Information Content of Option Prices: Comparing Analyst Forecasts to Option-Based Forecasts

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June 20, 2019

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Abstract

Finance researchers keep producing increasingly complex and computationally-intensive models of stock returns. Separately, professional analysts forecast stock returns daily for their clients. Are the sophisticated methods of researchers achieving better forecasts or are we better off relying on the expertise of analysts on the ground? Do the two sets of actors even capture the same information? In this paper, I hypothesize that analyst forecasts and forecasts constructed using option prices will be different because they draw on different information sets. Using hypothesis tests and quantile regressions, I find that option-based forecasts are statistically significantly different from analyst forecasts at every level of the forecast distribution. Then, using cross-sectional regressions, I show that this difference originates in the distinct information sets used to create the forecasts: option-based forecasts incorporate information about the probability of extreme events while analyst forecasts focus on information about firm and macroeconomic fundamentals.

1 Introduction

Using the Recovery Theorem (RT) \cite{Ross2015}, I can assess the informational content of options on any given day for a certain time horizon. But why do we need to

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*I am grateful to Joannie Tremblay-Boire, seminar participants at the University of Toronto, and conference participants at the Computing in Economics and Finance Conference for their feedback. All errors are my own.

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estimate the natural probability distribution from options if we already have analyst-based measures of expected returns? Does a forecast obtained from a model like the RT provide additional information (or different information) from a forecast obtained from an analyst? In other words, if presented with a forecast for a stock widely analyzed by analysts, would there be any value to using a model like the RT to obtain a separate forecast? In this paper, I hypothesize that stock market forecasts from analysts will be different from forecasts constructed using the natural probability distribution obtained from option prices, because the information sets on which these forecasts are based (and the incentives of the individuals creating these forecasts) are different. I test this hypothesis in two stages. First, we must determine if the two types of forecasts actually produce different results. Using hypothesis tests and quantile regressions, I show that option-based forecasts are statistically significantly different from analyst forecasts at every level of the expected return distributions. Quantile regressions are important here because it is possible that the information used to construct the forecasts is the same at the mean or median (toward the middle of the distribution) but differs at the extremes of the distribution.

Second, given that forecasts of analysts are different from forecasts from the RT, we must determine whether the two sets of actors rely on similar information when formulating their expectations. To do so, I first use partial information decomposition ([Williams and Beer, 2010], [Griffith and Ho, 2015], [Chan et al., 2016], [Flecker et al., 2011], [Makke et al., 2017]), which shows portions that are unique to each forecast and portions that are redundant and/or synergistic. Then, I estimate cross-sectional regressions to determine which specific information is actually used to construct the two types of forecasts. I analyze almost three hundred factors known to characterize market returns, such as, for example, the Fama–French factors. These factors fall into one of three categories: macroeconomic factors (such as consumption growth, inflation, and unemployment), stock market factors (such as book-to-market ratios, and dividend-price ratios), and probability factors (such as overall market crash probabilities, recession probabilities, and sentiment indices). Cross-sectional regression results indicate that
the forecasts are different because they are based on different information sets. While analyst forecasts use information related specifically to the firm and macroeconomic fundamentals, option-based forecasts tend to incorporate information related to the probability of extreme events. In general, analyst forecasts can be duplicated almost entirely (with an $R^2$ of about 90%) using six firm-specific and macroeconomic variables: the book-to-market ratio, a volatility index, the treasury bill rate, the probability of corporate default, inflation, and consumer sentiments. Option-based forecasts, on the other hand, tend to be harder to duplicate, arguably because they rely on a much larger information set. Five main factors—the previous period’s forecast, news shock indices, capital risk, fear indices, and consumption growth—explain about 16% of the RT forecast.

What might explain this discrepancy between analyst-based and option-based forecasts? I argue that the incentives facing professional analysts and option traders play a major role here. On average, analysts are more optimistic, but also more conservative about the future prospects of the stock market than are option market participants, who generally use options as a hedging instrument. On the one hand, analysts’ forecasts tend to capture slight variations from the status quo in the market because analysts are penalized (ultimately by losing their jobs) if their forecasts are “too out there.” Since firms that hire analysts are paid for their forecasts, it stands to reason that bad forecasters become unreliable which makes them dispensable. On the other hand, options market participants are using options to protect themselves against the possibility of future adverse movements. As such, an option-based forecast that uses the natural probability distribution will capture expected extreme movements in the market, and not the slight variations from the status quo captured in an analyst-based forecast.

Scholars have examined the value of forecast models compared to analyst forecasts in the past. For example, a strand of the literature compares time-series model forecasts with analyst forecasts (Brown and Rozell, 1978; Brown et al., 1987; Clement, 1999), finding that, on average, analyst forecasts are superior because analysts are capable of incorporating larger amounts of information into their models. The RT is too recent to
have been the object of such an analysis so far. As such, this article contributes to the comparison literature explicitly by comparing analyst-based forecasts to a new model: option-based forecasts.

Doing so also contributes to the growing literature focusing on the Recovery Theorem specifically. So far, researchers have been somewhat mixed on the RT’s forecasting ability. Several researchers have extended and/or tested the RT empirically and have found positive forecasting results (Sanford, 2017; Jensen et al., 2018; Audrino et al., 2015; Bakshi et al., 2017; Van Appel and Maré, 2018). Yet, others have questioned the legitimacy of the model, claiming that it does not recover what the model claims it recovers (Borovička et al., 2016). This particular study approaches the legitimacy question from a different angle: if the RT does not provide us with information beyond what is already available (in analyst forecasts, for example), then there would be little benefit in using models such as the RT or in extending research on the extraction of the natural probability distribution in the future. Ultimately, however, this article finds that the information content used in the RT is significantly different from that used in analyst forecasts.

