutional investors are more likely to act upon top picks, however, they are capable of discerning among good and bad top picks of sell-side analysts.

Finally, we turn our attention to retail traders. Unlike institutional investors, retail traders are typically less sophisticated and often have a relationship only with one investment advisor or broker. As such, it is potentially more difficult and costlier for retail traders to distinguish between good and bad analyst research.[9] In our context, we examine whether retail investors take all top picks at face value or discern among good and top picks. Examining this association is particularly relevant given the SEC warning advising retail investors to "do their homework before investing" in a company solely because of its "top pick" status.[10]

We identify retail trading from daily Trade and Quote (TAQ) data as in Boehmer, Jones, Zhang and Zhang (2019), Bushee, Cedergren and Michels (2020), and others. These papers take advantage of two institutional features of retail trading: i) the majority of stock trades by retail investors take place off-exchange (filled from broker's investors or sold to wholesalers) and are classified by TAQ using an exchange code "D", and ii) retail trades receive very small price improvements relative to the National Best Bid or Offer (ranging between 0.01 cents to 0.2 cents). Second, we identify transactions as retail purchases (sales) if a trade is executed just below (above) a round penny. To be conservative, we omit trades executed at a round penny or near half-penny. Finally, we define the retail order trading imbalance as the difference between retail purchases and sales for stock j at time t. We re-estimate equation (3) with total retail order imbalance over the [0, +1] event window serving as our dependent variable.

Consistent with the evidence presented for institutional investors, retail trades seem to exhibit more pronounced buying behavior around the announcement of top picks. For instance, the retail trading imbalance is 0.45% (1.57%) higher for top picks compared to buy recommendations in the same industry (by the same analyst). However, Table 10 suggests that retail investors cannot distinguish between good and bad top picks.

[9] This view is echoed by past academic research in the context of earnings surprises (Battalio and Mendenhall, 2005; Hirshleifer, Myers, Myers and Teoh, 2008) and stock recommendations (e.g. Malmendier and Shanthikumar, 2014).
[10] See SEC Investor Publication "Analyzing Analyst Recommendations", August 30, 2010.

Models 3 and 4 show that good top picks are associated with a *lower* retail trading imbalance relative to buy recommendations. In economic terms, the retail trading imbalance is roughly 1.5% to 1.8% *lower* following the announcement of good top picks relative to buy recommendations. Focusing on bad top picks, we likewise fail to find evidence that points to retail investors discerning bad top picks. In particular, unlike institutional investors, Models 5 and 6 show that the trading imbalance is not significantly lower for bad top picks relative to buy recommendations. Therefore, the trading on top picks by retail investors is mostly driven by top picks with relatively average ex post investment performance and these investors do not appear to discern between good and bad top picks.

7. Career and Reputational Consequences of Good and Bad Top Picks

So far, we have provided evidence that top pick designations receive significant attention from retail and institutional investors and the financial press, and that top picks outperform stock recommendations, on average. However, we also saw that not all top picks outperform, that bad top picks are more likely to be motivated by strategic bias than other top picks, and that institutional investors seem to be able to distinguish good top picks from bad ones. The obvious question is whether analysts who make bad picks suffer from doing so. Further, the attention-grabbing nature of top picks, coupled with these research outputs representing analysts' single best ideas, suggests that market participants are likely to infer an analyst's forecasting skill from the performance of their top picks. As such, we expect bad top picks to affect an analyst's career adversely and good top picks to help it. Further, it seems likely that bad top picks would reduce an analyst's credibility with investors, so that her future stock recommendations would receive less weight from them.

We first investigate whether analyst career outcomes relate to top picks. Analyst i is classified as a "*Good Top Picker*" if she is associated with a good top pick selection in year t as defined in Section 6.1."*Bad Top Picker*" analysts are identified analogously with the exception of being associated with a bad top pick selection in year t. Following the literature (Mikhail, Walther, and Willis, 1999; Hong, Kubik, and Solomon, 2000; Hong and Kubik, 2003), we assume an analyst experiences a positive career advancement if she moves from a lower status broker to a higher status one. Conversely, a negative career move is defined as moving from a higher to a lower status brokerage house. We follow Hong, Kubik, and Solomon (2000) and use the number of analysts employed by a broker k in year t to define high versus low status. An analyst movement is defined as a promotion if analyst i moves from a non-top 10 decile broker to a top 10 decile broker in year t+1.[11] Because analysts working for the highest decile brokers cannot move up, they are excluded from the analyses focusing on promotions. In a similar vein, an analyst move is defined as a demotion if analyst i moves from a top 10 broker to a non-top 10 broker in year t+1. If analyst i stops producing research in year t+1, we classify this analyst as having left the profession and exclude such analysts from promotion and demotion analyses.[12] Next, we estimate logistic regressions with a binary dependent variable that equals one if analyst i experiences demotion (or promotion) in year t+1, zero otherwise. The primary variables of interest are binary indicators that represent whether an analyst i designated a stock as a top pick in year t (*Top Pick Analyst*) and issued an over or underperforming top Pick (*Good/Bad Top Picker)* in year t, and zero otherwise. We further include a comprehensive set of analyst specific characteristics introduced in equation (1) along with an independent variable that captures the average investment value of buy recommendations issued by analyst i at year t (*Average Buy Rec Ret).* Standard errors are heteroskedasticity-consistent and double-clustered at the analyst and year levels. Formally, our econometric model (omitting time and analyst subscript) is as follows:

$$(Demotion/Promotion=1) = \beta_1\, Top\ Pick\ Analyst/Bad\ Top\ Picker/Good\ Top\ Picker + \beta_2\, Average\ Size\ in\ Portfolio + \beta_3\, Average\ BM\ in\ Portfolio + \beta_4\, Gexp + \beta_5\, Average\ Fexp + \beta_6\, Portfolio\ Size + \beta_7\, Portfolio\ Gics$$

[11] Further analyses consider a multinomial ordered logit model with three levels of dependent variable (1=promotion, 0=no job change, -1=demotion) and find consistent results. We also re-define analyst promotions or demotions based on movements from a lower to higher decile brokerage house and uncover robust results. However, one important shortcoming is that it is not completely clear whether an analyst move from a 7th decile broker to an 8th decile broker represents a significant promotion or if an 8th decile to 7th decile move represents a significant demotion.

[12] The evidence on analysts leaving the profession is mixed: Hong, Kubik and Solomon (2000) and Hong and Kubik (2003) argue that sell-side analysts leaving the profession are unlikely to obtain better jobs. Using hand-collected data from LinkedIn, Cen, Ornthanalai, Schiller (2011) find that 40% of analysts exiting sell-side research find immediate employment at buy-side institutions. Therefore, analysts who stop producing research at year t+1 are excluded from our analyses on demotions/promotions.

$+ \beta_8$ *Broker Ind. specialization* + β_9 *All-Star (t-1)* + β_{10} *Average Buy Rec Return* + β_{11} *Investment Bank Affiliation* + β_{12} *Average Relative EPS Optimism* + β_{13} *Average Report count* + β_{14} *Average Drop Coverage* + β_{15} *Average PMAFE* + β_{16} *Average Institutional Holding in Portfolio* + β_{17} *Average Turnover in Portfolio* + β_{18} *Average Dispersion in Portfolio* + *Year Fixed Effects* + ε *(4)*

Panel A of Table 11 presents results for demotions and shows top-pick-issuing analysts do not have significantly different rates of demotion compared to other analysts. Distinguishing among analysts based on the performance of their top picks, Model 2 of Panel A shows that bad top pickers are associated with an increased likelihood of demotion in the following year. Economically, the likelihood of demotion is roughly two times higher for analysts issuing bad top picks. To put this finding in perspective, all-star analysts are 55% less likely to be demoted. In contrast, the coefficient estimate on *Good Top Picker* implies that such analysts have a lower propensity to be demoted (albeit statistically insignificant). Interestingly, we fail to find evidence that negative career developments are related to the investment value of buy recommendations. In Models 3 and 4, we re-estimate logistic regressions after focusing only on a subset of analysts moving across brokers (i.e. exclude analysts who do not change jobs at year *t*+1). Our results continue to illustrate that bad top picks translate into negative career moves (*t*-statistic of 3.31). Further, analysts identifying good top picks are significantly less likely to be demoted (*t*-statistic of 2.35). Models 5-8 of Panel B in Table 11 fail to find any significant association between the issuance or performance of top picks and analysts moving up to higher status brokers. Therefore, it appears there are asymmetric career consequences to top picks, and rewards and punishments for identifying good and bad top pick stocks seem to be confined to demotions.

As an alternative way of investigating career implications of top picks, we further consider analysts' election to the Institutional Investor All-Star team roster. To the extent that institutional investors pay attention to top picks, they may also consider top picks' performance when they cast votes for All-star analysts. Anecdotal evidence also corroborates this view – narratives accompanying All-star analysts' profiles in the October issue of Institutional Investor Magazine (IIM) explicitly focuses on institutional investors' discussions of elected analysts' top picks. To test this question, Table 12 re-estimates equation (4) with the dependent variable taking the form of a binary variable that equals one if the analyst is selected to the all-star roster in year t+1, zero otherwise. Model 1 shows top-pick issuing analysts are, on average, more likely to be named to IIM's All-Star team. In Model 2, we find good top picks positively influence an analyst's odds of being selected into the All-Star roster. The odds of becoming an all-star analyst are 107% incrementally higher for good top pickers after explicitly controlling for other factors documented in the literature. Similarly, bad top pickers are associated with a lower probability of becoming an All-star. The coefficient on Bad Top Pickers is economically important, however, it lacks statistical significance at conventional levels (t-statistic of 0.89).

