Analyst Recommendations and Procyclical Policy

by

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Abstract

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This paper studies whether analyst recommendations were procyclically bias to US public corporations over the expansion and recession period between 2002 and 2014. Based on two estimates of the intrinsic value relative to the market value (Residual income Method and Price to Earnings to Growth ratio) and the Long Term Growth rate I find that equity recommendations were in fact pro-cyclical: analysts tightened their recommendation standards during economic downturns relative to expansion periods.

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1. Introduction and Related Literature

The purpose of an analysts' recommendation is to give insight into the intrinsic value of a firm relative to its market price. Although analysts do not necessarily have access to insider information, their expertise along with the concentration of information in their brokerage houses give them a unique position to assess the attractiveness of stocks. However, what they report might not always be what they believe. In a joint report by the NASD and the NYSE (2005) "On the Operation and Effectiveness of the Research Analyst Conflict of Interest Rules" four sources are cited as pressures on an analysts' objectivity: (1) Analysts Themselves, (2) Investment Banking, (3) Public Companies and (4) Institutional Shareholders. These pressures have been the topic of rigorous academic and regulatory research. Hong and Kubik (2003), for example, examine "security analysts' career concerns by relating their earnings and forecasts to job separation".[1] They find that, once accuracy was controlled for, analysts who are optimistic relative to the market average are more likely to receive promotion. Moreover, they find that for analysts who cover stocks underwritten by their employer, promotion depends less on accuracy and more on optimism. Baik (2006) comes to a similar conclusion but specifically points out that some of the optimism derives from self-selection.[2] Baik defines self-selection as the analysts' ability to choose for himself whether or not to release equity reports. This ability essentially gives another avenue

[1] With data from 1983 to 2000
[2] With data from 1983 to 2003

through which the aforementioned pressures on objectivity can manifest themselves. For example, if an analyst comes to a negative recommendation conclusion on a firm being underwritten by the analysts' employer, then he or she may choose to not publish their findings. The NASD and NYSE (2005) report goes into more detail about the incentives for these biases and the forms in which they manifest.[3] This stream of literature on bias goes hand in hand with literature that propose analysts' recommendations fail to produce abnormal returns.[4]

However, there is also a stream of literature that suggests, despite the pressures, analyst recommendations do in fact have market timing and stock picking abilities. Womack (1996) finds consensus (average) buy recommendations to have large initial returns and a positive short-lived drift (2.4%), even in cases where there is no new public news. Using data from 1985 through 1996 Barber et al. (2001) find statistical evidence that using analyst recommendations with daily re-balancing and a timely reaction to changes in recommendations yield abnormal returns. And, after changes to rules governing conflicts of interests for analyst in 2002, requiring the disclosure of the distribution of recommendations by individual analysts (along with other requirements), Barber et al. (2006) show that buy recommendations from analysts whose recommendation distributions leaned toward the pessimistic side (more hold/sells), significantly outperformed their peers as well as the market.

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[3] "Analysts were compensated based on involvement in investment deals. Analysts covered firms that were underwritten by their employer. Analysts covered firms in which they were invested. Provided investment bankers with prior notice of changes in recommendation. Issued "booster-shot" reports while clients divested. Failed to reveal conflict of interest in reports."

[4] Jensen (1968), Bidwell (1977), Diefenbach (1972) and Logue and Tuttle (1973), Fama (1991)

Finally, Abarbanell and Lehavy (2003) examine the reason behind the conflicting literature surrounding analyst accuracy and bias. They found that there is an asymmetry in the tails and in the middle of the distribution of analyst forecast errors which lead to inconsistent inferences. Specifically, they found that these asymmetries are correlated with the way firms recognize unexpected accruals and this correlation feeds into analysts forecast errors.

This paper contributes to this debate by identifying yet another possible source of bias in analyst recommendations: cyclical bias. Recicot and Theoret (2015) define cyclicality in two ways. First, a time series is procyclical (countercyclical) if it is positively (negatively) correlated with the business cycle, i.e. it increases (decreases) during an expansion and decreases (increases) during a recessionary period. Second, a time series is cyclical if it actually influences the amplitude of the business cycle. In this paper both definitions are adopted. If analysts tighten (loosen) recommendation standards during a recession relative to an expansionary period then the first definition is satisfied implicitly. Further, if investors make decisions based on these recommendations then it follows that the business cycle is amplified by these investment decisions. For example, if recommendations are overly optimistic during an expansion, over-investment will result and if they are overly pessimistic during a downturn, they will simply amplify the recession. (Auh 2015)

The methodology used in this paper closely follows that of Auh (2015) and Bradshaw(2004). Auh (2015) examined the procyclical credit policy of Credit Rating Agencies (CRA) by first estimating the credit quality of bonds and then mapping out the rating policy through an ordered probit specification. He found that procyclical policy has real economic implications through corporate credit spreads. Specifically, he found that, on average, 11 percent of increases in spreads could be attributed to procyclical policy. This paper will only follow Auh (2015) in identifying procyclicality. The effects on the real economy is a natural progression left for future study. Bradhaw (2004), Using four valuation methods[5], examined whether analyst forecasts and recommendation were consistent. He found little evidence to show consistency between recommendations and the Residual Income Method but found statistically significant evidence to show recommendation consistency with respect to the PEG and LTG methods.