Another relevant strand of the finance literature focuses on the drivers of analyst forecasts (such as the analyst’s career status, the boldness of a forecast, and so on) (Clement and Tse, 2005; Givoly et al., 2009; Bryan and Tiras, 2007). This literature, which focuses on characteristics of analysts themselves, does not identify what information analysts use in their forecasts. Instead, it tries to: 1) determine how good analysts are at forecasting stock prices/returns, and 2) what motives or characteristics drive these analysts to forecast the way that they do. My article advances this literature by analyzing the informational content driving the forecasts, and, by extension, by positing the underlying motivations/incentives of the actors producing them.

In addition, while the purpose of the article is not to test the efficacy of any given forecast, my results suggest a practical contribution: we might benefit from using multiple forecasts that rely on different information rather than a single forecast when forecasting the stock market. For example, if I include the RT, the analyst forecast,
and the interactions between these two forecasts in a multivariate forecast regression model, I am able to improve the monthly forecast $R^2$ to almost 46% (compared to about 26% for the RT alone). The implication, which is apparent in the PID analysis, is that each model produces unique and synergistic information that is leveraged by including them together in a forecast.

2 Models

In order to determine whether the information contained in the RT (the option-based forecast) is the same as the information contained in analyst forecasts, we first need to assess how each forecast is produced. Below, I derive the RT and show how a typical analyst forecast is obtained. Please note that analysts have been reported to create their forecasts in a multitude of ways. The model presented below is only one of many possibilities. That being said, the empirical results presented in this article use the actual empirical forecasts obtained from the International Broker’ Estimate System (I/B/E/S) database, and not a theoretical model of analyst behavior. This theoretical section aims to show the reader how and why the information used in forecasting can differ either as a result of the model itself or of the incentives of the market participant/analyst.

2.1 Stochastic Discount Factor

2.1.1 Market participants and their incentives

The goal of the average participant in the options market is to hedge for possible worst-case scenarios in the future (Leland 1998, Berkman and Bradbury 1996, Smith and Stulz 1985, Froot et al. 1993). For example, a firm that has just recently signed a contract to sell its products to a foreign firm might want to prevent adverse movements in the foreign exchange markets to limit losing money at the time of the goods exchange. To do so, the firm might look to the option market to limit its downside exposure to
the foreign currency.

A financial analyst, on the other hand, wants to aggregate as much information as possible to obtain a sensible idea of where the firm’s earnings are headed in the future (Ramnath et al., 2008; Mozes, 2003). More importantly, analysts have an incentive to be correct[^1] as often as possible in order to remain employed (Groysberg et al., 2011; Mikhail et al., 1999; Hong et al., 2000). As a financial analyst, one is trying to convince investors to purchase the reports that one puts out. If, on average, the analyst is wrong, then investors do not have an incentive to purchase their report. Furthermore, investment banks tend not to compensate for analyst “correctness,” but rather to terminate those that have poor forecast accuracies (Groysberg et al., 2011; Markov and Tan, 2006; Raedy et al., 2006).

As this intuitive discussion about the different motivations of the options trading community and financial analysts illustrates, we should expect a difference in analyst-based forecasts and option-based forecasts (obtained from the RT). On the one hand, we have a party (financial analyst) driven by the need to stay employed, which the literature has argued leads to conservative forecasts. On the other hand, we have another party (option market participant) trading these options, on average, because they are trying to limit their future downside exposure to a specific market. Now, we must turn to the more interesting question of how or what information is or is not used in the make-up of various stock market forecasts.

2.1.2 Back to the stochastic discount factor

The stochastic discount factor is the variable that discounts the future cash flow to today’s value. This value is a function of 1) the expected risk of the future cash flow, and 2) the risk aversion of a representative investor. We can obtain an estimate of the stochastic discount factor through both analyst forecasts and the option-based forecast. The difference is going to be in the information used to obtain the probability of getting

[^1]: "Correctness” for the purposes of this paper is about consistently being within a narrow margin of error rather than having a perfect forecast.
the future payout. The risk aversion of the representative investor will also differ by forecast: for the RT forecast, the representative investor is the average options market investor, while, for the analyst forecast, the representative agent is the average analyst.

We can write the expected future price of a stock as follows (Cochrane, 2009):

\[ p_t = E_t(\tilde{m}_{t+1}x_{t+1}) \]  

(1)

where \( p_t \) is the price of an asset at some time \( t \), \( E_t \) is the expectation operator, \( \tilde{m}_{t+1} \) is the stochastic discount factor (or the pricing kernel), and \( x_{t+1} \) is the future cash flow of the asset. The variable \( m_{t+1} \) in equation (1) is what incorporates the expected risk and the risk aversion. It is the adjustment to the price of an asset that makes it worthwhile for investors to purchase that asset given its level of risk.

Further, if we assume that we know the future payout (as is the case of for a state price) such that it is normalized to be equal to one, then the only unknown that is left in our equation is the stochastic discount factor. Regardless of the model used for the stochastic discount factor, its empirical estimation will be done with real-world data. As such, it stands to reason that the discount factor will be based on all available information at the moment we are trying to price the asset. This should be true regardless of whether we are referring to analysts or option traders. Hence, we can re-write equation (1) as follows:

\[ P_t = E(m_{t+1}|I_t) \]  

(2)

where the price equation is now a function of the information set at time \( t \).

