Cross-sectional PEG Ratios, Market Equity Premium, and Macroeconomic Activity*

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Abstract

By combining the loglinear present value framework and the Capital Asset Pricing Model (CAPM) logic, we establish a theoretic link between PEG ratios and time-varying expected returns of stocks. We separately use analysts' forecasts and model-based earnings forecasts to construct several PEG ratios. We then extract information contained in the cross-sectional PEG ratios to form various estimates of the market's expectations for aggregate returns and economic fundamentals. The estimate drawn on the analysts' forecasts as the information source outperforms alternative predictors and has considerable power in forecasting future market returns both in-sample and out-of-sample; such estimate is also able to forecast macroeconomic growth and unemployment rates. The results are robust to various econometric methods for standard-error adjustments.

JEL Classifications: E17; E44; G12; G14; G17; M40; M41
Keywords: PEG Ratios; Analysts' Forecasts; Model-based Earnings Forecasts; Predicting Market Equity Premium; Predicting Macroeconomic Activity

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1. Introduction

Traditional capital market research in accounting has mainly focused on the information role of accounting data at the disaggregate-level (e.g., Kothari, 2001). Against the backdrop of an emerging literature that explores the aggregate application of firms' accounting data, this paper examines the information content of PEG ratios, i.e., a firm's price-earnings ratio (PE) divided by the firm's expected growth, for aggregate stock market returns and macroeconomic activity. We approach this problem by joining three forces: combining the Campbell and Shiller's (1988a, b) loglinear present value framework and the Sharpe's (1964) or Lintner's (1965) Capital Asset Pricing Model (CAPM), extracting market-wide information from cross-section data of PEG ratios, and using analysts' forecasts of earnings and long-term growths as an information source. This paper is among the first few studies to explore the relevance of information content of the PEG ratio to asset pricing and, to our best knowledge, is the first paper to link PEG ratios to time-varying expected stock returns.

The motivation of our study is two-fold. First, researchers often use economic fundamental variables to predict aggregate market returns and macroeconomic activity (e.g., Fama and French, 1989; Konchitchki and Potatoukas, 2014), in which predictors are usually equal- or value-weighted average of disaggregate-level information. There exists an alternative way to extract aggregate-level information. The idea that cross-section data contain aggregate-level information is deeply rooted in modern asset pricing studies and receives a renewed interest (e.g., Chowdhry, Roll, and Xia, 2005; Polk, Thompson, and Vuolteenaho, 2006, PTV hereinafter; Kelly and Pruitt, 2013). For illustration, take the CAPM as an example. Measuring systematic risk by stock beta, the reward for bearing one unit of the beta risk is equal to the expected equity premium of the aggregate market. Therefore, the estimated loading on the stock betas against stock returns (or stock return proxies) in cross-section serves as an informative measure for the ex-ante market equity premium in time-series. In this framework, the weights used in aggregation are implicitly restricted by asset pricing theory. Further, because the fundamental sources of risk in the stock market are inevitably linked to fundamental features of the underlying economic environment (e.g., Cochrane, 2001), the cross-section estimate of the beta risk premium can also shed lights on future macroeconomic activities.

Second, the conventional valuation ratios such as price-dividend ratios, price-earnings ratios, and market-to-book ratios contain a time-varying expected future growth component, which attenuates the relation between those ratios and expected returns and reduces return predictability with those ratios (Menzly, Santos, and Veronesi, 2004). In contrast, the PEG ratio can be a more precise measure of expected returns than the conventional valuation ratios. Analytically, based on the loglinear present value framework, the PEG ratio is more able to isolate the expected stock return from the expected cash flow growth. Empirically, given that analysts' forecasts are forward-looking measures, those forecasts of future earnings and long-term growths can serve as a primary information source to construct a growth proxy for the calculation of the PEG ratio.