First, Bradshaws' (2004) valuation methods will be used to estimate the attractiveness of firms. Employing balance sheet and income statement information as inputs I calculate the intrinsic value for any given period as a function of current equity book value per share and residual income over the next two years. Two years is used as the discounting period for the residual income method as it is the usual timeline for which analysts make their recommendations. To get an estimate of intrinsic value as close as possible to its true value, instead of using analysts' projections, I take an ex-post approach so that the cash flows discounted were the ones that actually occurred. The PEG method is also used to derive an intrinsic value. By setting the PEG ratio to one, I solve for the price as in Bradshaw (2004). Finally, since Bradshaw (2004) also found a strong consistency between the Long Term Growth rate and recommendations, the Long Term

[5] Tow specification of the residual income method (one with constant terminal value and another with deteriorating terminal value, PEG method with 5 year long term growth and analyst projections of long term growth

Growth rate is also taken as an indicator of stock attractiveness. This growth rate is a good way to check the robustness of the results produced through the RIM and PEG methods. There are situations that the use of a ratio (i.e. intrinsic value over market price in PEG and RIM methods) can lead to incorrect interpretations. There will be further discussions of this in the following sections.

Next, Auhs' (2015) ordered probit specification will be used to map out the recommendation policy and test for cyclical bias. The questions being answered with this probit regression is: what does the intrinsic value of a firm have to be, relative to its market price, in order for analysts to prescribe a Buy, Hold or Sell recommendation? Further, are changes in policy related to the business cycle? The ordered probit specification is used here because the recommendations are discrete ordered classifications. The time series used in this model is longitudinal in nature so the cross section of firms is controlled for. What remains is to control for other firm specific characteristics: the industry in which the firm operates and the extent of leverage the firm uses. I account for the industry by using the Global Industry Classification Standards (GICS) and import Debt to Equity ratio in order to account for leveraging. The results show that recommendations are procyclically biased. I.e. analysts tightened recommendation standards during downturns relative to expansions. This evidence implies that a firm with a given intrinsic value (relative to its market price) is less likely to receive the same recommendation in a recession as they would in an expansion.

To my knowledge this paper is unique in its efforts to empirically answer the question of procyclicality with respect to analyst recommendations. However, many other papers have provided a theoretical foundation by citing incentives of procyclical behavior.[6]

The construction of the paper is as follows: Section 2 will give a brief motivation by drawing parallels with Auh (2015). Section 3 will cover the estimation process for intrinsic value using the RIM and the PEG methods as outlined by Bradshaw(2004). It will also discuss some literature surrounding these methods. Section 4 will take note of an issue in inference due to the way attractiveness of equities is measured (i.e. intrinsic value based on RIM and PEG methods taken as a ratio of market price). Section 5 will give insight into the ordered probit model. Section 6 will describe the data and sample selection process. Section 7 will discuss the results and some implications. Finally, section 8 will conclude.

2. Motivation

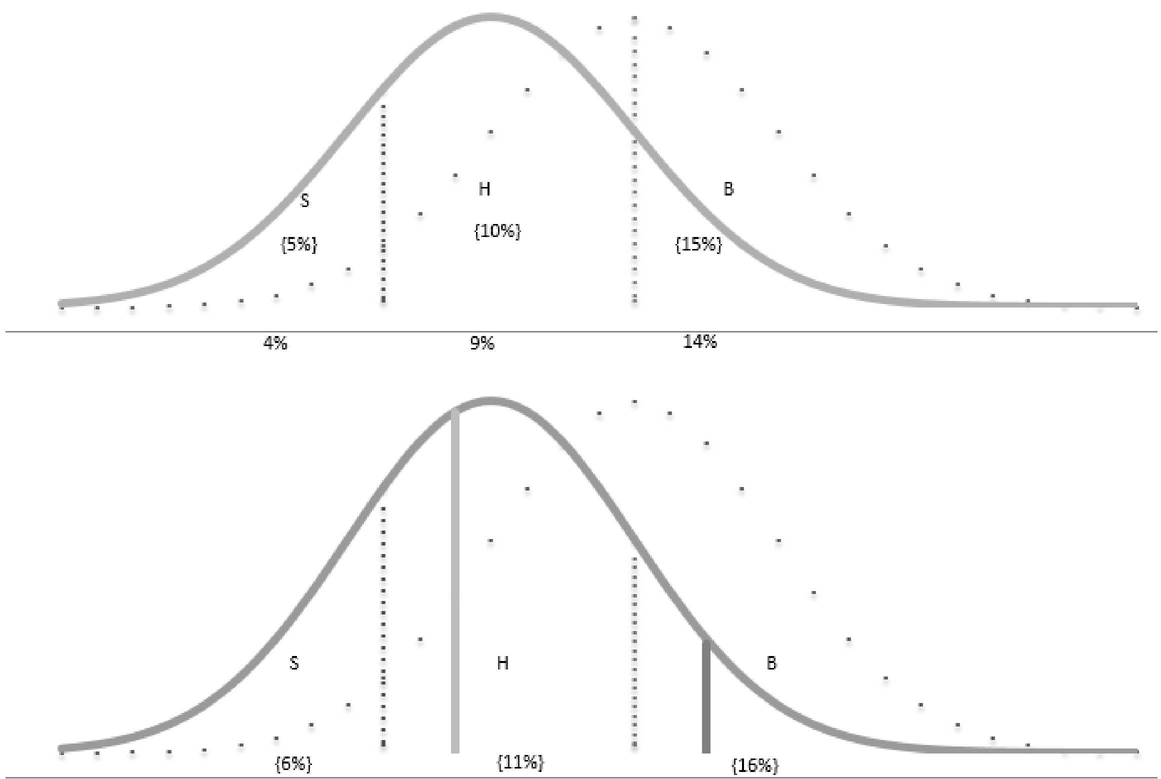
In order to gain a better understanding of the method this paper uses to show procyclicality, consider the following thought experiment which very closely follows that outlined by Auh (2015). Suppose that analysts only give out one of two recommendations on each stock; buy or sell. Further, suppose that the LTG rate is the only indicator of the recommendation. Then, if this rate is below some critical value, the growth prospects are unattractive and a Sell order is given. If the rate is above that critical value, the growth