Top picks are highly publicized in the financial markets. While a good top pick may help an analyst gain reputation, a bad top pick may result in reputational loss. If so, the investment value of top picks may affect investors' perception of a sell-side analyst's forecasting skill, resulting in stronger (weaker) market reactions to the *same* analyst's research on *non-top pick* firms. Note that this spillover is conditional on investors evaluating top picks and extrapolating an analyst's stock picking skill based on the performance of her best ideas. To shed light on this conjecture, Table 13 examines the association between top picks and the stock price reaction to recommendation revisions generated by the same analyst. Because analyst upgrades and downgrades convey opposite signals, Models 1-4 focus on recommendation upgrades while Models 5-8 repeat the analysis for downgrades.

In Models 1 and 5, we do not find evidence that top-pick-issuing analysts are associated with greater price impact for upgrades or downgrades. However, Models 2 and 6 provide suggestive evidence of reputational consequences of top picks for analysts. Stock market reactions to recommendation upgrades (downgrades) are 73 (92) basis points lower (higher) for bad top-pick issuing analysts after controlling for a battery of analyst, firm and broker specific characteristics along with the direction and magnitude of underlying recommendation revision. Other controls generally have expected signs—recommendation revisions by all-star analysts elicit more pronounced market reactions, so do revisions from analysts employed at larger brokerage houses.

Interestingly, while signed correctly, good top picks do not appear to translate into statistically significant reputational gains.

Overall, the evidence points to bad top picks being costly to sell-side analysts' careers in the form of demotions and reputational loss with investors, while good top picks are rewarded through promotions to higher status brokers and selections into IIM's All-star roster. These findings help us improve our understanding of how analysts gain and lose reputational capital in the labor and financial markets.

8. Conclusion

In this paper, we show that analysts make frequent use of the top pick designation after the regulatory changes and the Global Analyst Research Settlement of 2002. Shortly after the regulatory changes, many brokerage houses move to a three-tier rating system that reduces the granularity of the information provided to investors compared to the five-tier system prevalent before 2002. The top pick designation enables analysts to provide greater granularity of information to investors within the three-tier rating system. It is used to highlight the stock about which analysts have the highest conviction of best performance. We find that, on average, this designation has investment value for investors. It is also a designation that attracts much interest from institutional and retail investors as well as from the media. This level of attention may not be surprising since brokerages invest resources to publicize their top picks both through the media and through broker-hosted top pick conferences. We show that both institutional investors and retail investors trade in response to a stock receiving such designation.

The obvious issue with granularity of information is that it makes it possible for analysts to draw attention to specific stocks in a way that can be highly valuable to the firms that receive that attention. Analysts might therefore be tempted to use top designation to pursue objectives other than giving the best investment advice to investors. The three-tier system is largely viewed as a way to reduce the value of this discretion for analysts. Absent the temptation of analysts to use a valuable designation to pursue objectives that are not in the interest of investors, greater granularity is generally valuable to investors – at least up to a point. We investigate whether analysts use the top pick designation strategically. We find that on average they do not in that investors gain from following their advice. Not all top picks have superior investment performance. When we focus on the top picks with poor investment performance, we find that they are more likely to be designated for companies that are investment banking clients. However, the market is not fooled by potentially strategic top pick choices. The market reacts favorably to top pick designations in general, but not to those that are subsequently followed by poor performance. We also find that top pick designations that subsequently have poor investment performance affect institutional investors' trading less when they are announced. Finally, we find that analysts who have poor top pick designations suffer career consequences and their credibility is hurt. These findings suggest that the use of top pick designations help investors on average and that the marketplace disciplines analysts issuing bad top picks.

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Appendix A. Variable Descriptions

Variable	Definition
Top Pick	Indicator variable is one if analyst *i* assigns a top pick designation to stock *j* at time *t*, and zero otherwise. Information on Top Picks is manually obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*.
GSVI	Google Search Volume Index (GSVI) over the [0, +5] event window surrounding the announcement of analyst research on stock *j*. GSVI data is from 2004 to 2016 on S&P 500 firms.
AGSVI	Abnormal Google Search Volume Index (AGSVI) over the [0, +5] event window surrounding the announcement of analyst research on stock *j* calculated as GSVI minus the median value of GSVI over eight weeks preceding the announcement of a corresponding analyst research. GSVI data is from 2004 to 2016 on S&P 500 firms.
Bloomberg Search	Search activity on Bloomberg terminals over the [0, +5] event window surrounding the announcement of analyst research on stock *j*. Bloomberg scores of 0, 1, 2, 3 or 4 are transformed to continuous values with Bloomberg search scores taking the value of -0.350, 1.045, 1.409, 1.647 and 2.154, respectively. Bloomberg search activity data is from February 2010 to December 2016 on S&P 500 firms
% Financial Press Coverage	% of top picks/stock recommendations with financial media articles published on days [0, +5] relative to the announcement of analyst research. Financial media coverage data is from *RavenPack's Dow Jones Edition* that includes financial press articles from *Dow Jones Newswire* and *The Wall Street Journal*
# Financial Press Articles	Number of financial media articles published on top picks/stock recommendations [0, +5] event window relative to the announcement of analyst research. Financial media coverage data is from *RavenPack's Dow Jones Edition* that includes financial press articles from *Dow Jones Newswire* and *The Wall Street Journal*
Strong Buy	Indicator variable is one if a stock *j* is rated as Strong buy at time *t*, zero otherwise.
Size	The natural log of market capitalization (Size) of firm *j* at time *t*-1. Information on Size is obtained *from CRSP*.
BM	The natural log of Book to Market (BM) ratio calculated as book value of total equity dividend by market value of total equity for firm *j* at time *t*-1. Information on BM *is* obtained from *CRSP/Compustat*.
Institutional Holding	The natural log of total % Institutional ownership of for firm *j* at time *t-1* as reported by WRDS.
Turnover	The natural log of the average stock daily turnover (i.e., share volume scaled by shares outstanding) over the past twelve-months for firm *j* at time *t*. Information on Turnover is obtained from *CRSP*.
SSA Coverage	The number of sell-side analysts covering firm *j* at time *t-1* as reported by I/B/E/S.
Idiosyncratic Volatility	The natural log of the standard deviation of residuals from a daily time-series regression of past twelve-month firm returns against market returns and Fama-French Size and BM factors for firm *j* at time *t*
Dispersion	Earnings forecast dispersion of past twelve-month for firm *j* at time *t* as reported by I/B/E/S.

Past 12-m return	CRSP Value Weighted-index-adjusted buy-and hold abnormal returns over 12 months for firm *j* at time *t*.
Fexp	The total number of years that analyst *i* has covered firm *j* at time *t in* I/B/E/S.
Gexp	The total number of years that analyst *i* has appeared in I/B/E/S at time *t*.
Portfolio size	The number of firms followed by analyst *i* at time *t* as reported by I/B/E/S.
Portfolio Gics	The number of 4 digit GICS industries followed by analyst *i* at time *t* as reported by I/B/E/S.
Relative EPS Optimism	Indicator variable is one if analyst *i*'s current earnings forecast on firm *j* is more optimistic than the median consensus earnings forecast for firm *j* at time *t (*as reported by I/B/E/S), zero otherwise.
All-star	Indicator variable is one if analyst *i* is named to *Institutional Investor's* All-star team at time *t*, and zero otherwise. Information on All-star analysts are retrieved from *Institutional Investor Magazine*.
Drop Coverage	Indicator variable is one if analyst *i* dropped coverage of firm *j* at time *t*+1 as reported by I/B/E/S, zero otherwise
Top 10	Indicator variable is one if analyst works for a top decile brokerage house (*Top10*) at time *t* where broker size is calculated based on the number of employed analysts. Information on brokerage houses are retrieved from I/B/E/S.
Investment Bank Affiliation	Indicator variable is one if investment banking arm of analyst *i*'s brokerage house was the underwriter of firm *j*'s Initial Public offering (IPO)/seasoned equity offering (SEO) over the past two years, zero otherwise. Information on IPO and SEOs are obtained from SDC Platinum.
Broker Ind Specialization	Percentage of analysts following firm *j*'s 4 digit GICS industry *k* from analyst *i*'s broker at time *t* as reported by I/B/E/S
% Target Price Implied Return	Implied 12 month buy and hold return based on the 12 month price target issued by analyst *i* on stock *j* at time t as reported by I/B/E/S.
Target Price Implied Return Rank	The relative rank of stock *j*'s target price implied return (*% Target Price Implied Return*) among all buy rated stocks by analyst *i* at time *t*
Good Top Pick	Analyst *i's* Top pick *j* is classified as a "*Good Top Pick*" at year *t* if the abnormal stock performance of *Top pick j* (relative to buy rated stocks in analyst *i*'s portfolio at year *t*) falls under the *highest* quartile over its investment horizon compared to that of top picks by all analysts at year *t* for the same industry *j*. Abnormal stock outperformance is defined with DGTW characteristics adjusted returns accrued to a top pick and buy recommendation based on calendar-time portfolio methodology.
Bad Top Pick	Analyst *i's* Top pick *j* is classified as a "*Bad Top Pick*" at year *t* if the abnormal stock performance of Top pick *j* (relative to buy rated stocks in analyst *i*'s portfolio at year *t*) falls under the *lowest* quartile over its investment horizon compared to that of top picks by all analysts at year *t* for the same industry *j*. Abnormal stock outperformance is defined with DGTW characteristics adjusted returns accrued to a top pick and buy recommendation based on calendar-time portfolio methodology.
Good Top Picker	Indicator variable is one if analyst *i* is associated with a "*Good Top Pick*" at year *t*, zero otherwise.
Bad Top Picker	Indicator variable is one if analyst *i* is associated with a "*Bad Top Pick*" at year *t*, zero otherwise.
Average Buy Rec return	The average calendar-time portfolio DGTW adjusted investment returns accrued to buy recommendations issued by analyst *i* at year *t*.