### 2.2 Recovery Theorem (RT)

The Recovery Theorem (RT) by Ross (2015) is a methodology that allows us to extract a forecast for an asset for which options are traded. Ultimately, the methodology allows us to disentangle state prices into their individual components (the discount rate, the pricing kernel, and the natural probability distribution). To accomplish this, we must
first define state prices. In continuous time theory, state prices are defined as the second derivative of the option prices with respect to the strike price. Intuitively, they are the price of an asset that pays you one dollar at some future date, $T$, if the underlying asset reaches a specific state given a specific initial state. State prices are used because they effectively standardize the future payout from our asset. In essence, we remove part of the uncertainty of the future asset’s price, which then allows us to focus on extracting the stochastic component in the pricing equation. Mathematically, we can write the state price as follows:

$$s_{t,j} = \delta \frac{u'(c_{t+1,j})}{u'(c_{t,i})} f_{i,j}$$  \hspace{1cm} (3)

where $s$ is a vector of state prices, $i$ and $j$ are states (e.g. S&P 500 levels), $\delta$ is a discount rate, $u'$ is a marginal utility, and $f$ is the natural probability measure. What we want from this equation is the natural probability distribution of returns (in the case of this paper, we want the natural probability of returns for the S&P 500 – which is the asset that will be analyzed empirically). That means that we need to empirically obtain each component separately so that we can eventually solve for the natural probability distribution, $f$.

First, we must obtain state prices (the left-hand side of equation 3). State prices are derived as follows (Breeden and Litzenberger, 1978):

$$s(K,T) = \frac{\partial^2 \text{Call}(K,T)}{\partial K^2}$$  \hspace{1cm} (4)

where $s(K,T)$ is the state price, Call$(K,T)$ is the call option price, and $K$ is the strike price. These prices can be estimated empirically in various ways, but the method used in this paper is the method described in Sanford (2016).

Next, we need to derive contingent state prices. Contingent state prices are defined in the same way as state prices except that, for contingent prices, we generalize the
initial state and the final state transitions so that they are not solely dependent on the current state of the world. For example, if the current state of the S&P 500 is 1,000, state prices will be the prices for all transitions from an initial state of 1,000 to some future state, whereas contingent state prices will be all possible pairs from any current state to any future state. This is the only way for us to have enough equations to solve the entire RT system of equations. Contingent state prices are obtained for the RT as follows:

\[ s_{t+1} = s_t P, \quad t = 1, \ldots, m - 1 \]

\[ P \geq 0 \]

where \( s_{t+1} \) is the next period’s state price, \( s_t \) is the current period’s state price, and \( P \) is the contingent state price. More details on the exact estimation of the contingent state prices can be found in Sanford (2017). Rewriting equation 3 we get the following equation for the natural probability distribution, \( f \):

\[ f_{i,j} = 1 \delta p_{i,j} u'(c_i) u'(c_j) \]

where we can now use the result from equation 5 solving for contingent state prices. Separating the marginal utilities (and re-arranging) gives us:

\[ p_{i,j} \frac{1}{u'(c_j)} = \delta \frac{1}{u'(c_i)} f_{i,j} \]

Defining the marginal utilities in terms of \( z \) and then multiplying both sides by the respective \( z \)'s, we obtain:

\[ p_{i,j} z_i = \delta z_j f_{i,j} \]

Noting that \( p_{i,j} \) and \( f_{i,j} \) are entries to a matrix, we can re-write it as:

\[ P z_i = \delta z_j F \]
Since $F$ is a stochastic matrix we can write the previous equations as:

$$P\tilde{z}_i = \delta\tilde{z}_j$$

which is nothing more than an eigenvalue/eigenvector problem that can be solved using the Perron-Frobenius theorem (Meyer, 2000). At this point in the RT, we have all of the components to solve for the natural probability distribution as follows:

$$f_{i,j} = \frac{1}{\delta}p_{i,j} \frac{z_i}{z_j}$$

(6)

The only difference between the univariate RT (UVRT) derived above and the multivariate RT (MVRT) proposed in Sanford (2017) is in the derivation of the contingent state prices as follows:

$$s_{t+1} = s_t P + Ivol_t \eta, \quad t = 1, ..., m - 1$$

(7)

$$P \geq 0 \text{ and } \eta \geq 0$$

where the MVRT controls for the expected uncertainty as proxied by the implied volatility variable, $Ivol$, in the derivation of the contingent state prices. Otherwise, the two models, the UVRT and the MVRT, are identical. Once we have the natural probability distribution for the price equation, it becomes trivial to use it to obtain the expected return of an asset (see for example Cochrane (2009)).

### 2.3 Analyst Forecast

The main driver for financial analysts is not, as one might expect, to get the most accurate forecast possible. Rather, the analyst wants to be as close as possible within a certain margin of error (Mikhail et al., 1999; Lim, 2001; Gu and Wu, 2003; Ramnath et al., 2008). If the analyst is beyond that margin of error, they run the risk of losing their jobs over the long run. As such, the analyst, on average, uses the information
that allows them to construct a forecast that is accurate enough, but never so far off that the analyst runs the risk of losing their livelihood. In essence, the analyst is not irrational and choosing not to use all available information. Rather, the analyst has a bias (conscious or unconscious) that prevents her from using the information that might result in a forecast that is too far from the current level of the asset being analyzed.

A large literature [Mikhail et al., 1999; Lim, 2001; Gu and Wu, 2003; Ramnath et al., 2008] shows that analysts are not remunerated based on how well they can forecast earnings, for example. Instead, analysts are fired when their performance is deemed to be inadequate. In order to keep the mathematical problem simple, let us assume that analysts’ life earnings depend solely on their ability to become “superstar” analysts. This means that analysts are motivated by the potential to become a recognized analyst, a valuable commodity in the eyes of the analysts’ employer. We will assume that an analyst has two potential outcomes: either they can continue their work, and earn 1$, or they are terminated by their employer and they now earn 0$ in perpetuity. It is not necessary to become a superstar as an analyst, but this certainly motivates the analyst to perform better. To keep the problem even simpler, I assume that there is no probability of becoming a superstar. Instead, the analyst is faced with the prospect of either continuing to do her job (motivated by the prospect of becoming a “superstar”) or to get terminated (the model would simply include a third option in the more complicated model – to become a “superstar”). The probability of continuing to be an analyst (not getting terminated) is dependent on the analyst’s ability to forecast earnings. We model this “ability to forecast” as the average distance between the analyst’s forecast and realized earnings. For tractability purposes with the RT, we will assume that the proxy for earnings is the stock’s price. In other words, we can write the analyst’s performance as follows:

\[
\chi(P|I_t) = \sum_{t=1}^{n} \frac{E_t[P_{t+1}|I_t] - P_t^{r+1}}{n}
\]  