[6] Examples include Racicot and Theoret (2015), Stanislawek (2012), Joint report by the NASD and the NYSE (2005), Joint report by Toronto Stock Exchange, Investment Dealers Association and Canadian Venture Exchange (2001) and Barber et al. (2006)

prospects are favorable and a Buy order is given. Assume that, before the economic downturn, the distribution of the firms is divided evenly between Buy and Sell recommendations. During a downturn as a result of the general contraction of the economy, some of the recommendations change from a buy to a sell. Now if the recommendation standards tighten at the same time, i.e. analysts employ a procyclical policy, then it becomes more difficult for a firm to get a Buy recommendation. Therefore, only firms whose growth prospects are very high retain their Buy recommendations and firms that would otherwise receive Buy recommendations will now receive Sell recommendations. In this case the average LTG rate within each recommendation category could actually be better in a recession because firms with high LTG rates are now in the Sell category.

As a hypothetical situation consider the upper panel of Figure 1. Here there are three categories of recommendations: Buy, Hold, Sell. The dashed curve is the distribution during an expansion and, as the economy goes through a downturn, the distribution shifts to the left as illustrated by the solid line. The vertical lines are the critical values that determine which recommendation firms receive based on where they lie on the distribution of the LTG rate. For example a LTG rate of 5% describes a situation where the growth is low therefore a Sell order is recommended. An LTG rate close to 10% means that the firms' growth prospects are average and a Hold order is recommended. Notice that as the distribution shifts to the left and the economy contracts, average LTG rates fall within each category. Average LTG rate before the recession is in brackets and bellow the x-axis after the recession.

Figure 1: Rating Distribution over LTG



Now consider the lower panel of figure one where analysts employ a procyclical policy. Here the distribution shifts to the left but now since the recommendation policy is tightened, the critical values for the recommendation shift to the right (solid vertical lines). I.e. it is more difficult to receive the same rating as a firm had in the expansion phase of the economy. Therefore the average LTG rate for each rating category is actually higher in this case. Also, Notice that the area between the dashed and solid lines hold firms that have been downgraded even though their LTG rates did not change. This hypothetical shows that observing higher average LTG ratios during a recession is proof of a procyclical rating policy. Also, observing lower LTG rates during a recession could be a signal for countercyclicality. For a more formal approach to the proof refer to Auh (2015): Appendix A, Proposition 1.

3. Estimating Intrinsic Value

Analyst recommendations are essentially based on a divergence between the intrinsic or true value of the equity and the market's perception of that value, i.e. market price. The residual income method and the PEG ratio are used to estimate this intrinsic value and then taken as a ratio of market price. The resulting ratio is taken as an estimate of "attractiveness" to evaluate recommendation polcy.

A. Residual Income Method

The common and traditional approach to valuing equity is based on the Rubenstein (1976) Dividend Discount Model (DDM). According to this model the value of a firm is described as the present value of all future cash flows.

$$V_t = \sum_{k=0}^{\infty} (1+r)^{-k} D_{t+k} \tag{1}$$

Where V_t is the intrinsic value, D_t is the dividend and r_t is the discount rate. This model has the disadvantage that dividends are not always issued and when they are, the amount is arbitrary. Ohlson (1995) shows that, using the clean surplus relation, $BVPS_t = BVPS_{t-1} + EPS_t$, the DDM can be reformulated to:

$$V_{RI,t} = BVPS_t + \sum_{k=0}^{\infty}(1+r)^{-k}E[RI]_{t+k} + (1+r)^{-k}E[TV]_{t+k} \tag{2}$$

Where $BVPS_t$ is the book value per share, RI is $EPS_{t+k} - r * BVPS_{t+k-1}$, r is the equity cost of capital, EPS_t is the earnings per share, and TV_t is the terminal value. This model assumes: that the dividend payout policy remains the same through time (see Frankel and Lee 1998), that the DDM is representative of the equilibrium price and that the residual income of period k persists in perpetuity. The present value of this persistent residual income in period k is noted as the Terminal Value (TV).

$$E_t[TV_{t+k}] = r^{-k}E[RI]_{t+k} \tag{3}$$

A more detailed derivation of the residual income method can be found in Higgins (2011). Higgins (2011) also recommends a way to improve the accuracy of the RIM by addressing autocorrelation using statistical techniques. This extension is outside the scope of this paper, although the method could improve the recommendation estimation process. The advantage of the RIM is not only the fact that it incorporates earnings, but also; it has been shown that the method is successful in identifying mispriced stocks. (Frankel and Lee 1998)

