An Econometric Model to Forecast Equity Prices

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Abstract

Purpose
DCF models have become a sine qua non in stock pricing, being widely used by sell-side analysts to calculate target prices. On the other hand, time series models, such as ARIMA, are usually disregarded for this purpose under the theoretical framework provided by the efficient market hypothesis. This paper compared the short-term performance of stock price forecasts generated by an econometric model versus those of sell-side analysts.

Approach
Using a set of stock indices and individual stocks from Brazil and the US, and controlling for different levels of analyst coverage and share liquidity, we performed an in-sample test between an ARIMA (p,d,q) model with external regressor, the analysts’ EPS consensus, and analysts’ target price consensus. The test compared four measures: i) absolute percentage error, ii) standard deviation of errors, iii) correlation with the price at issuance date and iv) abnormal returns produced. To ensure comparability between both series, we used a rolling scheme for the training set.

Findings
Results were surprising. Average correlation between target price and price at issuance date reached 0.29 (ARIMA) versus 0.87 (analysts), while forecast error was reduced from 30.7% (analysts) to 10.5% (ARIMA). ARIMA was also more stable, having a standard deviation of 9.1%, against 14.3%. Finally, the model produced average abnormal returns of 30%, against 11.7%.

Value
The evidence supports the call that time series models can be an accurate source to generate stock price forecasts in the short term, or at least more accurate than the target prices issued by sell-side analysts, being a valuable finding for market participants.

Key words: forecast, stock prices, sell-side analyst, econometric model, ARIMA.
1. INTRODUCTION

Sell-side equity analysts, i.e. these that work for brokerage firms, give investors advice on stock picking. To convey their opinions on stocks, analysts issue a rating, mainly Buy, Neutral and Sell, and calculate a target price for each stock, for which they may employ a wide range of valuation techniques, from discounted cash flow (DCF) models to relative valuation and statistical analysis. Usually, but not necessarily, there is a correlation between the two variables (Bradshaw, 2002): if there is great upside potential, the analyst is encouraged to rate the stock as a Buy, as well as a Sell in case there is downside; if upside/downside is unattractive or the analyst is uncertain about future developments, the rating is Neutral.

However, many conflicts arise in a job that at first seems straightforward. Brokerage firms earn fees on the volume and number of transactions made by clients, and keep investment banking services with companies, spawning agency conflicts (Asquith, Mikhail & Au, 2005); public companies’ managers have yearly goals, on which their compensation depends; sell-side analysts see their target prices falling short of current stock prices and wonder whether they should revise it upwards (and vice-versa); costs, in terms of both time and human resources, of updating target prices are high, since there is need for revising inputs of many sheets-long DCF models; some stocks have upside or downside currently, but it is not clear whether it is truly an upside or if it is a “value trap”, i.e. fundamentals will change significantly, making the current assumptions that justify the target price unrealistic… The list goes long.

Those sorts of problems make the stock market look more like a market of speculators than a market of investors, in the terms of Graham & Dodd (1951). Yet, recent evidence suggests that most sell-side analysts are likely employing DCF models to reach their target prices (Gleason, Johnson & Li, 2013), a model that was developed to assess the potential value of a company in the long-term, not to forecast stock prices. Negative connotations apart, market participants make money in the short term, not in the long term: bonuses are set yearly for most of the industry, in both buy- and sell-sides, and target prices are issued on a 12-month basis.
Alternative models based on statistics and past data are usually disproved by financiers, who use efficient market theory to refute the idea that future prices hold any relation to past prices. As shown by Fama (1970) in a literature review on market efficiency, many of the studies that concluded for the existence of a “weak market form” tested for serial correlation of stock returns and for profitable trading strategies based on past performance, all of which found evidence of a random-walk pattern in stock prices. In addition, if there was a profitable trading opportunity, investors would exploit it, affecting prices and making the asset fairly-priced once again. This mechanism gives rise to non-stationarity in the time-series (Timmerman & Granger, 2004).

Nevertheless, recent evidence has found caveats in the efficient market hypothesis. When controlling for structural breaks, many markets exhibit stationary patterns. (Lee et al., 2009) This violates a condition of market efficiency: if prices are stationary, they revert to the mean, creating profitable trading strategies.

The objective of this paper was to build an econometric model to predict stock prices in the short-term, i.e. 12-months forward, that was more accurate than models currently used by sell-side analysts. Therefore, market participants can better assess possible stock performance in the short term and unnecessary costs in the industry can be eliminated, being this a relevant theme for both brokerage firms and investment funds alike. Moreover, the model was tested against expected returns, as measured by CAPM, to assess if such model could generate profitable risk-adjusted trading strategies.

The set up of the paper is as follows: i) literature review, with a summary on key concepts used in this paper; ii) methodology, where we develop the hypothesis of an econometric model to forecast equity prices and explain the methodology used to test whether it is better than models currently employed by sell-side analysts; iii) analysis, which contains analyses of the results and assessments of its potential implications; and iv) conclusion, with closing words on the topics discussed, the results obtained and steps for further research on the subject.