We first derive an analytic model in the loglinear present-value framework to establish the theoretic link between PEG ratios and time-varying expected returns. Capitalizing on this theoretic linkage, we then conduct empirical tests. We construct several PEG ratios by separately using analysts' forecasts (of earnings and long-term growths) and model-based earnings forecasts. We extract information contained in the cross-sectional PEG ratios to form estimates of the market's expectations for aggregate returns and economic fundamentals. The PEG-based equity premium proxy that uses analysts' forecasts as the underlying information source outperforms alternative predictors and has considerable power in forecasting one-month-ahead to one-year-ahead market returns in-sample and out-of-sample. We further take the cross-section beta-premium estimate to two applications, i.e., dissecting the return predictability with the PE ratio and forecasting macroeconomic activity. To do so, we also construct one proxy for macroeconomic fundamentals out of the loglinear present-value framework. Both the equity premium proxy and the fundamentals proxy have strong power in forecasting future macroeconomic growth and unemployment rates. The empirical results are robust to various econometric methods for standard-error adjustments including the Newey-West (1987) procedure, the Hodrick (1992) procedure, and the wild bootstrap procedure.

The empirical success of the PEG-based cross-section beta-premium estimate arises from three sources: embracing the guidance of an economic theory (CAPM herein), utilizing the implication of the loglinear present value framework, and incorporating growth/earnings forecasts of equity analysts. Superior performance of this estimate to valuation ratios and alternative cross-section beta-premium estimates highlights the importance of the three sources. Relative to conventional valuation ratios, the PEG ratio is arguably a more precise proxy for the expected return, as shown in the loglinear present-value relation. Relative to obtaining growth rates from the model-based earnings forecasts that use historical earnings as the underlying source, using analysts' forecasts in calculating the PEG ratio generates a more informative risk-premium estimate. Taken together, our results reaffirm the information content of cross-sectional PEG ratios for the aggregate stock market and macroeconomic fundamentals; our results also indicate that compared to historic earnings, financial analysts' forward-looking forecasts contain more accurate and salient information about the future movements in the aggregate stock market and the underlying economy.

Our paper makes several contributions. First, it complements the growing literature on the predictive content of earnings-related variables at the aggregate level. Kothari, Lewellen, and Warner (2006) report that aggregate earnings correlate negatively with concurrent aggregate market returns, which is confirmed by Sadka (2007), Sadka and Sadka (2009), and Cready and Gurun (2010). Hirshleifer, Hou, and Teoh (2007) find that one earnings component, accruals, positively forecasts future market returns at the aggregate level; Kang, Liu and Qi (2010) argue that the positive aggregate-level accrual-return relation is mainly due to discretionary accruals. Ball, Sadka, and Sadka (2009) show that aggregate earnings and aggregate prices are closely related in that firm-level accounting earnings has substantial undiversifiable variation, systematic earnings risk is correlated with return risk, and systematic earnings risk is priced. Konchitchki and Patatoukas (2014) show that aggregate accounting earnings growth is a significant leading indicator of GDP growth and is able to incrementally predict future GDP growth. Using earnings-related measures from alternative sources, Anilowski, Feng, and Skinner (2007) document evidence that aggregate earnings guidance, especially downward guidance, is associated with market returns; Howe, Unlu, and Yan (2009) find that changes in aggregate analyst recommendations forecast both future market excess returns and aggregate earnings growth. Unlike all these studies that aggregate firm-level proxies in an ad-hoc way and examine whether the aggregate ratios have predictive ability for aggregate returns, our study builds on an economic theory and imposes a structure on cross-section data, from which we extract the aggregate information to predict future aggregate returns and macroeconomic activities.

Second, our study adds to the studies of information contents in analysts' forecasts. Analysts' forecasts play an important role in earnings expectation formations and the price discovery process, but due to conflicts of interests, those forecasts are arguably subject to a potential bias. An emerging approach to overcome the drawbacks of using analysts' forecasts is to derive model-based earnings forecasts from historical earnings information in different contexts (e.g., Hou, van Dijk and Zhang, 2012; Li and Mohanram, 2013; So, 2013). The model-based earnings forecasts are shown to have less bias and outperform analysts' earnings forecasts in terms of computing implied cost of capital and predicting analyst forecast error at the firm level. To the contrary, we document evidence that, at the aggregate level, analysts' forecasts contain viable information about future equity returns and macroeconomic activities and such information cannot be subsumed by those model-based earnings forecasts, corroborating Howe, Unlu, and Yan's (2009) finding that analyst recommendations contain market- and industry-level information about future returns and earnings. Our evidence thus indicates that analysts' forecasts assimilate more market-wide and systematic information than the model-based earnings forecasts using historical accounting variables.