(8)

where \(E_t\) is the expectation operator at time \(t\), \(P_{t+1}\) is the expected price for the next
period (the one being estimated by the analyst), $P_{t+1}^r$ is the next period’s realized price and $I_t$ is the information set available to the analyst at time $t$. Substituting equation 1, we can rewrite equation 8 as follows:

$$\chi(P|I_t) = \sum_{t=1}^{n} \frac{E_t[m_{t+1}x_{t+1}|I_t] - P_{t+1}^r}{n}$$

where $m_{t+1}$ is the stochastic discount factor in the pricing equation and $x_{t+1}$ is the future payoff of the asset. Normalizing the future payoff $x_{t+1}$ like we did for the Recovery Theorem in the previous section, we obtain the following equation:

$$\chi(P|I_t) = \sum_{t=1}^{n} \frac{E_t[m_{t+1}I_t] - P_{t+1}^r}{n}$$

The implication of the model is that the analyst will formulate her forecast such that the average difference between her forecast and the realized price of the asset is minimized.\(^3\) This will, in essence, ensure that the probability of getting fired is smallest. Looking at equation 10, one should notice that the only thing that the analyst controls is how she formulates her expectation. Since the stochastic discount factor is unknown, she will use the information set available to her at time $t$ to estimate it. As such, the only piece of information that the analyst controls is the information set used to formulate the expectation. Thus, the analyst’s problem is an infinite horizon optimization problem:

$$\max_{I_t} V(\chi(P|I_t))$$

\(^3\)In reality, the problem would be more complicated than this because the analyst would want to minimize her chance of getting fired (being below the threshold $\alpha$) all while maximizing her probability of becoming a superstar. So, the more complicated problem would be a minimax optimization problem. For simplicity, I am only looking at the minimization problem.
where we can define the value function in equation (11) as a piece-wise function as follows:

\[
V(\chi(P|I_t)) = \begin{cases} 
1, & \text{if } \chi(P|I_t) \leq \alpha_t \\
0, & \text{if } \chi(P|I_t) > \alpha_t
\end{cases}
\] (12)

which can be understood as the analyst being allowed to continue in her current position if her overall (average) forecast (\(\chi(P|I_t)\)) is less than some threshold (\(\alpha_t\)). The analyst will choose the information that she uses to formulate her forecast so as to minimize the possibility of getting fired.

In an economy where markets are fully rational (Muth, 1961; Blanchard and Watson, 1982) and all available information is used to price assets, an option-based forecast should, ultimately, be the same as an analyst-based forecast. The model above aims to illustrate why the two forecasts may be different from one another even if option market participants and analysts are acting on the same information. It suggests that it is possible to obtain two different forecasts because of different incentives despite all parties acting on the same information set.

3 Methods

3.1 Data

Most data for this article come from the Wharton Research Data Services. More specifically, the return data for the S&P 500 were obtained from the CRSP database, the options data needed to apply the Recovery Theorem were obtained from the OptionMetrics database, and the analyst forecast data were obtained from the Institutional Brokers’ Estimate System (I/B/E/S) database. The I/B/E/S database reports all of the data from analyst reports for a specific stock. Using the individual forecasts from the analysts, I can then aggregate the information by looking at the median and/or the mean forecast for all analysts. Further, the aggregated forecasts can be used as
an expected distributions of analyst forecasts for the quantile regressions. Once the analyst forecasts are aggregated into a single forecast number, I match the date and horizon of the forecast to that of the RT. The most granular forecast that I can use is for monthly data. Because of missing data points in the I/B/E/S database, I end up with a total dataset spanning from September 2003 to July 2013 of monthly data points (103 data points total). When only the RT is analyzed, I use the entire sample which spans from February 1996 to August 2015 (235 data points). I use this particular period because it constituted the entirety of the data available about the S&P 500 at the time of analysis.

As I have noted above, the last portion of my statistical analysis examines which of almost 300 factors best explain the two forecasts. I will only discuss major ones here. The first 16 variables in table [1] are well documented in [Welch and Goyal (2007)]. The rest of the variables are worth mentioning since they might be more obscure. The variable Smooth Rec Prob by [Chauvet and Piger (2008)] represents the smoothed probability of a recession in the United States and was obtained from the FRED database. The Money Growth variable represents the monthly percentage change in the M3 supply of money, also from the FRED database. The Recession Indicator is the NBER-based recession indicator for the United States from the FRED database. The Macro Leading Index variable represents the expected growth rate of the American economy over the next six months, also obtained from the FRED database. The UMICH Sentiment is the University of Michigan’s consumer sentiment index. It is based on a consumer survey conducted by the University of Michigan, and gives a pulse of the average consumer sentiment in the United States. This indicator was obtained directly from the University of Michigan’s Surveys of Consumers website. Unclassified and News VIX are related to one another [Manela and Moreira (2017)]. News VIX stands for “news implied volatility”; it is the volatility implied by various news sources. Unclassified is the volatility implied by sources that cannot be classified as one of the five categories of the news VIX index. The Int Capital Risk variable, which stands for “intermediary capital risk factor,” represents shocks to the equity
capital ratio of financial intermediaries (He et al. 2017). Finally, the Consumption Growth variable represents the growth of consumption in the United States, and was obtained from the FRED database.