2. LITERATURE REVIEW
There are two types of general criticisms when using Statistics-based models to forecast equity prices. The first one, based on fundamentalist valuation techniques, says that such models do not capture the fundamental value drivers of a company, and thus are not be able to account for its potential price, being useless to valuation. The second one, based on the efficient market hypothesis (EMH), states that any attempt to produce forecasts of speculative assets prices using past data is misled, for there is no “money machine”.

Therefore, in order to discuss the matter of stock pricing, it is necessary to go through a wide range of subjects. In this review, we focus on i) sell-side analysts and the equity research process, to provide the reader with knowledge on the structure of the stock brokerage market and the valuation methodologies currently employed by practitioners; ii) the DCFF model, to assess the assumptions upon which current target prices are built; iii) the efficient market hypothesis, to explore the types of information embedded in equity prices and some of the reasons why statistical models to forecast stock prices are often refuted; and iv) time-series models, to highlight some key concepts for the development of an econometric-based equity forecasting methodology.

2.1. Equity Research and Sell-side Analysts

Brokerage houses employ financial analysts to assess stocks’ potential performance in order to issue recommendations to clients – and generate fees for the firm –, relying on information provided by the companies and their own forecasts. To accomplish such, analysts often employ discounted cash flow models (DCF), which are mathematically equivalent to residual-income models (RIM). However, given the considerable effort in modelling and updating DCF models and the constraints on forecasting income statement lines, analysts often make use of relative valuation tools, which rely on some sort of value-to-income relation (e.g. price-to-earnings, EV-to-EBITDA) to derive the fair value of a company. More than tools for valuation, multiples are useful to compare prices among completely different shares, serving as standardized measures. (Gleason, Johnson & Li, 2013)

1 For a demonstration of this statement, see Koller, Goedhart and Wessels (2010).
Although the source for the analyst’s recommendation does not necessarily have to be related to the target price – it might be based on an insider information, some trade opportunity etc. –, there is a high correlation between the stock rating and its upside potential to the target price, as pointed out by Bradshaw (2002).

The calculation of target prices is becoming widespread. While only 32.8% of the equity research reports from the INVESTEXT database exhibited target prices between 1997 and 2003, such number increased to 42.8% in the period between 2003 and 2013 (Gleason, Johnson & Li, 2013). Moreover, further evidence suggests that target prices bear ex-ante information of abnormal returns up to six months ahead, although such information is also embedded in EPS estimates (Brav & Lehavy, 2003). Thus, it is probable that the upward trend in issuance of target prices keeps pace.

Lohn and Mian (2006) also studied information conveyed by analysts’ forecasts. After dividing EPS forecasts into quintiles according to the precision of the forecasts, the authors showed that recommendations in the first quintile yielded excessive returns of 1.27% per month if compared to the ones in the last quintile. Their conclusion, drawn under an institutional perspective, was that sell-side analysts are rewarded a premium for the costly activity of gathering information about companies in a semi-efficient market form.

On the same lines, Brav and Lehavy (2003) measured the impact of target price, recommendations and EPS forecast revisions and concluded that the market reacts to revisions in such variables, deviating stock prices from long-term trends. Yet, if the deviation is very relevant, meaning the stock might be over- or undervalued, analysts will revise their forecasts again, driving current prices towards long-term trends. According to the authors, this iterative process between analysts’ forecasts and current prices creates a trend towards convergence of both series.

Evidences so far argued for a high correlation between analysts’ TP forecasts and actual prices, meaning that either i) the techniques employed in the calculation are accurate, or ii) they influence price formation. However, there is another strain of academicians going on the opposite way. Bradshaw and Brown (2006) point out that only 24% to 45% of the target prices issued by analysts are met. According to the authors, the market does not expect analysts to make very accurate forecasts for target prices, only for EPS, since brokerage
firms’ clients, mostly investment funds, use analysts’ EPS forecasts to fill models with their own assumptions. The authors finish by hypothesizing that sell-side analysts either i) do not have ability to calculate accurate target prices or ii) do not have incentives to do so.

Asquith, Mikhail and Au (2005) hypothesized that analysts deliberately manipulated target prices due to agency problems. Analysts’ bonuses are based on the brokerage firms’ profits, which are a function of the number and the volume of transactions made by clients. Thus, analysts have incentives to issue biased target prices in order to generate fees for the firm. Additionally, analysts have close relationships with the companies’ investor relations divisions. Thus, they might issue mitigate pessimistic target prices in order to maintain that relationship. Finally, brokerage firms often engage in investment banking operations, such as initial public offerings (IPOs). Sell-side analysts might issue more favorable target prices in order to increase profits from the firm’s underwriting business.

Still, it seems unlikely that 55% to 76% – based on Bradshaw and Brown’s numbers – of the target prices issued are subject to agency conflicts. Thus, it is probable there is another, wider reason for such discrepancy. If we look at the description of the equity research process, such as the made by Penman (2010), it is possible to divide it in three steps: i) making explicit forecasts for fundamental variables (e.g. Sales, COGS, EPS), ii) linking them to a valuation model (e.g. DCF, relative valuation, economic profit), in order to reach a target price and iii) add qualitative view, to be for the risk of earnings revisions, and issue a recommendation. As analysts’ fundamental estimates show almost no error, it is likely that the reason for the discrepancy lies in the second step of this process.