Analyst reports count	Number of all forecasts issued by analyst *i* on firm *j* in time *t* as reported by I/B/E/S.
PMAFE	The proportional mean absolute forecast error calculated as the difference between the absolute forecast error (*AFE*) for analyst *i* on firm *j* at time *t* and the mean absolute forecast error (*MAFE*) for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. Earnings forecasts are retrieved from I/B/E/S.
Revision	The magnitude of recommendation revision on stock *j* by analyst *i* at time *t* from previous recommendation level on stock *j* by analyst *i*.

Table 1. Sample Statistics

This table reports sample summary statistics over 1999-2016. Panel A presents summary statistics for the distribution of brokerage houses adopting 3-tier rating scales, stock coverage, and buy rated stocks from 3-tier brokerage houses. Panel B presents the distribution of top picks, number of brokerage houses issuing top picks, % of top picks generated by 3-tier brokers and % of buy rated stocks identified as a top pick at brokers with 3-tier rating scales. Panel C reports the distribution of top pick announcements across months. Panel D tabulates % overlap between the announcement of top picks and stock recommendations at I/B/E/S. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions.

Panel A. Distribution of 3-tier Brokerage houses

Year	No of Brokers with 3 Tier Ratings	% of IBES Brokers with 3 Tier Ratings	% of IBES Stocks covered by Brokers with 3 Tier Ratings	% Buy Rated Stocks at Brokers with 3 Tier Ratings
1999	104	35.99%	13.42%	75.10%
2000	103	35.52%	14.58%	73.01%
2001	79	31.60%	14.60%	68.06%
2002	89	34.90%	10.26%	63.60%
2003	195	61.13%	59.68%	50.47%
2004	235	66.76%	77.80%	51.03%
2005	237	67.14%	74.44%	52.58%
2006	232	71.17%	79.21%	50.87%
2007	222	72.79%	83.48%	54.83%
2008	229	74.84%	76.09%	51.61%
2009	238	73.68%	79.57%	52.12%
2010	282	80.11%	83.59%	57.20%
2011	250	78.37%	76.96%	58.05%
2012	247	76.71%	79.04%	53.11%
2013	228	73.55%	78.70%	53.04%
2014	249	78.55%	86.30%	57.95%
2015	259	81.45%	88.81%	54.93%
2016	231	75.24%	88.23%	49.38%

Panel B. Distribution of Top Picks

Year	No of Top Picks (N=3563)	No of Brokers issuing Top Picks	% of Top Picks by Brokers with 3 Tier Ratings	% Top Picks as of Buy Rated Stocks at Brokers with 3 Tier Ratings
1999	3	1	0.00%	0.00%
2000	5	3	0.00%	0.01%
2001	9	4	33.33%	0.04%
2002	29	10	72.41%	0.03%
2003	49	18	83.67%	0.16%
2004	128	32	93.75%	0.35%
2005	200	26	95.50%	0.36%
2006	193	29	88.08%	0.45%
2007	249	35	93.98%	0.78%
2008	196	30	94.90%	1.86%
2009	158	36	96.20%	0.50%
2010	240	43	98.75%	0.69%
2011	423	44	98.35%	1.36%
2012	376	44	96.54%	1.71%
2013	307	41	97.39%	1.42%
2014	330	53	97.88%	1.43%
2015	343	45	99.71%	1.26%
2016	325	47	98.46%	1.81%

Panel C: % Overlap between Top Pick and Stock Recommendation Announcement

Top Pick Coincides with Stock Coverage Initiations	Top Pick Coincides with Recommendation Upgrade	Top Pick Coincides with Recommendation Reiteration	Top Pick does not Coincide with any Recommendation Announcement
14.70%	3.54%	3.90%	81.13%

Panel D: Distribution of Top Pick Announcements Across Months

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
35.44%	15.59%	5.96%	4.30%	2.96%	3.31%	2.75%	1.87%	2.01%	3.21%	5.99%	16.61%

Table 2. Top Picks and Financial Market Attention: Retail vs Institutional Investors

This table presents average retail and institutional attention over (0, +5) event window following the announcement of top picks vs all buy recommendations issued i) in the same industry at the same year (i.e., industry-year matched) in Panel A, ii) by the same analysts at the same year (i.e., analyst-year matched) in Panel B. Panel C reports OLS regressions of average retail and institutional attention across top picks and buy recommendations. Retail attention is measured by average Google Search Volume Index (GSVI) and obtained from Google Trends from 2004 to 2016 for S&P 500 firms. Abenormal retail attention (Abnormal GSVI) subtracts the median value of GSVI over eight weeks preceding the announcement of a corresponding analyst research output from GSVI. Institutional attention is measured by institutional investors' search activity in Bloomberg terminals over 2011-2016 for S&P 500 firms. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Top picks vs Buy Recommendations (Industry-Year Matched)

Variable	Top Picks	Buy Recommendations	Difference
Mean GSVI [0, +5]	53.944***	46.176***	7.769***
	(66.62)	(126.80)	(8.91)
Mean Abnormal GSVI [0, +5]	6.797***	0.779***	6.019***
	(14.36)	(10.30)	(12.70)
Mean Bloomberg Search [0, +5]	1.135***	0.682***	0.453***
	(37.10)	(67.10)	(14.95)

Panel B: Top picks vs Buy Recommendations (Analyst-Year Matched)

Variable	Top Picks	Buy Recommendations	Difference
Mean GSVI [0, +5]	54.538***	46.455***	8.084***
	(46.32)	(41.83)	(5.21)
Mean Abnormal GSVI [0, +5]	5.949***	0.448	5.501***
	(10.17)	0.76)	(6.80)
Mean Bloomberg Search [0, +5]	1.130***	0.707***	0.406***
	(34.97)	(18.39)	(6.33)

Panel C. Top picks vs Buy Recommendations: Multivariate Analyses

	Top Picks vs Buy Recommendations (Industry-year matched)			Top Picks vs Buy Recommendations (Analyst-year matched)		
	GSVI	Abnormal GSVI	Bloomberg Search	GSVI	Abnormal GSVI	Bloomberg Search
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Top Pick	732.057***	631.538***	43.925***	766.787***	629.416***	42.856***
	(5.666)	(7.552)	(13.652)	(6.051)	(7.820)	(10.141)
Strong Buy	19.248	94.813	-3.116			
	(0.126)	(0.957)	(-1.256)			
Size	-51.621	3.978	23.001***	88.089	30.416	23.519***
	(-0.824)	(0.098)	(23.719)	(0.794)	(0.431)	(8.834)
BM	-642.075***	-251.122**	6.931**	4.484	-255.013	12.174
	(-4.068)	(-2.458)	(2.296)	(0.017)	(-1.524)	(1.458)
Institutional holding	-2780.044***	433.581	-21.079*	-1364.429	238.049	-0.763
	(-3.988)	(0.960)	(-1.737)	(-1.146)	(0.315)	(-0.023)
Turnover	88.285	-82.241	12.837***	134.722	86.016	26.422***
	(0.733)	(-1.054)	(6.185)	(0.618)	(0.621)	(4.506)
SSA coverage	-11.725**	1.244	0.389***	-21.218**	3.100	0.454*
	(-2.030)	(0.333)	(4.290)	(-2.201)	(0.506)	(1.791)
Idiosyncratic Volatility	-363.141*	131.415	16.342***	-215.045	173.769	-14.497
	(-1.819)	(1.016)	(5.111)	(-0.608)	(0.772)	(-1.553)
Dispersion	14199.249***	7823.525***	579.643***	9161.738**	8772.970***	538.898**
	(4.445)	(3.784)	(5.409)	(1.970)	(2.970)	(2.252)
Past 12-m return	-0.942	155.800**	0.004	-100.853	98.734	0.809
	(-0.813)	(2.076)	(0.193)	(-0.514)	(0.791)	(0.137)
Fexp	90.675***	0.103	0.376**	1.051***	0.023	0.010**
	(7.197)	(1.268)	(1.968)	(5.177)	(0.180)	(1.971)
Gexp	-32.602	-8.737	-0.085			
	(-0.956)	(-0.396)	(-0.604)			
Portfolio size	-16.930	-7.824	-0.169*			
	(-1.497)	(-1.069)	(-1.896)			
Portfolio Gics	86.056	45.744	-0.826**			
	(1.593)	(1.308)	(-2.459)			
Relative EPS Optimism	154.400*	97.392*	1.807	311.339**	139.830	6.262
	(1.835)	(1.786)	(1.115)	(2.104)	(1.487)	(1.517)
All-star	-265.633	108.695	0.993			
	(-1.140)	(0.721)	(0.452)			
Drop Coverage	18.594	1.190	0.474	372.055	367.581	-7.794
	(0.113)	(0.011)	(0.216)	(0.991)	(1.541)	(-0.721)
Top 10	318.148**	99.628	-0.035	600.140	-41.031	-18.391
	(1.987)	(0.959)	(-0.024)	(1.053)	(-0.113)	(-1.218)
Investment Bank Affiliation	-5.202**	-132.931	-0.053	-596.075*	-543.836**	-25.315*
	(-2.535)	(-0.998)	(-0.937)	(-1.753)	(-2.495)	(-1.935)