Bradshaw (2004) notes that the terminal value can drive a large portion of the price. He accounts for this by applying two different methods in his RIM process. First, he uses the assumption on period k residual income mentioned above and next refines it by assuming that the residual income fades over time. The second method is more consistent with economic theory (Hirshleifer 1976). However, Bradshaw (2004) also notes that the assumption that the terminal value is constant delivers a more optimistic outlook on intrinsic value. This is not an issue in mapping out recommendation policy as extensive research has noted the optimism of analyst recommendations.[7] Therefore using the simpler method of keeping residual income constant after period k should not skew the mapping of relative value on recommendations

B. Price to Earning to Growth Method

In theory the Residual Income Method, especially the fading RI specification, is broadly accepted. However, Block (1999) surveys analysts and finds that present value techniques are not broadly used in practice. Furthermore, Bradshaw (2004), Simon and Curtis (2011) and many others find that analyst recommendations are more accurately explained by growth based heuristics relative to rigorous valuation based models. In light

[7] Abarbanell and Lehavy (2003), Barber et al. (2005), Biak (2006), Simon and Curtis (2011), Bradshaw et al. (2013)

of these findings it is necessary to also use a growth based metric in mapping analyst recommendation policy. The PEG ratio:

$$\text{PEG} = \frac{P/E}{LTG}, \tag{4}$$

where P/E is the forward price to earnings ratio and LTG is the long term growth rate, as estimated by analysts, is a commonly used heuristic. Analysts use this metric as a refinement on the P/E ratio. The P/E ratio signals how much shareholders pay for each dollar of earnings (Ritt 2003). Therefore taking it as a ratio of the annual growth rate, it should give a signal as to whether the stock is selling at a premium or a discount. Note the famous Peter Lynch example in his book *One Up on Wall Street*; "If the P/E of Coca-Cola is 15, you'd expect the company to be growing at about 15 percent a year […] But if the P/E ratio is less than the growth rate, you may have found yourself a bargain."

In the analysts' world, there is a rule of thumb that if the PEG ratio is 1 then Hold is the recommendation, and the further it diverges from one, the stronger becomes the recommendation in that direction. So a PEG ratio below 0.5 is a strong buy and above 1.5 is a strong sell. (Gerstein 2002) Now, in determining consistency of the PEG ratio to analyst recommendations, Bradshaw (2004) backs out an implied intrinsic value from this ratio. Setting the PEG ratio to 1 and solving for price, the heuristic valuation can be obtained. This is essentially the fair value of the firm.

$$V_{PEG,t} = E_t[EPS_{t+k}] * LTG * 100 \quad (5)$$

Once again EPS is to be forward looking. k is 2 years and is consistent with analysts propensity toward long term earnings estimates.

These metrics ($V_{PEG,t}$ and $V_{RI,t}$) taken as a ratio of market price, gives a proxy for the attractiveness of the firm to investors. So the higher this ratio is, the higher is the intrinsic value relative to market price and therefore the higher is the stocks "attractiveness". Next, these metrics are taken as a ratio of market price and used to estimate the rating policy of analysts, and further how this policy changes with economic regime shifts.

4. Issues With Intrinsic Valuation Methods

"Intuitively, the rating policy is a function that maps the credit worthiness to credit ratings" (Auh 2015). The same intuition can be applied to the equity worthiness. However, there is a difference worth noting. For Auh (2015), it was the probability of default; here it is the attractiveness of equity i.e. potential for profit that is the indicator of policy. This does not change the reasoning behind the motivation provided earlier. However, there is a disparity in the properties of the metrics used by Auh (2015) relative to the properties of the metrics used here. As a proxy for the credit, Auh (2015) uses Distance to Default (DD) as the primary indicator and then checks the robustness of the results with another proxy, Expected Default Frequency (EDF). Both of these metrics are comparable across bonds. For example, the following comparison statement can be made in credit rating case: if the DD of a bond on company XYZ is higher than the DD of the bond on company ABC, then it is the case that the bond of company XYZ has a lower probability of default and is safer. A similar statement can be made about EDF. The same comparison statement, however, cannot be made for the metrics $V_{PEG,t}$ and $V_{RI,t}$. This is because the magnitude of the value is not an indication of potential. Instead, the indicator of profitability is actually about how far these metrics diverge from the market's perception of them. Buying the asset at the market price and realizing the earnings implied by the intrinsic value, assuming intrinsic value is greater, is where the attractiveness of the investment comes from. This is why it is important to take these metrics as a ratio of market price.

However, taking a ratio poses another problem. Note that if a distribution of analyst recommendations is taken over a ratio of intrinsic value to market price (as it was over LTG in Figure 1), then it might not be the case that this distribution shifts to the left in a recession. As emphasized in the motivation, this shift is required so that one can make the inference that: an increase in the average ratio within each recommendation class is indicative of procyclical policy. The issue is: the magnitude effect of the recession on intrinsic value relative to market price might be different. Intuitively a recession has the same directional effect on market price as it does on intrinsic value. When an economy contracts it is expected that the growth prospects of any individual firm deteriorates and therefore the intrinsic value declines. Since market participants know this, then market price of the firm will also drop. However, since market price is only a perception of intrinsic value, it might not be the case that intrinsic value and market price drop in the same proportion. Therefore it is possible that the ratio of intrinsic value and market price actually increases. I.e. the distribution shifts to the right. This would be the case if the market price drops by more than the intrinsic value. In this case, an increase in the average of any recommendation class cannot be inferred as an indication of procyclical policy. This is because the increase could simply be due to an overly pessimistic perception that the market might have on the effect of economic contraction on a firm's value.