Feedback about use of valuation models to forecast prices is ambiguous. Although there is research showing that the use of forward-based multiples (e.g. P/E, EV/EBITDA) is superior to both residual income models (RIM) and backward-based multiples (Liu, Nissim & Thomas, 2002), more recent studies – and with more accurate methodology – states the opposite. Gleason, Johnson and Li (2013) tested for the valuation methodology employed by analysts by creating pseudo-target prices based on RIM and on multiples and tested for the similarity between actual target prices to in order to infer the model used. After that, they tested the forecast accuracy and concluded that RIM were superior to multiples in forecasting, provided the earnings estimates used in RIM were accurate. Such data is consistent with the one presented in the introduction.
Still, RIM do not cope with a factor inherent to stock market – uncertainty. In the third step of the equity research process the analyst incorporates a qualitative view on possible forecasts revisions. (Penman, 2010) Since prices are a function of future variables, they cannot be known a priori, only estimated, and consequently are a function of market expectations, which are subject to change and may not be incorporated in the target price issued.

Moving from capital markets to the corporate side, Olsen, Plaschke and Stelter (2010), developed a methodology to decompose total shareholder return, being changes in expectations one of the key components, which accounted for 12% out of a 95.1% TSR in their sample. Therefore, they give recommendations for companies’ Investor Relations departments to manage capital markets expectations. Both findings support the view of an important role of changes in expectations as price movers. Since most analysts employ DCF models, it is useful to review some of the assumptions upon which most forecasts are usually drawn.

2.2. Discounted Cash Flow to Firm Model

From a fundamental perspective, it is possible to divide a company’s balance sheet in five parts: operating assets, non-operating assets, operating liabilities, debt & quasi-debt (or non-operating liabilities) and equity & quasi-equity (Koller, Goedhart & Wessels, 2010), such that:

\[
(\text{Operating Assets} - \text{Operating Liabilities}) + \text{Non Operating Assets} = \text{Debt} & \text{ quasi debt} + \text{Equity} & \text{ quasi equity} = \text{Total Funds Invested}
\]

(1)

Where the “operating” label refers to assets/ liabilities directly related to a company’s operations, e.g. accounts receivable, accrued expenses, fixed assets, while the “non-operating” ones are mostly byproducts of running a business, e.g. excess cash, marketable securities. The value of the funds invested, as opposed to their historical price used in the balance sheet, is the enterprise value. Most equity valuation models value the operating assets and isolate the equity in the previous equation to find the value of the company for shareholders (the “Equity” term on Equation 1).
As any financial asset, a company’s operating assets can be valued as the present value (PV) of its expected cash flows (Equation 2):

\[
Value \ of \ Operating \ Assets = \sum_{t=1}^{\infty} \frac{FCFF_t}{(1 + WACC)^t}
\]  

That is, the value of a company’s operating assets (VOA) is the present value of future cash flows generated by the firm (FCFF), discounted at a rate that reflects the underlying risk of the investment, namely its weighted average cost of capital (WACC).

As shown by Koller, Goedhart & Wessels (2010), we can disaggregate Equation 2 in the explicit forecast period and the perpetuity, the first and second terms of Equation 3 respectively:

\[
VOA = \sum_{t=1}^{\infty} \frac{FCFF_t}{(1 + WACC)^t} = \sum_{t=1}^{n} \frac{FCFF_t}{(1 + WACC)^t} + NOPLAT_{n+1} \left(1 - \frac{g}{RONIC}\right) \frac{1}{(1 + WACC)^n(WACC - g)}
\]

Where NOPLAT is the net operating profit less adjusted taxes, \(g\) is the revenue growth in perpetuity and RONIC is the return on incremental capital, whose ratio \(g/RONIC\) equals the reinvestment rate. Although this statement may sound straightforward to any person familiar with business valuation, market participants usually ignore the fact that no analyst has any visibility on what \(g\) and RONIC will be like in perpetuity, although perpetuity usually accounts for a significant share of the target price. Even in the explicit forecast period, analysts have to make assumptions on future margins and capital requirements for the business in order to estimate FCFF. To do so, they usually observe past data and adjust it to meet their expectations for future performance.

Finally, we add the value of the non-operating assets (VNOA) to the VOA to arrive at the enterprise value (EV) and remove the non-equity claims to find the fair value of equity (“Market Cap”). Note that the idiosyncratic factor in the valuation of operating assets is transmitted to the market capitalization estimate and, consequently, to the target price (Equation 4):
The use of alternative models that rely on statistical analysis are usually disproved by analysts due to a particular interpretation of the efficient market theory, which we review next.