Broker Ind Specialization	257.190	1.079	-0.828	7.641*	5.705**	-0.013
	(1.339)	(0.867)	(-0.389)	(1.747)	(2.053)	(-0.112)
Industry-Year Fixed Effects	Y	Y	Y	N	N	N
Analyst-Year Fixed Effects	N	N	N	Y	Y	Y
R^2	72.78%	65.32%	25.34%	68.59%	60.79%	74.38%
N	11,678	11,673	9,016	3,147	3,145	3,434

Table 3. Top Picks and Financial Press Coverage

This table presents average % financial press coverage and number of press articles over [0, +5] event window following the announcement of top picks vs all buy recommendations issued i) in the same industry at the same year (i.e., industry-year matched) in Panel A, ii) by the same analysts at the same year (i.e., analyst-year matched) in Panel B. Panel C reports OLS regressions of average press coverage across top picks and buy recommendations. Financial press coverage data are from *RavenPack's Dow Jones Edition* that includes news articles from *Dow Jones Newswire* and *The Wall Street Journal* over 1999 and 2016. Financial press articles' headlines are manually checked to ensure press articles belong to a corresponding analyst research. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Top picks vs Stock Recommendations (Industry-Year Matched)

Variable	Top Picks	Buy Recommendations	Difference
% Financial press coverage [0, +5]	0.477***	0.245***	0.232***
	(53.46)	(86.70)	(28.08)
# Financial press articles [0, +5]	1.954***	0.656***	1.297***
	(29.16)	(69.57)	(19.90)

Panel B: Top picks vs Buy Recommendations (Analyst-Year Matched)

Variable	Top Picks	Buy Recommendations	Difference
% Financial press coverage [0, +5]	0.476***	0.303***	0.173***
	(52.94)	(49.79)	(17.35)
# Financial press articles [0, +5]	1.950***	0.864***	1.086***
	(28.82)	(28.64)	(15.21)

Panel C. Top picks vs Buy Recommendations: Multivariate Analyses

	Top Picks vs Buy Recommendations (Industry-year matched)	Top Picks vs Buy Recommendations (Analyst-year matched)
	Model 1	Model 2
Top Pick	114.644***	110.652***
	(25.884)	(20.303)
Strong Buy	4.702***	
	(2.720)	
Size	4.321***	8.444***
	(6.927)	(5.248)
BM	-4.808***	5.822
	(-2.950)	(1.521)
Institutional holding	-30.578***	-20.535
	(-5.565)	(-1.478)
Turnover	-1.510	-2.776
	(-1.518)	(-1.137)
SSA coverage	2.378***	2.198***
	(30.816)	(11.218)
Idiosyncratic Volatility	15.320***	18.804***
	(7.505)	(3.748)
Dispersion	-14.189*	-5.030
	(-1.670)	(-0.201)
Past 12-m return	10.492***	12.287***
	(10.144)	(4.823)
Fexp	0.030***	0.024***
	(14.692)	(5.445)
Gexp	0.536***	
	(4.171)	
Portfolio size	0.116***	
	(3.344)	
Portfolio Gics	-1.383***	
	(-5.256)	
Relative EPS Optimism	6.658***	9.730***
	(5.159)	(3.151)
All-star	13.591***	
	(6.797)	
Drop Coverage	-15.674***	-12.440**
	(-9.927)	(-2.029)
Top 10	14.969***	-5.296
	(12.467)	(-0.472)
Investment Bank Affiliation	3.511	-4.938
	(1.507)	(-0.923)
Broker Ind Specialization	-0.001	-0.244***

	(-0.073)	(-3.422)
Industry-Year Fixed Effects	Y	N
Analyst-Year Fixed Effects	N	Y
R^2	10.73%	40.02%
N	110,551	35,206

Table 4. Characteristics of Top Pick Stocks

This table present logistic regression results for characteristics of top picks vs all buy recommendations issued between 1999 and 2016 i) in the same industry at the same year (i.e., industry-year matched) in Model 1, ii) by the same analyst at the same year (i.e., analyst-year matched) as in Models 2 and 3. The dependent variable equals one if a stock is designated as a top pick, and zero if a stock carries a buy recommendation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Top Picks vs Buy Recommendations (Industry-year matched)	Top Picks vs Buy Recommendations (Analyst-year matched)	Top Picks vs Buy Recommendations (Analyst-year matched)
	Model 1	Model 2	Model 3
Size	0.486***	0.638***	0.730***
	(5.580)	(3.867)	(4.506)
BM	-60.050***	-72.820***	-71.310***
	(-8.615)	(-5.370)	(-5.419)
Institutional holding	205.840***	238.740***	250.300***
	(9.230)	(6.535)	(6.972)
Turnover	21.900***	24.210***	23.760***
	(4.406)	(2.687)	(2.709)
SSA coverage	0.745***	1.390***	1.370***
	(3.091)	(2.951)	(2.965)
Idiosyncratic volatility	-74.120***	-47.860***	-43.840***
	(-9.589)	(-3.280)	(-3.066)
Dispersion	-1044.690***	-2613.410***	-1890.440***
	(-5.162)	(-6.224)	(-5.021)
Past 12-m return	0.187***	0.345***	26.290***
	(4.663)	(4.380)	(3.515)
Investment Bank Affiliation	68.090***	55.850***	57.490***
	(6.129)	(3.293)	(3.463)
Relative EPS Optimism	11.260***	16.510***	12.990***
	(7.038)	(4.523)	(3.733)
% Target Price Implied Return	58.590***	175.220***	
	(7.771)	(10.743)	
Target Price Implied Return Rank #1			98.960***
			(5.890)
Target Price Implied Return Rank #2			92.140***
			(5.843)
Target Price Implied Return Rank #3			101.680***
			(7.206)
Target Price Implied Return Rank #4			75.440***
			(5.451)
Target Price Implied Return Rank #5			56.200***
			(4.111)

Industry-Year Fixed Effects	Y	N	N
Analyst-Year Fixed Effects	N	Y	Y
R^2	2.10%	32.46%	31.48%
N	140,162	7,499	7,499

Table 5. Investment Value of Top Picks: Calendar-time Portfolios

This table presents calendar-time monthly portfolio returns of the investment value of top picks vs all buy recommendations issued i) by the same analyst at the same year (i.e., analyst-year matched) in Panel A ii) in the same industry at the same year (i.e., industry-year matched) in Panel B, between 1999 and 2016. For the calendar-time portfolio of top picks, we skip a trading day between the announcement of top pick and inclusion into the portfolio to ensure the information is publicly available to all market participants. Top pick portfolios are then rebalanced on a daily basis when a new top pick is announced or current top pick designation expires, is reiterated, or removed before its expiration. For buy recommendation portfolios, we follow an analogous methodology with the exception of expiration dates. Monthly abnormal portfolio returns are reported using Daniel, Grinblatt, Titman and Wermers (1997) (DGTW) characteristic-adjusted returns and risk-adjustments using the Fama and French (1993) three-factor model (*3*-Factor alpha), with the addition of Carhart (1997)'s momentum factor (4-Factor alpha*)*, the Pastor and Stambaugh (2003) liquidity factor (5-Factor alpha*)*, the Fama-French short-term reversal factor (6-Factor alpha*)*, and the long-term reversal factor (7-Factor alpha*)*. Information on Top Picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Top picks vs Buy Recommendations (Analyst-Year Matched)

	Top Picks	Buy Recommendations	Difference
DGTW	1.331***	0.514***	0.816***
	(6.065)	(2.870)	(3.250)
3-Factor alpha	1.349***	0.400*	0.948***
	(5.402)	(1.900)	(3.770)
4-Factor alpha	1.413***	0.473**	0.939***
	(5.715)	(2.290)	(3.730)
5-Factor alpha	1.319***	0.395*	0.924***
	(5.299)	(1.900)	(3.640)
6-Factor alpha	1.328***	0.364*	0.964***
	(5.328)	(1.750)	(3.800)
7-Factor alpha	1.303***	0.347*	0.955***
	(5.300)	(1.680)	(3.770)

Panel B: Top picks vs Buy Recommendations (Industry-Year Matched)