Third, our paper provides a theoretic foundation to justify the popularity of the PEG ratio in practice. Peter Lynch, the legendary Wall Street analyst and portfolio manager, proposes "a rule of thumb" for using the PEG ratio, coined by Farina (1969), as a basis of stock recommendations. Practitioners often prefer the PEG ratio to other conventional valuation multiples for asset valuations and stock recommendations (see, e.g., surveys of Block (1999) and Bradshaw (2002)). Despite the pervasive use of the PEG ratio, there have been few studies to link the PEG ratio to a fundamental valuation theory until recently. Easton (2004) and Ohlson and Juettner-Nauroth (2005) show that, under the restrictive assumptions that abnormal growth in accounting earnings is constant in perpetuity and expected dividends are zero, the PEG ratio is equal to the inverse of the squared expected return. However, both models are static under those assumptions. We go one step further to establish a theoretic link between PEG ratios and time-varying expected returns in a fairly general framework. Given the enormous empirical evidence on time-variations in risk premiums, our model is better able to characterize real-world situations.

Last but not least, our work contributes to the return predictability literature in several ways. Numerous studies have found, though without controversy, that market expected returns are time-varying and are predictable with various variables.[1] A body of such studies uses *ad-hoc* priced-related valuation ratios in predicting stock returns, which may introduce a mechanical relation between those variables and the market expected returns. Like PTV (2006), we construct *ex-ante* predictors based on an economic theory and a cross-section approach that is free from the mechanical-link concern. We find that the cross-section beta-premium estimate has considerable power in forecasting the market equity premium realizations, buttressing the evidence on the market return predictability. Moreover, in assessing the return predictability, we document that our beta-premium estimates based on the cross section of PEG ratios outperforms the beta-premium estimates based on the cross section of valuation ratios. Our study thus illustrates that the choice of disaggregated information source is critical to the empirical performance of information extraction. Furthermore, our study shows that the PE ratio's return forecasting power is comprised by its fundamentals component. If controlling for the fundamentals component properly, the predictive regression is able to recover the bulk of information content about the market equity premium, corroborating the finding of Menzly, Santos, and Veronesi (2004).

The remainder of the paper proceeds as follows. Section 2 develops a theoretic framework to link the PEG ratio, the loglinear present value model, and the CAPM. Section 3 describes the

[1] Campbell and Thompson (2008) and Goyal and Welch (2008) summarize the literature with detailed citations and present two opposite views on equity premium predictions. Koijen and Van Nieuwerburgh (2011) provide a recent survey of the literature. For simplicity we do not repeat the citations here.

data and summary statistics of various cross-section equity-premium estimates and explains the empirical method we use to deal with statistical issues of predictive regressions. Section 4 presents empirical evidence on the power of the cross-section beta-premium estimate based on PEG ratios in forecasting future market equity premiums and discusses the implications of the result. Section 5 assesses the power of the cross-section beta-premium estimates based on PEG ratios to forecast various macroeconomic activities. Section 6 concludes.

2. Theory

To motivate our empirical study we develop a theoretic framework to link the PEG ratio, the loglinear present value model, and the CAPM in this section. We first establish a theoretic connection between the PEG ratio and the expected return using the loglinear present value model. We then instill a CAPM-related economic explanation in the framework.

2.1 Reconciling present value models with PEG ratios

Campbell and Shiller (1988a, b) show that the (logged) price-dividend ratio of a stock can be expressed as a linear function of expected long-term rates of returns and expected long-term dividend growth rates of this stock. Formally,

$$pd_t = E_t\left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} - \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}\right] + k_{t}, \qquad (1)$$

where pd_t is log price-dividend ratio at time t, E_t denotes investor expectations based on the information available at time t, Δd_{t+j} is dividend growth in t+j, calculated as the change in the log of dividends per share, r_{t+j} is the log return during period t+j, ρ is a constant which is less than unity and can be viewed as a "discount factor," and k_t is an approximation error.