2.3. The Efficient Market Hypothesis

As described by Fama (1970), an efficient market is one in which all available information is priced within assets. Mathematically, let $\phi_t$ be the information available at time $t$, $p_t$ the price of an asset, $\tilde{p}_t$ its expected price, $r_t$ its effective return and $\tilde{r}_t$ the expected return:

$$E(\tilde{p}_t | \phi_t) = [1 + E(\tilde{r}_{t+1} | \phi_t)]p_t$$

(5)

In an efficient market,

$$E(r_t - \tilde{r}_{t+1} | \phi_t) = 0$$

(6)

Which means risk-adjusted (or “excess”) returns are not possible in an efficient market. Therefore, all price movements are due to changes in available information ($\phi_t$).

Fama (1970) further divides market efficiency theories in three categories, or levels, to account for differences in the type of information embedded in prices: i) weak form, in which only information on historical prices is considered; ii) semi-strong form, where other publicly-available information (e.g. news, company reports) are also taken into account; and iii) strong form, under which monopolistic information (e.g. insider information) is concerned.

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$^2$ As measured by “expected return theories”, such as CAPM, APT and Fama-French three factor model.
If there was a profitable trading strategy, market participants would instantly seize it, adjusting asset prices and eliminating the opportunity. This mechanism is likely to produce non-stationarity in prices of speculative assets, making any attempt to forecast it useless, unless the analyst selects a data window for the forecast, as resumed by Timmerman and Granger (2004).

Although there is evidence sustaining the efficient market hypothesis, recent evidence has found empirical caveats in the theory. In a recent study (Lee et al., 2009) researchers tested the stationarity of series of logs of monthly real stock prices across a panel of 32 developed and 26 emerging markets using a unit root test designed to control for structural breaks\(^3\) (i.e. major shocks in the economy, such as shocks in oil prices and debt crises). The authors found that, when controlling for such structural breaks, many stock markets exhibit stationary patterns. This finding violates a condition of market efficiency: if prices are stationary, they revert to the mean, creating profitable trading strategies.

The efficient market hypothesis is usually regarded as a proof against the use of statistical models to forecast stock prices. However, evidence from the weak form is mostly based on tests for serial correlation of stock returns and for profitable trading strategies based on past performance, all of which concluded that stock prices follow a random-walk pattern.

In another recent study, Pai and Lin (2005) developed a hybrid model of ARIMA and support vector machines (SVMs) to produce one-step-ahead forecasts of stock prices, measuring the errors produced by such estimates. The results were promising, having produced mean absolute errors (MAE) between 0.2% and 0.3% for their sample on average. However, they showed that SVMs did not improve ARIMA forecast for all of the stocks, although it did improve for most of the sample. Moreover, the study did not concern yearly forecasts and it used a Box-Jenkins methodology for selection of ARIMA parameters.

Even Eugene Fama himself produced a sequel article (Fama, 1991) to comment criticisms, evidence and recent developments in efficient market theory. The author emphasizes that there is evidence of multiple factors (e.g. dividend yields, earnings yields, differences in term-

\(^3\) Note that, in this sense, the structural break is the same as the “selection of a data window” proposed by Timmerman and Granger (2004).
structure of interest rates) that have explanatory power over cross-sectional stock returns, as shown by asset-pricing models.

In the following section, we review some basic theory on time-series models to introduce the theoretical framework upon which our methodology was built.

2.4. Time Series Models

It is useful to think of time series as a particular realization of a *stochastic process*, i.e. a collection of random observations for a set of variables ordered in time. In this sense, the observation is to its stochastic process in the time series as the sample is to the population in cross-sectional data. (Gujarati, 2004) As far as forecasting is concerned, time series models make inferences based upon a present set of data. Thus, it is important that the estimated parameters are valid throughout future periods.

For such condition to be met, the underlying stochastic process must be *stationary*, i.e. its mean and variance must be constant across time and the covariance between two periods must depend only on the gap between them, and not on the specific time at which the covariance is calculated. Therefore, the stationary stochastic process exhibits a trend of reversion to the mean and fluctuations have a constant range. On the other hand, *nonstationary* time series exhibit a time-varying mean, a time-varying variance or both. Thus, we can study its underlying stochastic process only for an isolated period. A *random walk model* (RWM) is a kind of non-stationary process in which:

\[ Y_t = \delta + Y_{t-1} + \nu_t \] (5)

Where \(\delta\) is a drift parameter and \(\nu_t\) is a white noise. Note that both mean \((E(Y_t) = Y_0 + t\delta)\) and variance \((var(Y_t) = t\sigma^2)\) vary indefinitely throughout the process, violating one of the conditions for stationarity. However, after differentiating a RWM, we find that:

\[ \Delta Y_t = Y_t - Y_{t-1} = \delta + \nu_t \] (6)
Which is a stationary process. Thus, a RWM is a difference stationary process (DSP). In this case, we call \( \delta \) the stochastic trend. (Gujarati, 2004). Therefore, RWM are a specific type of integrated stochastic processes. In general, if you have to differentiate a process \( d \) times to make it stationary, we call it an integrated process of order \( d \). Hence, it is important to evaluate the order of the process before making a model, since the dependent variable gets the greater order from the independent variables.\(^4\)