	Top Picks	Buy Recommendations	Difference
DGTW	1.331***	0.432***	0.899***
	(6.065)	(4.290)	(4.170)
3-Factor alpha	1.349***	0.178	1.171***
	(5.402)	(1.360)	(5.290)
4-Factor alpha	1.413***	0.283**	1.130***
	(5.715)	(2.430)	(5.130)
5-Factor alpha	1.319***	0.216*	1.103***
	(5.299)	(1.840)	(4.970)
6-Factor alpha	1.328***	0.123	1.205***
	(5.328)	(1.080)	(5.470)
7-Factor alpha	1.303***	0.112	1.191***
	(5.300)	(1.000)	(5.430)

Table 6. Investment Value of Top Picks: Panel Regressions

This table presents panel regressions of the investment value of top picks vs all buy ecommendations issued i) by rthe same analyst at the same year (i.e., analyst-year matched) in Model 1 ii) in the same industry at the same year (i.e., industry-year matched) in Model 2 between 1999 and 2016. For top picks, we skip a trading day between the announcement of top pick and inclusion into the portfolio to ensure the information is publicly available to all market participants. Top pick portfolios are then rebalanced on a daily basis when a new top pick is announced or current top pick designation expires, is reiterated, or removed before its expiration. For buy recommendation portfolios, we follow an analogous methodology with the exception of expiration dates. The dependent variable is characteristic-adjusted stock returns (DGTW). Regressions are run daily but are converted into monthly coefficients for ease of interpretation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. All-star information is retrieved from *Institutional Investor Magazine*. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Model 1	Model 2	Model 3	Model 4
Top Pick	0.644***	0.838***	0.593***	0.803***
	(4.385)	(6.218)	(4.064)	(5.965)
Strong Buy		0.198***		0.068*
		(5.077)		(1.732)
Size	-0.135***	-0.125***	-0.093***	-0.088***
	(-4.429)	(-11.223)	(-3.080)	(-7.901)
BM	0.323***	0.364***	0.335***	0.353***
	(4.068)	(10.856)	(4.232)	(10.502)
Institutional holding	-0.507*	-0.207*	-0.165	-0.008
	(-1.725)	(-1.870)	(-0.565)	(-0.068)
Turnover	-0.113**	-0.262***	-0.194***	-0.309***
	(-2.126)	(-12.907)	(-3.652)	(-15.254)
Dispersion	0.037**	-0.022***	0.029*	-0.026***
	(2.456)	(-3.405)	(1.906)	(-4.059)
Past 12-month return	-0.970***	-0.456***	-0.758***	-0.391***
	(-14.210)	(-16.990)	(-11.152)	(-14.562)
SSA coverage	-0.002	-0.003**	0.002	-0.001
	(-0.454)	(-2.131)	(0.357)	(-0.622)
Fexp	0.009	0.017***	0.012	0.016***
	(0.888)	(3.982)	(1.262)	(3.718)
Gexp		-0.005*		-0.007**
		(-1.941)		(-2.432)
Portfolio size		0.002**		0.001
		(2.108)		(1.555)
Portfolio Gics		-0.005		-0.001
		(-0.934)		(-0.124)
Relative EPS Optimism	-0.373***	-0.397***	-0.301***	-0.325***
	(-5.092)	(-13.575)	(-4.126)	(-11.084)
All-star		0.081*		0.051

		(1.948)		(1.237)
Drop coverage	-0.801***	-0.454***	-0.710***	-0.361***
	(-5.490)	(-12.434)	(-4.864)	(-9.851)
Top 10	-0.524*	-0.004	-0.192	-0.036
	(-1.720)	(-0.172)	(-0.626)	(-1.423)
Investment Bank Affiliation	0.394*	-0.161	0.410*	-0.140
	(1.849)	(-1.631)	(1.933)	(-1.424)
Broker Ind Specialization	0.302*	0.146***	0.360**	0.157***
	(1.715)	(4.388)	(2.053)	(4.715)
Year-month Fixed Effects	Y	Y	Y	Y
Industry-Year Fixed Effects	N	Y	N	Y
Analyst-Year Fixed Effects	Y	N	Y	N
Industry Fixed Effects	Y	N	Y	N
R^2	0.21%	0.10%	0.20%	0.09%
N	5,677,086	24,621,739	5,536,592	23,991,011

Table 7. Characteristics of Good and Bad Top Pick Stocks

This table present logistic regression results for characteristics of Good (Bad) Top Picks vs all Buy Recommendations issued i) in the same industry at the same year (i.e., industry-year matched) in Model 1, ii) by the same analyst at the same year (i.e., analyst-year matched) in Model 2 between 1999 and 2016. The dependent variable equals one if a stock is designated as *Good (Bad) Top Pick*, and zero if a stock carries a buy recommendation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively

Panel A: Good Top picks vs Buy Stock Recommendations

	Good Top Picks vs Buy Recommendations *(Industry-year matched)*	Good Top Picks vs Buy Recommendations *(Analyst-year matched)*
	Model 1	Model 2
Size	0.878**	1.260**
	(2.412)	(2.234)
BM	-92.460***	-66.690*
	(-2.611)	(-1.843)
Institutional holding	201.800**	441.010***
	(2.137)	(3.529)
Turnover	37.870*	61.070**
	(1.760)	(2.293)
SSA coverage	-0.697	-3.130**
	(-0.697)	(-2.204)
Idiosyncratic volatility	-92.840***	-53.180
	(-2.804)	(-1.200)
Dispersion	-187.370	-7048.920***
	(-0.493)	(-3.614)
Past 12-m return	-0.039	-0.051
	(-0.187)	(-0.179)
Relative EPS Optimism	12.020**	30.740**
	(2.143)	(2.400)
% Target Price Implied Return	80.260***	237.100***
	(2.903)	(4.465)
Investment Bank Affiliation	8.520	273.570
	(0.142)	(1.268)
Industry-Year Fixed Effects	Y	N
Analyst-Year Fixed Effects	N	Y
R^2	0.57%	28.05%
N	42,952	730

Panel B: Bad Top picks vs Buy Stock Recommendations

	Bad Top Picks vs Buy Recommendations (*Industry-year matched*)	Bad Top Picks vs Buy Recommendations (*Analyst-year matched*)
	Model 1	Model 2
Size	0.535	0.646
	(0.939)	(0.991)
BM	-56.240	60.440
	(-1.605)	(1.441)
Institutional holding	369.850***	150.110
	(2.999)	(1.096)
Turnover	-4.400	40.590
	(-0.174)	(1.537)
SSA coverage	-0.811	1.230
	(-0.601)	(0.597)
Idiosyncratic volatility	-57.990	-168.800***
	(-1.504)	(-3.162)
Dispersion	-210.160	-4199.320***
	(-0.374)	(-3.249)
Past 12-m return	0.362**	0.179
	(2.178)	(0.712)
Relative EPS Optimism	4.570	-7.160
	(0.609)	(-0.571)
% Target Price Implied Return	60.480	52.380
	(1.471)	(1.216)
Investment Bank Affiliation	103.520**	139.980**
	(2.187)	(2.139)
Industry-Year Fixed Effects	Y	N
Analyst-Year Fixed Effects	N	Y
R^2	0.53%	33.77%
N	41,426	620

Table 8. Top Picks and Market Reactions

This table presents panel regressions of cumulative CRSP VW-Index adjusted returns (i.e., CAR) over [0,+1] event window surrounding the announcement of a top pick relative to all buy recommendations i) issued in the same industry at the same year (i.e., industry-year matched) ii) issued in the same industry by the same analyst at the same year (i.e., analyst-year matched) between 1999 and 2014. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. All-star information is retrieved from *Institutional Investor Magazine*. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Top Picks vs Buy Recommendations *(Industry-year matched)*	Top Picks vs Buy Recommendations *(Analyst-year matched)*	Good Top Picks vs Buy Recommendations *(Industry-year matched)*	Good Top Picks vs Buy Recommendations *(Analyst-year matched)*	Bad Top Picks vs Buy Recommendations *(Industry-year matched)*	Bad Top Picks vs Buy Recommendations *(Analyst-year matched)*
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Top Pick	0.315***	0.218**				
	(3.836)	(2.043)				
Good Top Pick			0.945***	0.576**		
			(2.644)	(2.012)		
Bad Top Pick					-1.206**	-0.664***
					(-2.433)	(-2.669)
Strong Buy	0.463***		0.288***		0.333***	
	(17.553)		(6.820)		(7.461)	
Size	-0.002***	0.000	0.000	-0.004	-0.001	0.020***
	(-2.977)	(0.042)	(0.296)	(-0.946)	(-1.532)	(3.358)
BM	-0.073***	0.231	-0.097***	1.326***	-0.073***	-0.788***
	(-5.719)	(1.196)	(-3.909)	(2.729)	(-2.834)	(-2.585)
Institutional holding	0.953***	-0.120	0.742***	-0.698	0.740***	4.889**
	(8.984)	(-0.230)	(4.558)	(-0.411)	(4.255)	(2.163)
Turnover	-0.178***	-0.167	-0.129***	-0.713*	-0.050	-0.010
	(-6.794)	(-1.142)	(-2.914)	(-1.961)	(-1.080)	(-0.027)
SSA coverage	-0.018***	-0.010	-0.024***	-0.014	-0.020***	-0.035
	(-12.348)	(-1.495)	(-10.172)	(-0.807)	(-7.945)	(-1.184)
Dispersion	0.000	-1.881	0.000***	-25.336***	0.000***	47.549***
	(1.462)	(-0.528)	(7.556)	(-3.653)	(9.512)	(4.518)
Past 12-month return	0.664***	0.771***	0.746***	-0.097	0.902***	0.595