<table>
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<th>Variable</th>
<th>n</th>
<th>Min</th>
<th>q1</th>
<th>x̅</th>
<th>x̄</th>
<th>q3</th>
<th>Max</th>
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<td>0.00232</td>
<td>0.05809</td>
<td>0</td>
</tr>
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<td>-0.16698</td>
<td>-0.01246</td>
<td>0.01299</td>
<td>0.00786</td>
<td>0.03252</td>
<td>0.10901</td>
<td>0</td>
</tr>
<tr>
<td>Smooth Rec Prob</td>
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<td>0.10000</td>
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<td>0.45000</td>
<td>100.00000</td>
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</tr>
<tr>
<td>Money Growth</td>
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<td>0.48193</td>
<td>0.51209</td>
<td>0.63670</td>
<td>2.29745</td>
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</tr>
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<td>Recession Indicator</td>
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<td>0.00000</td>
<td>0.00000</td>
<td>0.11064</td>
<td>0.00000</td>
<td>1.00000</td>
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</tr>
<tr>
<td>Macro Leading Index</td>
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<td>-2.68000</td>
<td>0.69000</td>
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<td>0.91247</td>
<td>1.53500</td>
<td>1.94000</td>
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<td>UMICHE Sentiment</td>
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<td>70.45000</td>
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<td>79.26408</td>
<td>90.30000</td>
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<td>Unclassified</td>
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<td>0.00381</td>
<td>0.00594</td>
<td>0.02789</td>
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</tbody>
</table>

Table 1: Descriptive Statistics

### 3.2 Estimation

The analysis proceeds in four steps. First, I conduct hypothesis tests to determine whether the analyst-based and option-based forecasts are the same. Second, I estimate cross-sectional quantile regressions to determine if there are significant differences between the forecasts in the tails compared to the forecasts at the median. It is possible
that the information used to construct the two forecasts is the same at the mean or median (towards the middle of the distribution) but differs when we compare the extremes of the distribution. The quantile regressions are done first between the forecasts and the realized return and then between the forecasts themselves. Third, using partial information decomposition (see section 3.2.1 below), I separate the information content of the forecasts into portions that are unique, synergistic, and redundant across forecasts. Fourth and finally, I estimate cross-sectional regressions to determine which specific information is actually used to construct the two types of forecasts. I analyze almost three hundred factors known to characterize market returns, such as, for example, the Fama–French factors. The factors fall into one of three categories: macroeconomic factors, stock market factors, and probability factors. Macroeconomic factors are variables that are derived from macroeconomic data such as consumption growth, inflation, and unemployment. Stock market factors are variables that are known to affect a stocks behavior specifically such as book-to-market ratios, and dividend-price ratios. Finally, probability factors are variables that reflect the probability of certain events occurring such as overall market crash probabilities (the probability that the market decreases by 20%), recession probabilities, and sentiment indices. This portion of the analysis aims to answer the question of which information specifically is used in constructing the two forecasts.

3.2.1 Partial Information Decomposition

Partial information decomposition methods are fairly new and seldom used in financial economics research (Williams and Beer, 2010; Griffith and Ho, 2015; Chan et al., 2016; Flecker et al., 2011; Makkeh et al., 2017). The concept, from information theory, is to decompose the information available from multiple variables into what is known as synergistic information, unique information, and redundant information. Redundant information in the context of PID is “bad” because it indicates that two or more independent variables provide the same information. Unique information, on the other
hand, is the amount of information that is unique to a specific independent variable. This is information that would not be available if that variable were not included. Finally, synergistic information is the information that would not be available if both variables were not included together in the model. As an example, in a multivariate regression, we can think of synergistic information as the information gleaned from interaction effects. PID analysis allows us to estimate numerically how much of the information in our multivariate analysis is unique, synergistic, or redundant. In the context of this paper, we are interested in determining what, if any, information is different between the analyst-based and option-based forecasts. Using PID language, we want to quantify the unique and synergistic information across our forecasts. If most of the information is redundant, it indicates that the information contained in the forecasts is the same.

In other words, PID is concerned with the statistics of how two (or more) random variables, called source variables, jointly or separately specify/predict another random variable, called a target random variable. The source variables can provide information about the target uniquely, redundantly, or synergistically. Together, the four partial information terms add up to the mutual information, $I$, as follows:

$$I(Z; X_1, X_2) = Synergy(Z; X_1, X_2) + Unique(Z; X_1) + Unique(Z; X_2) + Redundency(Z; X_1, X_2)$$

(13)

where $Z$ is the target variable (realized return) and $X_1$ and $X_2$ are the source variables (the analyst-based and option-based forecasts). To support this article’s hypothesis, we would need to find that we have uniqueness (information that is unique to each of the forecast variables) and synergy (information that complements each of the forecast variables together), but little to no redundancy (information that is already contained within both of the forecast variables).
4 Results

4.1 Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>n</th>
<th>Min</th>
<th>q₁</th>
<th>̅x</th>
<th>̅x</th>
<th>q₃</th>
<th>Max</th>
<th>#NA</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-0.00212</td>
<td>0.00244</td>
<td>0.00472</td>
<td>0.00694</td>
<td>0.07449</td>
<td>0</td>
</tr>
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<td>MVRT</td>
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<td>-0.19411</td>
<td>-0.02140</td>
<td>0.02041</td>
<td>0.01577</td>
<td>0.06392</td>
<td>0.18340</td>
<td>0</td>
</tr>
<tr>
<td>UVRT</td>
<td>235</td>
<td>-0.05701</td>
<td>-0.00409</td>
<td>0.00320</td>
<td>0.00342</td>
<td>0.00964</td>
<td>0.04832</td>
<td>0</td>
</tr>
<tr>
<td>Return</td>
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<td>-0.01754</td>
<td>0.01769</td>
<td>0.00693</td>
<td>0.03542</td>
<td>0.13022</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 2: Descriptive Statistics