Autoregressive integrated moving average models (ARIMA) use a combination of past data of the differentiated independent variable \( (\Delta^d Y_{t-i}) \) and the moving average of errors \( (\nu_{t-i}) \) to issue forecasts (Equation 9):\(^5\):

\[
Y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta^d Y_{t-i} - \sum_{i=1}^{q} \theta_i \nu_{t-i} + \nu_t \tag{7}
\]

The coefficients \( \alpha_0, \beta_i \) and \( \theta_i \) can be estimated with the use of ordinary least squares (OLS), generalized least squares (GLS) or maximum likelihood (ML) methods. However, to implement such model, it is necessary to determine precisely which orders of differentiation \( (d) \), autoregressive lags \( (p) \) and moving average lags \( (q) \) the model should use. To accomplish such, Hyndman and Khandakar (2008) developed an algorithm, implemented through the statistical software R, to optimize such procedure. The algorithm performs successive KPSS tests to determine the differentiation level \( (d) \) and selects the lags \( (p \) and \( q) \) by minimizing the Akaike Information Criteria (AIC) of the model (Equation 10):

\[
\text{AIC} = e^{k/n} \sum_{i=1}^{n} (y_i - \hat{y}_i) / n \tag{8}
\]

Where \( k \) is the number of regressors and \( n \) is the size of the sample.

In this literature review, we have seen that equity research analysts employ DCF models to calculate their target prices, relying on a combination of past data and self-judgement as inputs. Moreover, the efficient market hypothesis provides evidence that many find contrarian to statistical forecasting of stock prices; yet, as we saw, it can actually favor the estimation of

\(^4\) Except in the case where both dependent variables have the same order and there is cointegration.

\(^5\) ARIMA models are usually described with the use of lag operators. In this paper, we use the simplistic notation \( \Delta^d Y_{t-i} \) to make it more visual.
coefficients in time-series models. Now, we can proceed to the methodology used to build and test the model.

3. METHOD

Regardless of the valuation approach employed by the analyst, the value of a company is not a function of an objective variable, but rather of expectations. As discussed, the more efficient the market, the lesser the opportunities to make abnormal returns on trades based on past performance. However, that does not mean expectations, and consequently prices, will not be shaped by past performance. On the contrary, we argue that expectations are the main driver of equity price formation in the short term. Mathematically:

\[ P_t = f(P_{t-n}, FCF_{t+n}) \]  

Assuming future performance is a function of past performance and of an expected change in performance, \( \pi \), we have

\[ FCF_{t+n} = f(FCF_{t-n}, \pi) \]  

Additionally, assuming prices change as a function of FCF and a term for market efficiency, \( \phi \), we have:

\[ \Delta P = f(FCF_{t-n}, \phi) \]  

Thus, replacing in Equation 11:

\[ P_t = f(P_{t-n}, \pi, \phi) \]  

If the stock price series is stationary, or at least if non-stationarity can be eliminated through differentiation, future equity prices can be forecasted using a time-series model with an external regressor to account for \( \pi \).

We can compare forecasts made with this model to the target price and assess whether it is a better forecast tool on a 12-months basis than models currently employed by sell-side
analysts. In this sense, since most analysts employ DCF-based models, as inferred by Gleason, Johnson and Li (2013), a better performance by the time-series model might also suggest time-series models are better for short-term forecasts than DCF-based, although the evidence shall not be conclusive.

Among many options to implement Equation 14, we tested four:

1) “Model 1” – a mix of ARIMA(p,d,q) with the last twelve months EPS (TRAIL_EPS), used for estimation, and the EPS consensus (BEST_EPS), used for forecasting:

\[ P_t = \delta + \sum_{i=1}^{p} \alpha_i \Delta^d P_{t-i} - \sum_{i=1}^{q} \theta_i v_{t-i} + \beta EPS_t + u_t \]

2) “Model 2” – a mix of ARIMA(p,d,q) with the last twelve months EPS (TRAIL_EPS) and use an ARIMA(p’,d’,q’) of TRAIL_EPS for forecasting.

3) “Model 3” – a mix of ARIMA(p,d,q) with the EPS consensus (BEST_EPS) and use an ARIMA(p’,d’,q’) of BEST_EPS for forecasting.

4) “Model 4” – mix of ARIMA(p,d,q) with the earnings surprise (EPS_SUR), defined as the difference between BEST_EPS and TRAIL_EPS, and use an ARIMA(p’,d’,q’) of EPS_SUR for forecasting:

\[ P_t = \delta + \sum_{i=1}^{p} \alpha_i \Delta^d P_{t-i} - \sum_{i=1}^{q} \theta_i v_{t-i} + \beta EPS_{SUR} + u_t \]

Each of the models was applied to S&P 100 index, Ibovespa index and to a set of individual stocks from such indices selected from the 1st, 2nd, 3rd and 4th quartile based on the i) number of sell-side analysts covering the stock and ii) share liquidity (“tiebreaker”), measured as the average daily traded value in the past 90 days in the period between February 25th, 2011 and February 25th, 2014, using Bloomberg data. Such methodology was employed to select stocks in order to control for differences in analyst coverage and share liquidity, which might have generated a bias in the sample otherwise.
To verify the validity of the model, we divided the data into training set and test set and made an in-sample test to measure i) bias, measured as the correlation between the forecast and the price at the issuance date; ii) accuracy, measured as the absolute percentage error (APE); iii) stability, measured as the standard deviation of errors produced by the forecast; and iv) abnormal returns, measured as the 12-months return based on a buy-and-hold (or short-and-hold) strategy less the expected return, given by a CAPM model with rolling 24-month raw betas, Treasury-bill rates (“FED rates”) and a market risk premium of 5%.