	(21.902)	(4.852)	(14.620)	(-0.231)	(14.529)	(1.075)
Idiosyncratic volatility	1.318***	1.511***	1.590***	1.881***	1.508***	1.340*
	(30.276)	(6.821)	(22.261)	(2.823)	(19.875)	(1.665)
Fexp	0.047***	0.018	0.057***	-0.126**	0.052***	0.125*
	(11.548)	(1.074)	(8.815)	(-2.157)	(7.511)	(1.739)
Gexp	0.013***		0.016***		0.018***	
	(4.482)		(3.820)		(4.016)	
Portfolio size	-0.020***		-0.034***		-0.030***	
	(-10.916)		(-10.539)		(-9.097)	
Portfolio Gics	-0.027***		-0.016		-0.008	
	(-3.296)		(-1.123)		(-0.572)	
Relative EPS Optimism	0.027***	-0.020	0.005	-0.146***	0.019*	0.632***
	(4.331)	(-0.504)	(0.459)	(-2.931)	(1.685)	(3.183)
All-star	0.196***		0.283***		0.186**	
	(4.563)		(3.629)		(2.193)	
Drop coverage	-0.215***	-0.423	-0.238***	2.250*	-0.175**	2.771***
	(-5.662)	(-1.406)	(-3.639)	(1.831)	(-2.560)	(2.775)
Top 10	0.322***	-0.090	0.311***	-0.551	0.339***	-6.565***
	(11.707)	(-0.123)	(6.995)	(-0.627)	(7.066)	(-2.800)
Investment Bank Affiliation	-0.043	0.057	-0.027	-7.326***	-0.021	-1.135
	(-0.409)	(0.170)	(-0.174)	(-4.308)	(-0.112)	(-1.204)
Broker Ind specialization	-0.075**	1.363***	-0.066	4.856***	-0.053	1.087**
	(-2.032)	(3.211)	(-1.089)	(5.439)	(-0.843)	(2.164)
Industry-Year Fixed Effects	Y	N	Y	N	Y	N
Analyst-Year Fixed Effects	N	Y	N	Y	N	Y
R^2	4.41%	33.28%	6.44%	35.24%	5.99%	36.48%
N	166,459	8,322	48,740	927	48,017	800

Table 9. Institutional Trading Behavior of Top Picks

This table presents panel regressions of the interactions between institutional trading imbalance over [0, +1] surrounding the announcement of a top pick relative to all buy recommendations i) issued in the same industry at the same year (i.e. industry-year matched) ii) issued in the same industry by the same analyst at the same year (i.e., analyst-year matched) between 1999 and 2014. The dependent variable equals the total institutional trading imbalance over [0,+1] surrounding the announcement of a top pick or a stock recommendation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information is obtained from CRSP/Compustat. Information on daily institutional trading is from *Ancerno Ltd* from 1999 to 2014. All-star information is retrieved from *Institutional Investor Magazine*. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Top Picks vs Buy Recommendations (*Industry-year matched*)	Top Picks vs Buy Recommendations (*Analyst-year matched*)	Good Top Picks vs Buy Recommendations (*Industry-year matched*)	Good Top Picks vs Buy Recommendations (*Analyst-year matched*)	Bad Top Picks vs Buy Recommendations (*Industry-year matched*)	Bad Top Picks vs Buy Recommendations (*Analyst-year matched*)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Top Pick	1.128***	1.271***				
	(3.162)	(2.632)				
Good Top Pick			2.991**	5.043***		
			(2.091)	(2.968)		
Bad Top Pick					-4.709***	-3.582*
					(-3.317)	(-1.784)
Strong Buy	0.084		0.028		0.296*	
	(0.743)		(0.174)		(1.688)	
Size	-0.001	0.013	-0.004	-0.020	-0.013***	-0.065
	(-0.588)	(1.566)	(-1.538)	(-0.593)	(-4.483)	(-0.681)
BM	0.007	0.672	-0.658***	-1.238	-0.070	-3.923
	(0.050)	(0.976)	(-3.081)	(-0.519)	(-0.323)	(-1.000)
Institutional holding	-0.524	-1.817	-1.419**	4.449	2.982***	1.996
	(-1.112)	(-0.763)	(-2.074)	(0.418)	(4.030)	(0.193)
Turnover	0.688***	1.622***	-0.336**	-1.728	1.396***	0.767
	(6.412)	(2.700)	(-2.127)	(-0.582)	(8.523)	(0.585)
SSA coverage	0.000	0.020	0.043***	-0.041	-0.004	0.348**
	(0.000)	(0.654)	(4.943)	(-0.362)	(-0.396)	(1.989)
Dispersion	0.532	3.232	1.050	-52.104	-0.417	193.569***
	(1.279)	(0.370)	(1.119)	(-0.702)	(-0.774)	(3.409)
Past 12-month return	0.841***	0.162	0.922***	1.677	0.693***	-1.251

	(7.744)	(0.268)	(5.960)	(0.451)	(3.760)	(-0.597)
Idiosyncratic volatility	0.318*	0.947	0.653**	-3.707	1.282***	-5.141
	(1.860)	(1.009)	(2.524)	(-0.978)	(4.785)	(-1.559)
Fexp	-0.021	-0.091	-0.054**	-0.532*	0.059**	-0.590*
	(-1.180)	(-1.243)	(-2.126)	(-1.836)	(2.000)	(-1.922)
Gexp	-0.008		0.001		-0.002	
	(-0.714)		(0.063)		(-0.111)	
Portfolio size	0.001		-0.013*		-0.011	
	(0.769)		(-1.711)		(-1.264)	
Portfolio Gics	-0.008		0.035		-0.004	
	(-0.394)		(0.962)		(-0.098)	
Relative EPS Optimism	-0.301**	0.344	-0.364*	3.878*	-0.116	-2.669
	(-2.339)	(0.509)	(-1.828)	(1.866)	(-0.550)	(-0.623)
All-star	0.344*		0.442		0.688*	
	(1.744)		(1.394)		(1.956)	
Drop coverage	0.083	0.637	-0.233	-11.245	-0.137	-6.641
	(0.516)	(0.424)	(-0.934)	(-1.288)	(-0.537)	(-1.039)
Top 10	0.211*	1.420	0.185	-0.726	-0.130	-7.413
	(1.846)	(0.763)	(1.107)	(-0.090)	(-0.720)	(-1.338)
Investment Bank Affiliation	0.080	-0.507	0.403	17.764	0.247	2.525
	(0.256)	(-0.499)	(0.831)	(1.334)	(0.348)	(0.490)
Broker Ind specialization	0.324**	4.155**	0.685***	23.986***	0.367	0.535
	(2.112)	(2.304)	(3.061)	(3.342)	(1.624)	(0.230)
Industry-Year Fixed Effects	Y	N	Y	N	Y	N
Analyst-Year Fixed Effects	N	Y	N	Y	N	Y
R^2	0.67%	26.23%	0.79%	32.57%	2.51%	47.20%
N	117,518	6,976	38,226	272	29,475	219

Table 10. Retail Investors' Trading Behavior of Top Picks

This table presents panel regressions of the interactions between retail trading imbalance over [0,+1] surrounding the announcement of a top pick relative to all Buy Recommendations i) issued in the same industry at the same year (i.e., industry-year matched) ii) issued in the same industry by the same analyst at the same year (i.e., analyst-year matched) between 1999 and 2016. The dependent variable is the total retail trading imbalance over [0,+1] surrounding the announcement of a top pick or a stock recommendation. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. Financial Statement information are obtained from CRSP/Compustat. Information on daily retail trading is from *TAQ* from 1999 to 2016. All-star information is retrieved from *Institutional Investor Magazine*. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Top Picks vs Buy Recommendations (*Industry-year matched*)	Top Picks vs Buy Recommendations (*Analyst-year matched*)	Good Top Picks vs Buy Recommendations (*Industry-year matched*)	Good Top Picks vs Buy Recommendations (*Analyst-year matched*)	Bad Top Picks vs Buy Recommendations (*Industry-year matched*)	Bad Top Picks vs Buy Recommendations (*Analyst-year matched*)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Top Pick	0.446*	1.573***				
	(1.909)	(6.463)				
Good Top Pick			-1.516**	-1.840**		
			(-2.337)	(-2.046)		
Bad Top Pick					0.299	-1.706
					(0.281)	(-1.067)
Strong Buy	-0.119*		-0.095		-0.070	
	(-1.814)		(-1.010)		(-0.660)	
Size	0.009***	0.011***	0.008***	0.023	0.010***	0.019
	(7.500)	(2.750)	(5.333)	(1.065)	(4.545)	(0.518)
BM	0.057	0.186	0.159	3.090	0.197	0.618
	(0.576)	(0.453)	(1.105)	(1.476)	(1.176)	(0.263)
Institutional holding	-2.828***	0.142	-2.459***	3.167	-2.319***	2.475
	(-9.395)	(0.160)	(-5.880)	(0.782)	(-5.324)	(0.603)
Turnover	0.928***	0.085	0.985***	2.134	1.019***	0.583
	(11.235)	(0.279)	(9.020)	(0.972)	(7.998)	(0.618)
SSA coverage	-0.014***	-0.024*	-0.012**	-0.020	-0.012**	-0.128
	(-3.684)	(-1.875)	(-2.308)	(-0.333)	(-2.264)	(-1.275)
Dispersion	0.837	2.801	2.718	-25.541*	0.006	78.596***
	(1.198)	(0.488)	(1.544)	(-1.693)	(0.013)	(3.228)