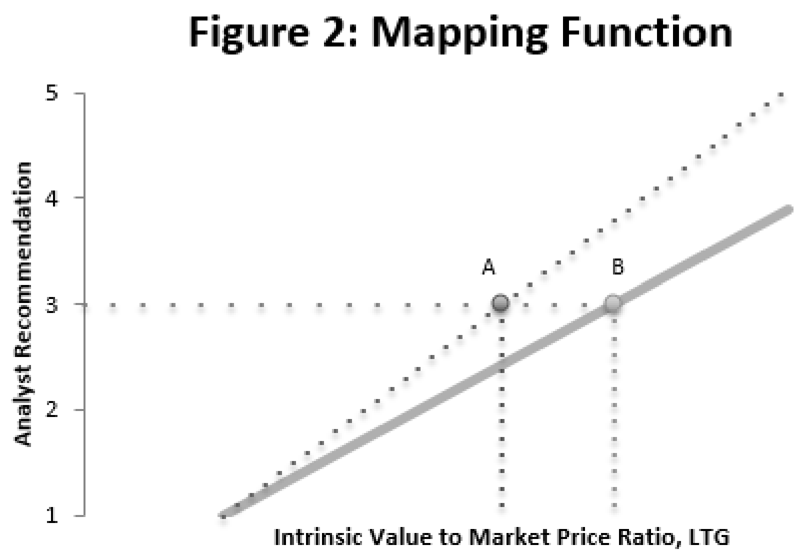
On the other hand, if the intrinsic value declines by more than the market price, then there is no issue. The distribution shifts to the left as in Section 1 and the inference is not only viable but also robust. Robust because the procyclical policy would have to be excessively strong to show an increase in the ratio of each recommendation class despite the fact that the ratio has the extra deteriorating effect of the mismatch in the scale effect of the recession on the numerator and denominator. In other words: the recession shifts the distribution to the left, if intrinsic value declines by more than the market price then the distribution shifts even further to the left, finally, if it is observed that the average of the ratio of intrinsic value to market price actually increases for each recommendation class as the economy contracts, then it must be the case that there is a strong procyclical policy in place. Once again, procyclical policy is defined as a tightening of recommendation standards in times of recession and loosening of standards in times of expansion.

Ideally, the way to deal with this is to measure the magnitude effect of a recession on intrinsic value and market price, then control for this difference in calculating the ratio. However, in this paper it is enough to use the LTG as a robustness check. LTG does not exhibit the issues that the ratio of intrinsic value and market price do. It is a rate therefore it is comparable across firms and a change in its value will be the result of a net affects. It is a particularly effective robustness check because Bradshaw (2004) has shown evidence to suggest that it has the most explanatory power in mapping analyst recommendations.

5. Estimation of Rating Policy

Here the purpose is to estimate the rating policy using the metrics produced in the previous section. Suppose that these metrics fully capture the attractiveness of the investment. Then, intuitively, if the ratio of intrinsic value to market price is high, then it means that the stock is more valuable than the market perceives it to be. Therefore it deserves a Buy or Strong Buy recommendation. If it is low, then it deserves a Sell or Strong Sell recommendation. In other words, the slope of the mapping function should be positive in the case of $V_{PEG,t}/P_t$, $V_{RI,t}/P_t$ and LTG rate.

The purpose of this paper is to find changes in the slope of this mapping function that are due to changes in the economic regime. If during the recession the slope of the mapping function is flatter, then it must be the case that recommendation policy is procyclical and analysts are tightening their standards. If however the slope is unchanged or even steeper, then the procyclical inference cannot be made. And the null hypothesis is rejected. Figure 2 illustrates this intuition.



If analyst recommendations are procyclical then they tighten their standards during the recession relative to an expansion. Therefore the mapping function corresponding to the recession is the solid line in Figure 2 with the flatter slope. Note that in order to get the same recommendation, the metric has to be higher in the recession phase relative to the expansion phase. For example, as the economy shifts into a recession, in order to maintain a Hold recommendation by analysts, a firm has to accumulate more value, point B, relative to point A before the recession. Therefore a shift in the mapping function is indicative of procyclical policy. Moreover the distance between the functions is the degree of procyclical policy.

In order to test whether a procyclical policy is employed, an ordered probit specification is used. Analysts essentially collect information on a firm and make an interpretation of its potential for profit. There is a wide range of variables that affect profitability and the analysts must weigh them against each other to come up with a recommendation. Now if we assume that there is a latent qualitative score that is a linear function of the intrinsic value to market price, then we can impose the following relationship.

$$Score_{i,t} = (\beta_1 + \beta_1 \cdot Regime_t) \cdot Metric + \gamma \cdot Z_i + u_{i,t} \tag{6}$$

$$Score_{i,t} = X \cdot \beta + u_{i,t} \tag{7}$$

Where $Regime_t$ is a dummy variable with a value of 1 during the recession and a value of 0 otherwise, Z_i is a matrix of firm specific characteristics like the leverage ratio and the industry in which the firm operates, and $u_{i,t}|X \sim N(0,1)$. Note that the same relationship is imposed on the ratio of intrinsic value (as calculated by the RIM and PEG method) to market price as well as the LTG rate.