All such statistics were compared to the ones produced by Bloomberg’s target price consensus, which is the average of target prices issued by registered analysts in the last 3 months (estimates older than 3 months are excluded) in order to assess the strengths and weaknesses of both each approach. An important methodological aspect in this study are the lags in variables. As target prices are issued with a 12-month investment horizon, we limited the first data available to the ARIMA models to the previous year in order to ensure comparability, as an ARIMA model with more recent data points would obviously perform better in the very short term. For instance, consider the following estimates for S&P 100 index between February 26th, 2014 and February 25th, 2015 (Graph 1), for which we used model 1.

Graph 1 – S&P 100 (OEX) results for Model 1
In this case, the ARIMA model can use price data from February 25th, 2014 when making a forecast for the following day, so it is not directly comparable to the target price that was issued 12 months earlier (i.e. they have different $\phi_t$, in terms of Equation 5). In this paper, our concern is about the last data point in that series, i.e. February 25th, 2015, which is the 12-month forecast – for which target price performed better, in this case. Thus, to tackle such issue, we used rolling data, estimating one equation per data point and taking the forecast from the last date, finding a series that has the same $\phi_t$ as the target price. To accomplish such, we built a program in R (programming language) to loop the Hyndman & Khandakar’s ARIMA optimization function (Hyndman & Khandakar, 2008) using maximum likelihood estimation and AIC through each data point of the set for each of the four models proposed.

4. RESULTS
All of the proposed time-series models outperformed sell-side target prices on average, being “Model 1” (the one that uses sell-side analysts’ consensus for EPS as external regressor) the most effective. This suggests that time-series models are more effective on a 12-months basis on average than the models currently employed by analysts. Some of the advantages of the time-series models are that they are unbiased (Table 1), more dynamic, more precise (Table 2), in some cases, more stable (Table 3) and generated higher abnormal returns (Table 4). Their main issue regards abnormal estimates, but analysts can project the whole series in order to tackle this issue. Additionally, time-series models can be more cost-efficient; Model 2, for instance, does not need inputs from sell-side analysts at all, saving investors millions of dollars.
### Table 1 – Summary of Correlations with Price at the Time of Issuance

<table>
<thead>
<tr>
<th>Asset</th>
<th>ADTV (90 days, LC mn)</th>
<th># of sell-side analysts</th>
<th>Analysts’ Target Price</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>OEX Index</td>
<td>n.a.</td>
<td>n.a.</td>
<td>0.80</td>
<td>0.77</td>
<td>0.77</td>
<td>0.77</td>
<td>0.71</td>
</tr>
<tr>
<td>IBOV Index</td>
<td>n.a.</td>
<td>n.a.</td>
<td>0.55</td>
<td>0.64</td>
<td>0.64</td>
<td>0.64</td>
<td>0.64</td>
</tr>
<tr>
<td>AAPL Stock</td>
<td>1,649.4</td>
<td>57</td>
<td>0.94</td>
<td>(0.77)</td>
<td>(0.77)</td>
<td>(0.74)</td>
<td>(0.79)</td>
</tr>
<tr>
<td>VZ Stock</td>
<td>204.3</td>
<td>37</td>
<td>1.00</td>
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<td>0.52</td>
<td>0.51</td>
<td>0.59</td>
</tr>
<tr>
<td>GILD Stock</td>
<td>428.3</td>
<td>30</td>
<td>0.97</td>
<td>0.83</td>
<td>0.87</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>MDT Stock</td>
<td>131.8</td>
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<td>0.63</td>
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<td>0.63</td>
<td>0.77</td>
</tr>
<tr>
<td>CCR03 Stock</td>
<td>80.7</td>
<td>24</td>
<td>0.97</td>
<td>0.86</td>
<td>0.87</td>
<td>0.86</td>
<td>0.88</td>
</tr>
<tr>
<td>KROT3 Stock</td>
<td>225.4</td>
<td>18</td>
<td>0.89</td>
<td>(0.39)</td>
<td>(0.39)</td>
<td>(0.38)</td>
<td>(0.41)</td>
</tr>
<tr>
<td>CMIG4 Stock</td>
<td>48.0</td>
<td>16</td>
<td>0.58</td>
<td>(0.20)</td>
<td>(0.20)</td>
<td>(0.20)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td>0.87</td>
<td>0.28</td>
<td>0.30</td>
<td>0.29</td>
<td>0.32</td>
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</table>