Past 12-month return	0.109	-0.199	0.107	0.397	0.206	-0.388
	(1.457)	(-0.695)	(0.944)	(0.289)	(1.638)	(-0.575)
Idiosyncratic volatility	0.992***	0.781*	1.103***	1.761	1.190***	-2.438
	(9.254)	(1.768)	(7.130)	(0.919)	(7.447)	(-1.397)
Fexp	-0.007	-0.078**	-0.021	0.210	-0.032*	-0.472**
	(-0.700)	(-2.484)	(-1.500)	(0.851)	(-1.963)	(-2.538)
Gexp	-0.002		0.001		0.000	
	(-0.299)		(0.111)		(0.000)	
Portfolio size	-0.001		-0.001		0.000	
	(-0.417)		(-0.222)		(0.000)	
Portfolio Gics	0.011		0.012		0.013	
	(0.753)		(0.571)		(0.542)	
Relative EPS Optimism	-0.002	0.061	0.111	-0.678	-0.010	0.270
	(-0.027)	(0.210)	(0.986)	(-0.754)	(-0.083)	(0.178)
All-star	0.232**		0.051		-0.016	
	(2.107)		(0.304)		(-0.088)	
Drop coverage	0.088	-0.875	0.050	-5.462**	0.145	-0.400
	(0.954)	(-1.318)	(0.411)	(-2.109)	(1.008)	(-0.240)
Top 10	0.158**	0.948	0.196**	2.073	0.182*	-5.330
	(2.300)	(0.837)	(2.021)	(1.365)	(1.676)	(-1.509)
Investment Bank Affiliation	0.107	-1.099*	0.443	-7.544***	0.026	0.522
	(0.393)	(-1.735)	(1.191)	(-2.776)	(0.068)	(0.244)
Broker Ind specialization	-0.085	0.745	-0.041	0.490	-0.170	0.602
	(-0.944)	(0.806)	(-0.313)	(0.321)	(-1.221)	(0.293)
Industry-Year Fixed Effects	Y	N	Y	N	Y	N
Analyst-Year Fixed Effects	N	Y	N	Y	N	Y
R^2	1.69%	39.70%	2.07%	32.29%	2.03%	31.29%
N	65,254	4,529	30,928	219	27,053	223

Table 11. Career Consequences of Top Picks: Demotion vs Promotions

This table presents logistic regression results on the career consequences of top picks for sell-side analysts. The dependent variable equals one if analyst *i* experiences demotion or promotion at year *t*+1, and zero otherwise. An analyst movement is defined as a demotion (promotion) if an analyst *i* moves from a top 10 (non-top 10) decile broker to a non-top 10 (top 10) decile broker. Analyst *i* is classified as a "*Good (Bad) Top Picker*" at year *t* if abnormal stock outperformance of her top pick selection (relative to buy rated stocks in analyst *i*'s portfolio at year *t*) falls under the highest (lowest) quartile compared to that of top picks of all analysts at year *t* for the same industry *j*. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. All-star information is retrieved from *Institutional Investor Magazine*. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and time level. Year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Panel A. Demotion				Panel B. Promotion			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Top Pick Analyst	23.590		-5.930		-18.030		-21.590	
	(1.286)		(-0.251)		(-0.540)		(-0.539)	
Bad Top Picker Analyst		111.640***		218.310***		-53.750		6.620
		(3.864)		(3.311)		(-0.740)		(0.069)
Good Top Picker Analyst		-90.310		-155.880**		-10.410		-1.330
		(-1.521)		(-2.358)		(-0.143)		(-0.015)
Average Size in Portfolio	-2.020	-1.930	-14.530**	-14.100**	-9.800**	-9.780**	-3.630	-3.570
	(-0.415)	(-0.395)	(-2.218)	(-2.143)	(-2.192)	(-2.188)	(-0.599)	(-0.589)
Average BM in Portfolio	-44.150***	-44.250***	1.970	1.930	-50.040***	-49.960***	-8.330	-8.190
	(-5.966)	(-5.972)	(0.192)	(0.187)	(-5.445)	(-5.436)	(-0.713)	(-0.702)
Average Fexp	4.410	4.660	4.370	4.550	-4.600	-4.690	-6.620	-6.760
	(1.202)	(1.266)	(0.871)	(0.897)	(-1.165)	(-1.187)	(-1.329)	(-1.360)
Gexp	3.080**	2.960**	3.480*	3.460*	-0.886	-0.870	-3.420*	-3.370*
	(2.139)	(2.056)	(1.758)	(1.730)	(-0.642)	(-0.630)	(-1.954)	(-1.937)
Portfolio size	-0.555	-0.545	-1.320	-1.550	2.160***	2.150***	1.860*	1.810*
	(-0.803)	(-0.793)	(-1.375)	(-1.610)	(2.983)	(2.974)	(1.824)	(1.775)
Portfolio Gics	-6.250*	-6.130*	-0.855	-0.360	-15.550***	-15.520***	-6.900*	-6.780*
	(-1.894)	(-1.858)	(-0.200)	(-0.083)	(-4.829)	(-4.820)	(-1.721)	(-1.691)
Broker Ind Specialization	30.320	30.130	42.840	43.740	2.390	2.470	22.310	22.920
	(1.475)	(1.463)	(1.504)	(1.528)	(0.166)	(0.172)	(1.224)	(1.258)
All-star	-79.200***	-78.050***	-85.030***	-83.230***	51.650	51.660	109.850**	108.250**

	(-4.922)	(-4.851)	(-4.403)	(-4.270)	(1.442)	(1.442)	(2.270)	(2.241)
Average Buy Rec return	-40.550	-41.459*	-54.736	-54.433	-13.572	-13.514	-13.611	-13.716
	(-1.638)	(-1.679)	(-1.434)	(-1.421)	(-0.500)	(-0.498)	(-0.358)	(-0.361)
Investment Bank Affiliation	-219.870***	-223.590***	-132.860	-163.010*	55.970	56.860	365.400***	370.030***
	(-2.837)	(-2.874)	(-1.600)	(-1.852)	(0.795)	(0.808)	(2.772)	(2.806)
Average Relative EPS Optimism	67.590**	68.770**	88.080*	91.660**	-26.590	-27.160	-94.830**	-95.190**
	(2.088)	(2.126)	(1.936)	(2.004)	(-0.777)	(-0.794)	(-2.184)	(-2.192)
Average Report count	5.600**	5.390**	6.770*	5.790	9.160***	9.180***	8.980**	8.950**
	(2.121)	(2.042)	(1.870)	(1.586)	(3.148)	(3.155)	(2.326)	(2.319)
Average Drop Coverage	303.440***	302.660***	170.540***	170.600***	77.190***	77.450***	-149.280***	-149.330***
	(13.256)	(13.222)	(5.188)	(5.163)	(2.727)	(2.736)	(-4.189)	(-4.190)
Average PMAFE	21.100***	21.190***	24.830**	25.480**	6.440	6.410	-14.000	-13.920
	(3.231)	(3.245)	(2.099)	(2.141)	(0.756)	(0.752)	(-1.143)	(-1.136)
Average Institutional holding	-51.820	-51.020	17.120	22.230	92.230**	92.390**	43.470	42.610
	(-1.235)	(-1.218)	(0.294)	(0.380)	(2.125)	(2.129)	(0.759)	(0.744)
Average Turnover	34.670***	34.420***	3.680	3.070	30.370***	30.330***	8.180	8.340
	(3.781)	(3.754)	(0.303)	(0.252)	(3.227)	(3.223)	(0.691)	(0.704)
Average Dispersion	-75.070	-79.730	-138.220	-203.220	-780.910**	-775.900**	-1122.150***	-1130.640***
	(-0.229)	(-0.243)	(-0.313)	(-0.457)	(-2.292)	(-2.280)	(-2.588)	(-2.607)
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	2.17%	2.24%	10.96%	12.17%	1.52%	1.52%	9.82%	9.80%
N	17,407	17,407	1,516	1,516	13,436	13,436	1,664	1,664

Table 12. Career Consequences of Top Picks: Selection into Institutional Investors' All-Star team