Table 2 shows the descriptive statistics for the analyst forecast, the multivariate RT (MVRT), the univariate RT (UVRT), and the realized returns, respectively. The columns are as follows: \( n \) is the number of observations in the sample, \( \text{Min} \) is the minimum value, \( q₁ \) is the first quantile value, \( ̅x \) is the median, \( ̅x \) is the mean, \( q₃ \) is the third quantile, \( \text{Max} \) is the maximum value, and \( \#\text{NA} \) is the number of missing values in the sample. The descriptive statistics presented in Table 2 give a good indication of just how different the forecasts are in comparison to the realized return. First, focusing on the tail values by looking at the min and max values, we notice that the closest value to the realized return is the one from the MVRT (with a minimum at -0.19411 compared to -0.23884 for the realized return). The analyst and UVRT forecasts are both quite far from the value for the realized return (-0.05701 and -0.01513, respectively). This is the first indication that the forecast obtained from the MVRT accounts for a lot more of the variation in the returns than any of the other forecast models. Granted, at this point we do not yet know the specific timing of the values obtained so it is important, since this is a time-series analysis, that we look into that next. Figures 1 through 3 compare the timings and differences between the CDFs of the realized returns and various forecasts.
The time series plots in figure 1 are ordered as follows: top left is the plot for the realized return, top right is the plot for the MVRT, bottom left is the plot for the UVRT, and bottom right is the plot for the analyst forecasts. The analysts forecasts (bottom right graph) seem to have a lot less variation than the other time series graphs. This is in line with the quantile–quantile plots in figure 2. Ultimately, the time series shows that the analyst forecasts have fairly consistent results (positive) and that their negative forecasts have a tendency to be small negative forecasts. This is in line with my proposition that analysts tend to be much more conservative than option traders. The largest positive forecast (from table 2) is about 7.5% while the largest negative expected return is about -1.5%. This is certainly not the case for the UVRT (bottom left graph) and MVRT (top right graph) which both have substantially larger negative and positive expected returns. The swings seem to be much larger for the MVRT than for the UVRT, which makes sense since the MVRT adds a control for the expected volatility in its model derivation. We are including a lot more expected uncertainty in the MVRT forecast compared to the others. The next questions that arise are: 1)
how far are these distributions from a normal distribution?, and 2) how far are these distributions from their empirical counterparts?

![QQ Plots](image)

Figure 2: QQ Plots

Figure 2 presents the quantile–quantile (QQ) plots for the realized return, MVRT, UVRT, and analyst forecasts. The QQ plot shows how far the quantiles for an empirical distribution (the dots) are from a theoretical normal distribution (diagonal line) (Hyndman and Fan, 1996). As the asset pricing literature shows, most of the forecasts are fairly normally distributed. The only exception is at the tails, which clearly deviate from the normal distribution for all of the empirical distributions. Ultimately, all of these empirical distributions exhibit fat tails (Rachev et al., 2005; Cont, 2001). The most notable fat tail is on the right side of the distribution in the QQ plot for the analyst forecasts. This indicates that, on average, the analysts are very optimistic (high expected returns) whenever forecasts are positive. Analysts seem to produce very large positive forecasts, but negative forecasts that are in line with the normal distribution. The MVRT and UVRT are much closer to the realized return. This is an indication that the UVRT and MVRT are much more realistic in their expectations of future
movements of stock prices. Still, the UVRT does seem to exhibit fatter tails than the MVRT.

![Figure 3: Empirical CDFs](image)

The left graph in figure 3 shows the empirical cumulative density function (ecdf) for the MVRT (black line) compared to the expected return from the analysts (red line) and the realized return (blue line). The right graph in figure 3 compares the ecdf of the UVRT (black line) to the expected return from the analysts (red line) and the realized return (blue line). Clearly, the RT (both UVRT and MVRT) forecasts a fatter tail than both the realized return (blue line) and the expected return from the analysts (red line). It is important to note that the empirical CDFs are compared in “real-time.” This means that the graphs show the distributions of the different forecasts moved forward by one month compared to the actual realized return. This is so that the realized return and the different forecasts are compared at the same time interval.

---

4For example, the one-month forecast for February would have been obtained in January. So the comparison would be between the January forecasts for February and the realized return for February so that we are comparing apples to apples.
4.2 Hypothesis Testing

We want to answer the following question: why do we need a model like the Recovery Theorem when we have forecasts available from financial analysts? In other words, is there value in forecasts from models that obtain the stochastic discount factors from options like the RT, or are we better off using the forecast from analysts? The first test in this paper is a hypothesis test as follows:

\[ H_0 : \mu_{UV\, RT} = \mu_{\text{analyst}} \]
\[ H_a : \mu_{UV\, RT} \neq \mu_{\text{analyst}} \]  

(14)

where \( \mu_{UV\, RT} \) is the expected return for the univariate RT and \( \mu_{\text{analyst}} \) is the expected return obtained from the analyst forecast. The null hypothesis from equation (14) can be rejected at the 1% level of significance (p-value = 0.00348) with 103 monthly observations. This result indicates that the information set used for the UVRT forecast is likely different than that used by analysts.