### Table 2 – Summary of Errors

<table>
<thead>
<tr>
<th>Asset</th>
<th>ADTV (90 days, LC mn)</th>
<th># of sell-side analysts</th>
<th>Mean Error - Target Price</th>
<th>Error Stdev - Model 1</th>
<th>Error Stdev - Model 2</th>
<th>Error Stdev - Model 3</th>
<th>Error Stdev - Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>OEX Index</td>
<td>n.a.</td>
<td>n.a.</td>
<td>6.6%</td>
<td>3.9%</td>
<td>4.2%</td>
<td>4.1%</td>
<td>9.7%</td>
</tr>
<tr>
<td>IBOV Index</td>
<td>n.a.</td>
<td>n.a.</td>
<td>33.6%</td>
<td>9.9%</td>
<td>10.2%</td>
<td>9.6%</td>
<td>12.5%</td>
</tr>
<tr>
<td>AAPL Stock</td>
<td>1,649.4</td>
<td>57</td>
<td>26.2%</td>
<td>16.2%</td>
<td>16.8%</td>
<td>17.7%</td>
<td>18.8%</td>
</tr>
<tr>
<td>VZ Stock</td>
<td>204.3</td>
<td>37</td>
<td>18.6%</td>
<td>16.0%</td>
<td>16.1%</td>
<td>16.1%</td>
<td>16.3%</td>
</tr>
<tr>
<td>GILD Stock</td>
<td>428.3</td>
<td>30</td>
<td>27.1%</td>
<td>17.3%</td>
<td>23.3%</td>
<td>27.7%</td>
<td>32.6%</td>
</tr>
<tr>
<td>MDT Stock</td>
<td>131.8</td>
<td>25</td>
<td>14.5%</td>
<td>2.7%</td>
<td>0.3%</td>
<td>2.9%</td>
<td>19.1%</td>
</tr>
<tr>
<td>CCR03 Stock</td>
<td>80.7</td>
<td>24</td>
<td>20.9%</td>
<td>15.5%</td>
<td>10.7%</td>
<td>15.2%</td>
<td>12.5%</td>
</tr>
<tr>
<td>KROT3 Stock</td>
<td>225.4</td>
<td>18</td>
<td>28.4%</td>
<td>11.2%</td>
<td>9.7%</td>
<td>10.5%</td>
<td>9.1%</td>
</tr>
<tr>
<td>CMIG4 Stock</td>
<td>48.0</td>
<td>16</td>
<td>85.0%</td>
<td>10.9%</td>
<td>10.9%</td>
<td>10.6%</td>
<td>12.8%</td>
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<tr>
<td>ENBR3 Stock</td>
<td>17.5</td>
<td>12</td>
<td>45.9%</td>
<td>1.5%</td>
<td>1.5%</td>
<td>1.5%</td>
<td>2.2%</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td>30.7%</td>
<td>10.5%</td>
<td>10.4%</td>
<td>11.6%</td>
<td>14.6%</td>
</tr>
</tbody>
</table>

### Table 3 – Summary of Standard Deviations of Errors

<table>
<thead>
<tr>
<th>Asset</th>
<th>ADTV (90 days, LC mn)</th>
<th># of sell-side analysts</th>
<th>Error Stdev - Target Price</th>
<th>Error Stdev - Model 1</th>
<th>Error Stdev - Model 2</th>
<th>Error Stdev - Model 3</th>
<th>Error Stdev - Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>OEX Index</td>
<td>n.a.</td>
<td>n.a.</td>
<td>4.7%</td>
<td>4.0%</td>
<td>3.9%</td>
<td>3.9%</td>
<td>4.7%</td>
</tr>
<tr>
<td>IBOV Index</td>
<td>n.a.</td>
<td>n.a.</td>
<td>10.0%</td>
<td>6.2%</td>
<td>6.4%</td>
<td>6.1%</td>
<td>8.9%</td>
</tr>
<tr>
<td>AAPL Stock</td>
<td>1,649.4</td>
<td>57</td>
<td>25.2%</td>
<td>12.9%</td>
<td>12.7%</td>
<td>10.7%</td>
<td>7.3%</td>
</tr>
<tr>
<td>VZ Stock</td>
<td>204.3</td>
<td>37</td>
<td>7.1%</td>
<td>5.3%</td>
<td>5.3%</td>
<td>5.4%</td>
<td>5.3%</td>
</tr>
<tr>
<td>GILD Stock</td>
<td>428.3</td>
<td>30</td>
<td>15.6%</td>
<td>20.6%</td>
<td>26.1%</td>
<td>59.8%</td>
<td>25.8%</td>
</tr>
<tr>
<td>MDT Stock</td>
<td>131.8</td>
<td>25</td>
<td>10.0%</td>
<td>1.1%</td>
<td>0.3%</td>
<td>3.4%</td>
<td>8.0%</td>
</tr>
<tr>
<td>CCR03 Stock</td>
<td>80.7</td>
<td>24</td>
<td>12.6%</td>
<td>5.7%</td>
<td>7.6%</td>
<td>5.7%</td>
<td>6.7%</td>
</tr>
<tr>
<td>KROT3 Stock</td>
<td>225.4</td>
<td>18</td>
<td>12.6%</td>
<td>9.5%</td>
<td>9.6%</td>
<td>9.5%</td>
<td>8.1%</td>
</tr>
<tr>
<td>CMIG4 Stock</td>
<td>48.0</td>
<td>16</td>
<td>32.0%</td>
<td>22.8%</td>
<td>23.0%</td>
<td>22.5%</td>
<td>24.2%</td>
</tr>
<tr>
<td>ENBR3 Stock</td>
<td>17.5</td>
<td>12</td>
<td>13.3%</td>
<td>3.2%</td>
<td>3.3%</td>
<td>3.2%</td>
<td>3.2%</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td>14.3%</td>
<td>9.1%</td>
<td>9.8%</td>
<td>13.0%</td>
<td>10.2%</td>
</tr>
</tbody>
</table>
Table 4 – Summary of Abnormal Returns