Next, the latent $Score_{i,t}$ variable is mapped on to the number-coded recommendation category $Rating_{i,t}$. As in Auh (2015), I distinguish cut-off points between each recommendation classing. For example, the cutoff between a strong Sell and Sell recommendation is denoted as θ_1. Suppose analysts assign recommendations based on the latent $Score_{i,t}$ variable as follows.

$$Score_{i,t} = \begin{Bmatrix} 1\ if\ Score_{i,t}\ \leq \theta_1 \\ j\ if\ \theta_1 \leq Score_{i,t}\ \leq \theta_{j+1} \\ 5\ if\ Score_{i,t}\ > \theta_4 \end{Bmatrix} \tag{7}$$

Then for $j = 1$,

$$\begin{aligned} \Pr\left(Rating_{i,t} = 1\right) &= \Pr\left(Score_{i,t}\ \leq \theta_1\right) \\ &= \Pr\left(X \cdot \beta + u_{i,t} \leq \theta_1\right) \\ &= \mathrm{F}(\theta_1 - X \cdot \beta) \end{aligned} \tag{8}$$

and for $j = (2, \dots, 4)$

$$\begin{aligned} \Pr\left(Rating_{i,t} = 1\right) &= \Pr\left(\theta_j \leq Score_{i,t}\ \leq \theta_{j+1}\right) \\ &= \Pr\left(\theta_j \leq X \cdot \beta + u_{i,t} \leq \theta_{j+1}\right) \\ &= \mathrm{F}\left(\theta_j - X \cdot \beta\right) - \mathrm{F}(\theta_{j+1} - X \cdot \beta) \end{aligned} \tag{9}$$

finally for $j = 5$

$$\begin{aligned} \Pr\left(Rating_{i,t} = 1\right) &= \Pr\left(Score_{i,t}\ > \theta_4\right) \\ &= \Pr\left(X \cdot \beta + u_{i,t} > \theta_4\right) \\ &= 1 - \mathrm{F}(\theta_4 - X \cdot \beta) \end{aligned} \tag{10}$$

Here, $F(\cdot)$ is the standard normal CDF. In this case the ordered probit model is concerned with how changes in the score, which is mapped based on the metrics used to estimate the attractiveness of equity, translate to changes the probability of observing a given recommendation (Jackman 2000). In ordered to solve for the parameters and cut-off points we need to use Maximum Likelihood Estimation (MLE). To do so first we create an indicator variable ε_j which is 1 when $Rating_{i,t} = j$ and 0 otherwise. Then ε_j is used in the log likelihood function as follows

$$\ln L = \sum_{j=1}^{5} \varepsilon_j \ln\left[F_j - F_{j-1}\right] \tag{11}$$

Where $F_j = \mathrm{F}(\theta_j - X \cdot \beta)$ and $F_{j-1} = \mathrm{F}(\theta_{j-1} - X \cdot \beta)$

An ordered probit regression essentially maximizes this likelihood function by choosing the parameters and cutoff points. Thereby estimating the likelihood that a firm will get a specific recommendation j given the latent reference score as described by equation (6). As in Figure 2, since the recommendation is increasing in intrinsic value to market price, β_1 should be positive. Furthermore, if there is a procyclical recommendation policy in place, β_2 should be negative. The intuition is as follows: since β_2 is the coefficient of the interaction term $(Regime_t) \cdot \frac{V_{RIM,i,t}}{P_{i,t}}$, when $Regime_t = 1$, i.e. the economy is in a recession, recommendation policy should be tighter and a firm has to be more profitable to receive the same recommendation. In other words the mapping function should be flatter, as depicted by the solid line in Figure 2.

6. Data Description

The data used in this paper is comprised of information compiled by Bloomberg Finance LP. on US domiciled corporations actively traded as of December 2014. The list of 13204 corporations was filtered to include only companies actively covered by at least 10 analysts within the time period spanning 2002 to 2014. Monthly Consensus Equity Recommendations[8] were retrieved for this list of 1472 companies. Bloomberg describes this number, ranging from 1 to 5, as an average of the recommendations made by the analysts covering the firm. However, since the recommendations are coded as 1 for Strong Sell, 2 for Sell, 3 for Hold, 4 for Buy and 5 for Strong Buy, a 4.56, for example is not directly interpretable. And since the ordered probit regression requires ordinal data, the number reported by Bloomberg was averaged over each calendar quarter starting on January 1, 2002 and rounded to the nearest integer.

To test changes in recommendation standards I use two metrics to estimate the difference in market price and intrinsic value. First I import quarterly data on Trailing 12 Month Earnings Per Share (EPS)[9], Cost of Equity (RR)[10], Total Shareholder Equity[11],

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[8] Bloomberg estimates current analyst rating. A scale between 1 and 5 is used
5 is the strongest ranking buy or similar where as 1 Is the weakest ranking. If the best data source override is an individual broker this will be that brokers ranking. If the source is BST or BLI it will be the average ranking of all brokers, which updated in the appropriate time period.

[9] Calculated by adding diluted EPS adjusted (IS147) for last four quarters, two semi annuals or annuals. Diluted EPS for continuing operations returned in the periodicity selected using the fundamental period override (DS323, FUND_per). Calculated with trailing 12 m diluted EPS from continuing operations for annual periodicity and diluted EPS fro continuing ops of interim periodicity

[10] Derived by the capital asset pricing model Cost of equity=risk free rate +beta X country risk premium The default value for the risk free rate is the countries long-term bond rate (10-year)

[11] Firms total assets minus its total liabilities. Figure is reported in millions. Common Equity + Minority Interest + Preferred Equity

and Diluted Weighted Average Shares Outstanding[12] to calculate Residual Income (RI). The income statement items are taken from continuing operations so that random, non-recurring items do not skew the RI.