Next, we will look at the hypothesis test for the MVRT as follows:

\[ H_0 : \mu_{MV\, RT} = \mu_{\text{analyst}} \]
\[ H_a : \mu_{MV\, RT} \neq \mu_{\text{analyst}} \]  

(15)

where \( \mu_{MV\, RT} \) is the expected return for the multivariate RT and \( \mu_{\text{analyst}} \) is the expected return obtained from the analyst forecast. The null hypothesis from equation (15) can be rejected at the 10% level of significance (p-value = 0.05297) with 103 monthly observations. Again, this is an indication that the information set used for the MVRT forecast is likely different than that used by analysts.
4.3 Cross-Sectional Quantile Regressions

Quantile regressions [Koenker and Hallock, 2001; Yu et al., 2003; Koenker and Xiao, 2002] can help determine where, on average, we see differences in the distributions of the forecasts. Specifications for the quantile regressions follow Koenker and Hallock (2001). Figures below present the results. Figures 4 through 9 are the results for the different forecasts compared to the realized return. Figures 10 through 13 are the results for the RT forecasts compared to the analyst forecast.

Figure 4: Quantile Regression – Analyst
Figure 5: Quantile Regression Results – Analyst

Figure 6: Quantile Regression – MVRT
Figure 7: Quantile Regression Results – MVRT

Figure 8: Quantile Regression – UVRT
Figure 9: Quantile Regression Results – UVRT

Figure 10: Quantile Regression – UVRT vs Analyst
Figure 11: Quantile Regression Results – UVRT vs Analyst

Figure 12: Quantile Regression – MVRT vs Analyst
The results we see here are quite persistent and very similar to the results from the QQ-plots above. Ultimately, the middle of the distributions have a tendency to be quite similar and of a good fit, while the tails of the distributions are different. This finding is in line with my hypothesis: analysts tend to be conservative in their forecasts, which leads to large discrepancies in the left tails, while the RT incorporates much more uncertainty into its forecasts.

4.4 Partial Information Decomposition

As discussed in section 3.2.1, we use partial information decomposition to separate the information from a number of source variables into synergistic, unique, and redundant information. Redundant information indicates that the variables included in the model contain the same information. Unique information is information contained in a single specific variable. And synergistic information is information that no individual variable
contains, but that many variables together contain (i.e., the whole is greater than the parts).

Figure 14: UVRT Decomposition

Figure 15: MVRT Decomposition

Figure 14 shows the partial information decomposition with the UVRT and Figure 15 shows the partial information decomposition with the MVRT. In the case of the UVRT decomposition, most of the unique information is coming from the UVRT forecast (unique_2), while the analyst forecast contributes little additional unique information (unique_1). The same is true for the MVRT decomposition. In both figures, we see redundancy, which means that a significant amount (almost half) of the same information is contained in both forecasts. Interestingly, we also find synergy from including both variables (the RT forecast and the analyst forecast) together in the model. The takeaway here should be that, although the analyst forecast does contain information important to forecasting returns, it includes little unique information that is not already contained in the RT.
Table 3: MVRT – Information Decomposition

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MVRT</td>
<td>0.2813***</td>
<td>0.2684***</td>
<td>0.2327***</td>
</tr>
<tr>
<td></td>
<td>(0.0481)</td>
<td>(0.0420)</td>
<td>(0.0457)</td>
</tr>
<tr>
<td>Analyst Forecast</td>
<td>−1.4139***</td>
<td>−1.4950***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2478)</td>
<td>(0.2486)</td>
<td></td>
</tr>
<tr>
<td>Interaction$_{AF \times MVRT}$</td>
<td>4.5519†</td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(2.4479)</td>
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<td>Constant</td>
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<td>0.0094*</td>
<td>0.0103***</td>
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<tr>
<td></td>
<td>(0.0040)</td>
<td>(0.0037)</td>
<td>(0.0037)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.2533</td>
<td>0.4367</td>
<td>0.4558</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>103</td>
<td>103</td>
<td>103</td>
</tr>
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</table>

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$

To corroborate findings from the PID, table 3 shows the results for forecast regressions including the MVRT and analyst forecasts as independent variables. For the purposes of this paper, a forecast regression is a regression with one (or multiple) forecast at time $t$ as the independent variable and the realized return at time $t+1$ as the dependent variable. The MVRT alone (column 1) produces a 0.2533 $R^2$ for our forecast regression. Column 2 adds the analyst forecast. We notice that there is substantial benefit to having both the analyst-based and MVRT-based forecasts as independent variables in our regression. Finally, column 3 shows the synergy by adding an interaction term between the two independent variables. Again, we notice an improvement in the forecast.
Table 4: UVRT – Information Decomposition

Table 4 illustrates the same pattern as Table 3. Adding the analyst-based forecast into the regression seems to lead to a larger improvement in forecasting. Otherwise, the results for the MVRT and the UVRT are quite similar.

### 4.5 Cross-Sectional Factor Regressions

Now that we strongly suspect that different forecasts are based on different information sets, we might want to know what information exactly is being used in formulating expectations at any given time period. For example, an analyst who recommends a certain price for the S&P 500 index on any given day has constructed her price using information available to her on that specific day. A cross-sectional factor regression attempts to, at the aggregate level, determine what specific information analysts and option pricers might have used when constructing their prices. As many other researchers have noted over the years, it is very difficult to find every factor included in an investor’s or an analyst’s decision process when prices are constructed. If we assume that markets are fully rational, it would follow that all available information, no matter how unimportant, would be incorporated in an investor’s/analyst’s pricing model. As such, in this article, I limit my analysis to the five or so most important
factors in each pricing model.

The regressions in this section are simple linear regressions where the independent variables are the potential factors that might explain the information being used to formulate the different forecasts (the dependent variables). The regression specification is as follows:

\[ E_t[r_{t+1}] = \alpha + \sum_{i=1}^{n} \beta_i x_{i,t} + \epsilon \]  

(16)

where the dependent variable \( E_t[r_{t+1}] \) is the expected return obtained from the forecast, \( \alpha \) is the regression intercept, \( x_{i,t} \) is the factor \( i \) that explains the forecast at time \( t \), \( \beta_i \) is the coefficient for factor \( i \) and \( \epsilon \) is the error term for the regression. I obtained the factors included in these regressions from the current literature on factor models (Fama and French, 1993, 1996, 2012; Welch and Goyal, 2007; Martin, 2017). I include factors that are not only known to affect stock prices, but that are also known to affect or forecast the macroeconomy (Estrella and Mishkin, 1998; Chauvet and Piger, 2008; Manela and Moreira, 2017).