<table>
<thead>
<tr>
<th>Average Abnormal Return</th>
<th>Target Price</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>OEX Index</td>
<td>7.7%</td>
<td>7.7%</td>
<td>7.7%</td>
<td>7.6%</td>
<td>7.7%</td>
</tr>
<tr>
<td>AAPL Stock</td>
<td>21.2%</td>
<td>34.3%</td>
<td>34.3%</td>
<td>34.2%</td>
<td>34.1%</td>
</tr>
<tr>
<td>VZ Stock</td>
<td>-12.9%</td>
<td>20.4%</td>
<td>20.4%</td>
<td>20.4%</td>
<td>20.3%</td>
</tr>
<tr>
<td>GILD Stock</td>
<td>48.2%</td>
<td>51.2%</td>
<td>51.2%</td>
<td>50.4%</td>
<td>50.6%</td>
</tr>
<tr>
<td>MDT Stock</td>
<td>-9.7%</td>
<td>14.0%</td>
<td>14.3%</td>
<td>14.0%</td>
<td>2.1%</td>
</tr>
<tr>
<td>Mean (ex-OEX)</td>
<td>11.7%</td>
<td>30.0%</td>
<td>30.0%</td>
<td>29.8%</td>
<td>26.8%</td>
</tr>
</tbody>
</table>

Maybe one of the best features of a time-series model is that it is not prone to behavioral biases. Data from AAPL stock shows this clearly (Graph). When the stock began rising in early 2012, sell-side analysts raised their target prices as well – thus, the sudden increase in the target price series in early 2013. An investor that became excited with the new target prices and bought the stock would have had a negative return 12 months later. On the other hand, one that had not bought the stock in early 2011 due to the unattractive upside potential would have missed the rise in the coming year. Nevertheless, an investor that had used a time-series model instead would have made a profit on both occasions – despite the upside error in forecast in the first half of the cycle.

Graph 2 – AAPL stock results for Model 1
Evidence is striking. Sell-side analysts’ target prices are, on average, more correlated to current prices than an autoregressive model whose main input in the share price (Table 1). The reasons for such bias are probably related to the kind of issues discussed in the Introduction. As unusual as such statement may sound, this finding favors the use of time-series models as unbiased estimators by market analysts.

Another interesting feature was the frequency of update in the target prices. For CMIG4 stock, they were stable during a long period, which might be explained by the high cost (in terms of time and modelling) of updating it. On the other hand, the time series model is dynamic (and easier to update), reducing its APE (Graph 3).

However, even when target prices were more dynamic, did the time series model outperform them, as in the case of S&P 100 (Graph 4).
Such significant error from sell-side analysts provides evidence to the claim of Bradshaw and Brown (2006) that they are paid for other reasons than the target prices they issue.

A frequent issue in the time-series model is that, since it extrapolates recent trends for 12-months, some data points had abnormal errors (the “spikes” in the forecast series in Graph 5), yet on average, they performed better.
To correct such issue, an analyst could forecast the whole series for a period of 10 or 20 data points and calculate the simple average. This way, abnormal errors would be excluded from the forecast.

5. CONCLUSION

In this paper, we argued for the use of an econometric model to replace discounted cash flow models as the source for 12-month target prices as a way to improve assessment of potential returns for equity investments in the short term. Forecasts produced by ARIMA models with EPS regressors showed to be less biased, more accurate, more stable and produced greater abnormal returns than the sell-side analysts’ target price consensus. Assuming the majority of sell-side analysts use DCF models, as recent evidence shows, it is possible to advocate for the use of time-series models to forecast stock prices in a 12-months horizon, rather than DCF models.

Nevertheless, since this study was based on average figures, there might be sell-side analysts currently outperforming the model. For this reason, it is advisable to run a backtest comparing his/ her performance using his/ her current valuation method and the time-series model proposed on this study. Further studies on this matter should focus on broadening the sample and depth of the abnormal returns test and ensuring greater comparability. Since this study used consensus figures, it is not possible to state whether all of the target prices were based on DCF models or if a particular analyst employing a DCF model outperformed time series models. Finally, further studies could use hybrid models of ARIMA and SVMs in order to have a better assessment of non-linear trends in the data. Yet, results look promising so far.
References