Next, I Import Trailing 12 Month Price/Earning Ratio (P/E)[13] and the Long Term Growth Rate (LTG)[14] in order to calculate the PEG Ratio. However Bloomberg Finance LP. only reports LTG from 2005 and on. Therefore the period from 2002 to 2005 is supplemented by calculations illustrated in the following example. Corporation 1284849D US Equity had a Trailing 12 Month EPS of \$0.99 in the second quarter of 2002 and a Trailing 12 Month EPS of \$1.465 in the first quarter of 2005. So the annual EPS growth rate (13.96%) was calculated as $[(\frac{EPS_{Q1,2005}}{EPS_{Q2,2002}})^{\frac{1}{3}} - 1] * 100$.

Once this data was compiled there were a series of filters for situations where the individual firm did not add any significant information or unnecessarily skewed the data. If a firm did not have ongoing operations through the recession (second quarter of 2007 to first quarter of 2009) they were excluded from the analysis. For example if a firm became insolvent before 2007, they were not included. Further if a firm only became public after 2007, they were also not included. There were also a series of companies for whom there were substantial amounts of missing information. For example, earnings

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[12] Weighted average number of shares used to calculate diluted EPS. Diluted shares are entered as disclosed even if reported EPS is antidilutive the value is quoted in millions

[13] This field represents the price to earning ratio for profits from continuing operations for each diluted share. This field uses RR844 trailing 12 month diluted EPS from continuing operatopms or IS147 diluted EPS from continuing operations if only annual exists)

[14] The best LTG EPS is the compounded annual growth rate of the operating earnings per share EPS over the company's next full business cycle (typically 3-5 years)

were incorrectly reported, there was no observable price or there were no filings to retrieve shares outstanding or total shareholders' equity from. These companies were also excluded. For the remaining 894 firms that were operational for at least 33 calendar quarters, after discounting 2 years of residual income cash flows, the industry of operation was imported. Bloomberg Finance LP. uses the GICS for industry classification.

Finally, once the data was filtered, $\frac{V_{RIM,i,t}}{P_{i,t}}$ and $\frac{V_{PEG,i,t}}{P_{i,t}}$ were calculated as described in section 5. These values along with the LTG rate had large and negative outliers. Note in table 1 that the range of LTG rate is from -765.5 to 56880.19%, yet the mass of the data is contained within the 25^{th} to the 75^{th} percentiles, ranging from 7.06 to 16.93%. Similar dispersions are true about the other metrics. In order to correct for this issue a natural log transformation was used as prescribed by Cleveland (1984). Also note that the ratios of intrinsic value to market price have negative minimums. For $\frac{V_{RIM,i,t}}{P_{i,t}}$, this was due to cases where negative present value of residual income exceeded book value per share. For $\frac{V_{PEG,i,t}}{P_{i,t}}$, this was due to a negative growth rates. Since log of a negative number is not possible I use the transformation: $\log(\text{metric} + \min(\text{metric}))$. This transformation fixes the issue. However, it also shifts the distribution to the right. This is not an issue in this model because it is specifically interested in changes in recommendation due to changes in the metric not the magnitude of the metric.

Table 1: Descriptive Statistics

	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
$\frac{V_{RIM,i,t}}{P_{i,t}}$	38567	0.49	0.81	-69.59	0.33	0.47	0.64	42.7
$\frac{V_{PEG,i,t}}{P_{i,t}}$	38567	0.86	8.47	-358.48	0.33	0.64	0.97	593.15
LTG	38567	14.44	498.57	-765.05	7.06	12	16.93	56880.19

Note, in Table 2, that as the economy moves into a recession (2007 and 2008) Strong Buy and Buy recommendations decrease while Hold recommendations increase. This serves as evidence to support the motivation in Section 1. The distribution is in fact shifting to the left. Also note that analysts are optimistic as noted by Abarbanell and Lehavy (2003), Barber et al. (2005), Biak (2006), Simon and Curtis (2011) and Bradshaw et al. (2013). Even through the recession, Sell and Strong Sell recommendations were extremely low relative to Hold and Buy recommendations. This finding supports the use of the perpetual period k residual income used in the discounting procedure discussed in Section 2, Subsection A.

Table 2: Distribution of Recommendations Over Time

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Strong Sell	5	6	8	6	1			1				
Sell	39	72	53	41	39	33	45	46	11	9	13	11
Hold	299	393	375	368	370	346	398	439	328	276	337	258
Buy	611	609	681	702	700	730	691	690	751	760	702	554
Strong buy	318	199	224	182	204	180	174	126	157	177	147	70
Total	813	824	868	893	894	894	894	894	894	894	894	893

7. Results

This section examines the result of the ordered probit model outlined in Section 4. The left 3 columns of Table 3 show the results when the intrinsic value is estimated by the Residual Income Method and the metric is $\frac{V_{RIM,i,t}}{P_{i,t}}$, the middle 3 columns show the result when intrinsic value is estimated by the Price to Earnings to Growth method and the metric is $\frac{V_{PEG,i,t}}{P_{i,t}}$, finally, the right three columns show the results when Long Term Growth rate is used as the predictor. Three specifications were used with each metric. The first specification uses just the metric as the predictor and the other two specifications use controls for firm specific characteristics: leverage ratio and industry of operation. The $Metric \cdot Regime$ interaction term is significant across all specifications. However, the coefficient on $\frac{V_{PEG,i,t}}{P_{i,t}}$ is not. This might be due to the fact that there were many observations for which the PEG was negative, usually due to negative earnings in a given period. For the cases where the negative earnings were indicative of distress within the firm, the PEG provided usefull information. However, whenever these negative earnings were a one-off, it might be the case that they mislead the Maximum Likelihood Estimation procedure.