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
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<tbody>
<tr>
<td>( MVRT_{t-1} )</td>
<td>-0.0727</td>
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<td>-0.0755</td>
<td>-0.1176†</td>
<td>-0.1172†</td>
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<td>(0.0645)</td>
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<td>Unclassified News</td>
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<td>0.0007</td>
<td>-0.0067**</td>
<td>-0.0062**</td>
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</tr>
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<td></td>
<td>(0.0010)</td>
<td>(0.0010)</td>
<td>(0.0019)</td>
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</tr>
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<td>Intermediary Capital Risk</td>
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<td>0.1836*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td>(0.0799)</td>
<td>(0.0792)</td>
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<td>(0.0018)</td>
<td>(0.0016)</td>
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<td>Consumption Growth</td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(1.2863)</td>
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<td>-0.1098***</td>
<td>-0.0841**</td>
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<td></td>
<td>(0.0059)</td>
<td>(0.0113)</td>
<td>(0.0111)</td>
<td>(0.0277)</td>
<td>(0.0294)</td>
</tr>
<tr>
<td>( R^2 )</td>
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<td>0.0077</td>
<td>0.0471</td>
<td>0.1293</td>
<td>0.1524</td>
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<tr>
<td>Num. obs.</td>
<td>235</td>
<td>235</td>
<td>235</td>
<td>235</td>
<td>235</td>
</tr>
</tbody>
</table>

\(*p < 0.001, **p < 0.01, *p < 0.05, †p < 0.1\)

Table 5: MVRT – Cross-Sectional Regressions
In table 5, the dependent variable is the current expectation obtained from the multivariate RT (MVRT). Out of the hundreds of variables examined in the course of this research, the five variables in the table—the previous period’s forecast from the MVRT, unclassified news, intermediary capital risk, the News VIX, and consumption growth—had the most explanatory power for the MVRT’s cross-section.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$UVRT_{t-1}$</td>
<td>-0.0565</td>
<td>-0.0966</td>
<td>-0.0946</td>
</tr>
<tr>
<td></td>
<td>(0.0658)</td>
<td>(0.0646)</td>
<td>(0.0632)</td>
</tr>
<tr>
<td>Recessions</td>
<td>0.0111***</td>
<td>0.0097***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0028)</td>
<td>(0.0028)</td>
<td></td>
</tr>
<tr>
<td>Money Growth</td>
<td></td>
<td></td>
<td>0.0080***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0024)</td>
</tr>
<tr>
<td>Constant</td>
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<td>0.0018†</td>
<td>-0.0021</td>
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<td>(0.0009)</td>
<td>(0.0009)</td>
<td>(0.0015)</td>
</tr>
<tr>
<td>$R^2$</td>
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<td>0.0669</td>
<td>0.1106</td>
</tr>
<tr>
<td>Num. obs.</td>
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<td>235</td>
<td>235</td>
</tr>
</tbody>
</table>

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$

Table 6: UVRT – Cross-Sectional Regressions

In table 6, the dependent variable is the current expectation obtained from the univariate RT (UVRT). Out of the hundreds of variables examined in the course of this research, the three variables in the table—the previous period’s forecast from the UVRT, the recession indicator, and money growth—had the most explanatory power for the UVRT’s cross-section.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
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<td>-0.0416***</td>
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Table 7: Analyst Forecasts – Cross-Sectional Regressions

***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.1
Table 7 shows the results for the current expectation obtained from the analyst forecasts as the dependent variable. Here, the smooth recession probability variable, the VIX, the book to market variable of the companies in the Dow Jones Industrial Average, the t-bill rate for the 3-month treasury bills, the default rate for firms rated AAA, the default rate for firms rated BAA, the inflation rate, the macro leading index, and the University of Michigan’s consumer sentiment index are the key explanatory variables. Please note that the high $R^2$ values in this table are not surprising since analysts are using the same information to formulate their expectations as other investors. All of this data is made available to the public, which indicates that analysts, on average, use unsurprising data in formulating their expectations. These variables are commonly known to be good (general) indicators of where the economy is heading. If analysts are indeed trying to stay conservative, one would expect them to use data that is conservative in nature.

One conclusion that can be drawn from this set of tables (tables 5 to 7) is that the information used by analysts to create their forecasts does seem to be quite different from the information used to formulate the RT forecast.

5 Conclusion

Is there a benefit to using a stock forecast obtained from the RT compared to a forecast created by a financial analyst? Do we need option-based forecasts when we already have perfectly good forecasts from professional analysts? First, using simple two-sided hypothesis tests and using quantile regressions, I determined that the option-based and analyst-based forecasts were statistically different from one another. One interesting conclusion came from the quantile regressions where we can see that the difference mostly stems from the forecasts in the tails. The RT tends to forecast much larger movements in the tail than analysts. In other words, it takes a lot for analysts to forecast large stock market movements. Based on this sample, analysts predict small deviations from the status quo rather than large potential deviations from the current
trend of the market.

But what information are these forecasts based on? Do they rely on the same information sets? Using cross-sectional regressions with each forecast as the dependent variable, I was able to ascertain that the RT forecast mostly uses information such as: news based uncertainty indices, capital risk, news-based volatility indices, and macroeconomic uncertainty. On the other hand, analyst forecasts appear to be based on information such as: t-bill rates, book to market values, and other macroeconomic variables.

**References**