This table presents logistic regression results on the career consequences of top picks for sell-side analysts. The dependent variable equals one if analyst i was voted an all-star in the October issue of *Institutional Investor Magazine* in year t, and zero otherwise. Analyst i is classified as a "*Good (Bad) Top Picker*" at year t if abnormal stock outperformance of her top pick selection (relative to buy rated stocks in analyst i's portfolio at year t) falls under the highest (lowest) quartile compared to that of top picks of all analysts at year t for the same industry j. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. All-star information is retrieved from *Institutional Investor Magazine*. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. T-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and time level. Year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Model 1	Model 2	Model 3	Model 4
Top Pick Analyst	60.670***		101.350***	
	(4.736)		(5.306)	
Bad Top Picker Analyst		-14.750		-92.140
		(-0.386)		(-0.896)
Good Top Pick Analyst		72.770***		89.050**
		(2.646)		(2.298)
Average Size in Portfolio	50.430***	50.260***	55.670***	55.240***
	(17.820)	(17.823)	(12.947)	(12.907)
Average BM in Portfolio	-16.070***	-16.640***	-15.720**	-16.200**
	(-3.176)	(-3.289)	(-2.008)	(-2.080)
Average Fexp	6.030***	6.160***	-14.470***	-14.160***
	(3.486)	(3.561)	(-4.019)	(-3.955)
Gexp	3.990***	3.990***	0.540	0.576
	(5.089)	(5.096)	(0.394)	(0.420)
Portfolio size	6.220***	6.280***	7.250***	7.350***
	(19.021)	(19.205)	(14.414)	(14.671)
Portfolio Gics	-10.120***	-10.410***	-23.260***	-23.610***
	(-3.614)	(-3.718)	(-4.624)	(-4.703)
Broker Ind Specialization	-126.740***	-127.040***	-157.980***	-160.360***
	(-10.131)	(-10.163)	(-7.459)	(-7.546)
All-star (t-1)	534.620***	535.620***		
	(43.571)	(43.688)		
Average Buy Rec return	46.257**	45.245**	2617.270	2554.560
	(2.207)	(2.161)	(0.826)	(0.811)
Investment Bank Affiliation	187.890***	190.780***	1.553***	1.624***
	(7.101)	(7.221)	(4.055)	(4.268)
Average Relative EPS Optimism	-48.980***	-51.710***	-17.510	-19.130
	(-2.638)	(-2.785)	(-0.630)	(-0.689)
Average Report count	7.990***	8.310***	9.990***	10.330***
	(6.242)	(6.543)	(5.911)	(6.186)
Average Drop Coverage	-241.910***	-241.980***	-216.690***	-214.910***
	(-13.583)	(-13.579)	(-6.912)	(-6.875)
Average PMAFE	-21.390***	-21.680***	-28.180***	-27.710***

	(-3.332)	(-3.372)	(-2.636)	(-2.614)
Average Institutional holding	-5.060	-2.490	57.010	59.850
	(-0.173)	(-0.085)	(1.251)	(1.315)
Average Turnover	-8.070	-8.870	-11.100	-11.800
	(-1.349)	(-1.486)	(-1.213)	(-1.295)
Average Dispersion	410.800**	400.070**	566.880**	554.380**
	(2.242)	(2.180)	(2.054)	(2.009)
Year Fixed Effects	Y	Y	Y	Y
R^2	20.94%	20.91%	3.60%	3.54%
N	34,520	34,520	30,627	30,627

Table 13. Reputational Consequences of Top Picks with Financial Markets

This table presents panel regression results on the reputational consequences of top picks with financial markets. The dependent variable is DGTW-adjusted stock market reactions over [0, +2] event window surrounding the announcement of upgrades or downgrades by the same analyst for *non-top pick* stocks. Analyst *i* is classified as a "*Good (Bad) Top Picker*" at year *t* if abnormal stock outperformance of her top pick selection (relative to buy rated stocks in analyst *i*'s portfolio at year *t*) falls under the highest (lowest) quartile compared to that of top picks of all analysts at year *t* for the same industry *j*. Information on top picks is obtained from *Thomson Reuters Investext* and *Thomson Reuters Eikon*. Analyst and brokerage house information is retrieved from I/B/E/S. All-star information is retrieved from *Institutional Investor Magazine*. Financial Statement information is obtained from CRSP/Compustat. Appendix A provides a detailed description of the data collection and screening process. Refer to Appendix B for detailed variable descriptions. *T*-statistics are in parentheses with heteroskedastic-consistent standard errors double clustered at the analyst and firm level. Industry-year and analyst-year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Upgrades (Non-top pick Firms)				Downgrades (Non-top pick Firms)			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Top Pick Analyst	-0.005				-0.008			
	(-0.029)				(-0.036)			
Bad Top Picker		-0.731**		-0.721**		0.924**		0.903**
		(-2.104)		(-2.073)		(2.293)		(2.238)
Good Top Picker			0.198	0.164			-0.475	-0.436
			(0.645)	(0.534)			(-1.253)	(-1.149)
Revision	0.517***	0.517***	0.517***	0.517***	0.786***	0.785***	0.786***	0.785***
	(8.560)	(8.562)	(8.555)	(8.558)	(10.982)	(10.969)	(10.981)	(10.968)
Size	-0.482***	-0.482***	-0.482***	-0.482***	0.764***	0.764***	0.764***	0.764***
	(-17.934)	(-17.920)	(-17.936)	(-17.921)	(23.809)	(23.813)	(23.813)	(23.816)
BM	-0.088**	-0.089**	-0.089**	-0.089**	0.166***	0.166***	0.166***	0.166***
	(-2.279)	(-2.289)	(-2.281)	(-2.291)	(3.609)	(3.612)	(3.615)	(3.618)
Institutional holding	-0.160	-0.160	-0.160	-0.160	1.035***	1.037***	1.036***	1.038***
	(-1.247)	(-1.248)	(-1.251)	(-1.251)	(6.848)	(6.863)	(6.856)	(6.870)
Turnover	0.153***	0.154***	0.153***	0.153***	-0.628***	-0.629***	-0.628***	-0.629***
	(3.744)	(3.748)	(3.740)	(3.746)	(-13.000)	(-13.024)	(-13.002)	(-13.024)
Earnings Forecast Dispersion	4.136***	4.152***	4.137***	4.153***	-5.671***	-5.669***	-5.669***	-5.666***
	(4.639)	(4.657)	(4.640)	(4.657)	(-5.630)	(-5.628)	(-5.628)	(-5.625)
Past 12-month return	-0.402***	-0.402***	-0.402***	-0.402***	0.267***	0.268***	0.267***	0.268***
	(-6.454)	(-6.457)	(-6.453)	(-6.457)	(3.722)	(3.732)	(3.724)	(3.733)

SSA coverage	-0.024***	-0.024***	-0.024***	-0.024***	0.004	0.004	0.004	0.004
	(-6.408)	(-6.422)	(-6.405)	(-6.419)	(0.970)	(0.971)	(0.967)	(0.968)
Fexp	0.011	0.011	0.011	0.011	-0.001	-0.001	-0.001	-0.001
	(1.148)	(1.156)	(1.137)	(1.147)	(-0.110)	(-0.111)	(-0.093)	(-0.095)
Gexp	0.011	0.011	0.010	0.010	-0.266*	-0.261*	-0.264*	-0.259*
	(0.110)	(0.107)	(0.102)	(0.101)	(-1.932)	(-1.894)	(-1.921)	(-1.886)
Portfolio size	0.004	0.004	0.004	0.004	-0.002	-0.002	-0.002	-0.002
	(1.531)	(1.530)	(1.529)	(1.528)	(-0.776)	(-0.779)	(-0.774)	(-0.777)
Portfolio Gics	0.019	0.019	0.019	0.019	-0.033	-0.033	-0.033	-0.033
	(0.715)	(0.710)	(0.722)	(0.715)	(-1.038)	(-1.040)	(-1.051)	(-1.052)
Relative EPS Optimism	-0.001	0.000	-0.001	0.000	0.245***	0.245***	0.246***	0.245***
	(-0.014)	(-0.008)	(-0.012)	(-0.006)	(4.130)	(4.122)	(4.138)	(4.130)
All-star	0.317**	0.317**	0.317**	0.316**	-0.385**	-0.382**	-0.382**	-0.379**
	(2.329)	(2.324)	(2.324)	(2.320)	(-2.325)	(-2.308)	(-2.308)	(-2.292)
Drop Coverage	-0.182**	-0.182**	-0.181**	-0.182**	0.166*	0.165*	0.165*	0.165*
	(-2.341)	(-2.347)	(-2.337)	(-2.344)	(1.909)	(1.904)	(1.909)	(1.903)
Top 10	0.254***	0.256***	0.253***	0.255***	-0.086	-0.088	-0.085	-0.087
	(2.809)	(2.827)	(2.800)	(2.819)	(-0.780)	(-0.796)	(-0.772)	(-0.788)
Investment Bank Affiliation	-0.016	-0.012	-0.016	-0.012	-0.609**	-0.608**	-0.608**	-0.607**
	(-0.074)	(-0.054)	(-0.073)	(-0.054)	(-2.328)	(-2.324)	(-2.322)	(-2.318)
Broker Ind Specialization	-0.060	-0.061	-0.060	-0.061	0.028	0.028	0.026	0.027
	(-0.730)	(-0.743)	(-0.727)	(-0.740)	(0.277)	(0.284)	(0.264)	(0.272)
Year-month Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Industry-Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Analyst Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	26.88%	26.89%	26.88%	26.89%	33.18%	33.19%	33.18%	33.54%
N	46,552	46,552	46,552	46,552	46,914	46,914	46,914	46,914