Table 3: Order Probit Results

		$\frac{V_{RIM,i,t}}{P_{i,t}}$			$\frac{V_{PEG,i,t}}{P_{i,t}}$			LTG	
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\boldsymbol{Metric}$	0.849*** (0.194)	0.842*** (0.194)	0.845*** (0.194	0.099 (0.09)	0.099 (0.09)	0.095*** (.09)	0.193*** (0.048)	0.19*** (0.048)	0.1877*** (0.048)
$\boldsymbol{Metric \cdot Regime}$	-0.01** (0.004)	-0.01** (0.004)	-0.01** (0.004)	-0.008** (0.003)	-0.007** (0.003)	-0.007**	-0.007** (0.002)	-0.007** (0.002)	-0.007** (0.002)
Leverage	N	y	Y	N	Y	Y	N	Y	Y
Industry	N	N	Y	N	N	Y	N	N	Y
$\boldsymbol{\theta_1}$	-0.124 (0.826)	-0.159 (0.826)	1.419*** (1.063)	-3.149*** (0.530)	-3.157*** (0.530)	-1.62 (0.855)	-2.482*** (0.317)	-2.506*** (0.318)	-0.974 (0.74)
$\boldsymbol{\theta_2}$	1.031 (0.824)	0.998 (0.825)	2.576*** (1.062)	-1.993*** (0.528)	-2.000*** (0.528)	-.464 (0.853)	-1.325*** (0.314)	-1.348*** (0.315)	0.184 (0.738)
$\boldsymbol{\theta_3}$	2.874*** (0.825)	2.841*** (0.825)	4.420*** 1.062	-0.152 (0.528)	-0.158 (0.528)	1.379 (0.853)	0.517 (0.314)	0.496 (0.314)	2.028** (0.738)
$\boldsymbol{\theta_4}$	5.072*** (0.825)	5.040*** (0.835)	6.618*** (1.063)	2.046*** (0.528)	2.040*** (0.528	3.577*** (0.853)	2.716*** (0.314)	2.694*** (0.315)	4.226*** (0.738)
N	38,568	38,568	38,568	38,568	38,568	38,568	38,568	38,568	38,568

Table 3 provides statistically significant evidence that the original intuition is correct, i.e. that analysts employ a procyclical recommendation policy. As discussed in Section 4, β_1 is positive and β_2 is negative. This means that as the economy moves into a recession the function that maps the attractiveness of a company to recommendations becomes flatter. However, the magnitude of these coefficients are not directly interpretable. Following a similar approach to that of Auh (2015) in showing procyclical rating policy by Credit Rating Agencies, I produce probabilities of achieving a specific recommendation during the recession relative to the expansion. Specifically I estimate the $Prob(R = r|Regime = 1)$ and $Prob(R = r|Regime = 1)$ from the ordered probit regression specified in Equation (7). I then take the difference between these probabilities. What this does is transform changes in the slope of the mapping function to changes in the probability of receiving a specific recommendation from analysts.

Table 3 shows the results of this method. Note that the probability of achieving a Strong Buy recommendation as the economy moves into a recession declines by 0.57% while the probability of receiving a hold recommendation increases by 1.26%. Strong Sell and Sell recommendations, however, do not increase dramatically, this is easily explained by the optimism of analysts noted earlier. As noted before, analysts have many pressures on their objectivity and this is evident by the fact that the probability of hold recommendations increase more then sell and strong sell recommendations during the recession.

Table 3: Probability of Achieving Recommendation

	Strong Sell	Sell	Hold	Buy	Strong Buy
Expansion	0.0001132***	0.0048525***	0.2254867***	0.6975467***	0.0720109***
	(0.000232)	(0.0004373)	(0.0076866)	(0.0050206)	(0.0037279)
Recession	0.0001307***	0.0054886***	0.2381765***	0.6899389***	0.0662654***
	(0.000272)	(0.0005224)	(0.0086939)	(0.0058623)	(0.0038443)
Difference in Probability	0.00175%	0.06361%	1.26898%	-0.76078%	-0.57455%

Note also that under both recommendation policies (the tight one during a recession and the generous one during expansion) the lowest and highest recommendations are given to the least attractive and the most attractive firms, respectively. The implication of this is that changes in the probabilities of receiving a specific recommendation, for the least and most attractive firms, is actually understated by this methodology. This means that the changes in the probabilities of receiving a specific recommendation for firms who currently have a Strong Buy or Strong Sell, reported in Table 3, are biased. It is very likely that the probability for receiving a Strong Buy recommendation during the recession decreases by more than 0.57%. Refer to Auh (2015) for a more in-depth discussion.

8. Conclusion

This papers concludes with statistically significant evidence that analyst recommendations are procyclical: analysts are more generous in times of economic prosperity relative to times of economic contraction. It has been well noted that there is pressure on an analyst's objectivity. After the rule changes in 2002 and the evaluation report of the effect of the changes by the NASD and NYSE (2005), many of these pressures have been mitigated. However, this paper provides evidence for suspicions that analysts do not rate through the cycle. The implication is that during upturns, their optimism aids in creating asset price bubbles through over investment and during a downturn their pessimism exaggerates the extent of contraction.

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