Equation (1) states that the log price-dividend ratio equals the present value of all expected future dividend growth rates less the present value of all expected future rates of return. Following the same logic, Nelson (1999) and Sharpe (2002) express the log price-earnings ratio as:

$$pe_t = \sum_{j=1}^{\infty} \rho^{j-1} E_t(\Delta e_{t+j}) - \sum_{j=1}^{\infty} \rho^{j-1} E_t(r_{t+j}) + k_t, \qquad (2)$$

where pe_t is log price-earnings ratio at time t, Δe_{t+j} is earnings growth in t+j and is calculated as the change in the log of earnings per share, k_t is an approximation error. In a similar vein of spirits, Vuolteenaho (2002) develops a log book-to-market model, and Jiang and Lee (2007) propose a lonlinear cointegration model with valuation ratios. As such, these loglinear models yield important economic implications on conventional valuation ratios like price-dividend ratio, price-earnings ratio, or book-to-market ratio: these (logged) valuation ratios either, if adjusted for future growth rates in fundamentals, provide the optimal forecast of the discounted value of all future expected returns, or, if adjusted for future expected returns, make the optimal forecast of the discounted value of all future growth rates in fundamentals.

The above loglinear models also suggest that conventional valuation ratios are jointly determined by either expected long-term cash flows and/or expected long-term discount rates. On the one hand, the conventional valuation ratios are only noisy proxies for expected returns when changes in the valuation ratios are also due to expected fundamental growth rate variation (see e.g., Fama and French, 1988; Goetzmann and Jorion, 1993; Menzly, Santos, and Veronesi, 2004). On the other hand, the conventional valuation ratios are only noisy proxies for expected fundamental growth when expected return variations drive changes in the valuation ratios.

If the approximation error k_t is negligible, we can rewrite equation (2) as:

$$pe_t = ltg_t - ltr_t \,, \qquad (3)$$

where the long-term earnings growth $ltg_t = \sum_{j=1}^{\infty} \rho^{j-1} E_t(\Delta e_{t+j})$, and the long-term expected return, $ltr_t = \sum_{j=1}^{\infty} \rho^{j-1} E_t(r_{t+j})$. Note that a widely-used valuation heuristic, the PEG ratio, is defined as price-earnings ratio divided by an earnings growth rate. Formally:

$$PEG_t = \frac{P_t/E_t}{g_t} \qquad (4)$$

Taking logs on both sides of equation (4) and using equation (3), we obtain our PEG model as in the following equation:

$$peg_t \equiv log(PEG_t) = pe_t - ltg_t = -ltr_t \quad . \qquad (5)$$

By extending the loglinear present value model from conventional valuation ratios to the PEG ratio, this framework lays out a theoretical foundation for the valuation heuristic and thus helps instill a (long-term) risk-related finance intuition into the practitioners' ad-hoc "rule-of-the-thumb" story for the PEG ratio. Specifically, equation (5) shows that the PEG ratio is inversely related to the expected (long-term) return only: a higher (lower) PEG ratio implies a lower (higher) expected return, and vice versa. Therefore, the PEG ratio can serve as a proxy for the expected return. Moreover, because the conventional valuation multiples like price-earnings ratio, price-dividend ratio, and price-book ratio are related to both the expected return and the expected fundamental growth, the isolation of the expected return from the expected growth as shown in equation (5) indicates that the PEG ratio contains less noise and can be more informative of the expected returns than those conventional valuation ratios.

2.2 Combining PEG ratios with CAPM

In this subsection we further incorporate CAPM with the above loglinear framework for the PEG ratio to motivate our empirical design. The CAPM implies that the equity premium of a stock is proportional to the equity premium of the market and the proportion is the stock's beta. That is,

$$E_t(r_{i,t+1})-r_{f,t} = \beta_{i,t}[E_t(r_{m,t+1})-r_{f,t}] \tag{6}$$

If the long-term expected return ltr_t is a proxy for the expected return $E_t(r_{t+1})$ long-term, then we can combine equations (5) and (6) to obtain the following relation:

$$-peg_t \approx r_{f,t} + \beta_{i,t}[E_t(r_{m,t+1})-r_{f,t}] \tag{7}$$

Equation (7) shows that the PEG ratio of a firm is log-linearly related to the market equity premium. It is well known that that the market equity premium is generally positive. Therefore, per equation (7) a firm's PEG ratio can be low in the following three cases: 1) when the market equity premium is high, 2) when the risk-free interest rate is high, and (3) when the firm has a positive beta and the beta is high. The first two cases often arise when the economy is in recession or the business condition is poor, and the third case often occurs for the firm that has a sensitive co-movement with the market in the same direction.

Equation (7) provides us the key intuition to construct a new market equity premium predictor based on the cross section of PEG ratios. The intuition is similar to the one we use in empirically testing the CAPM. That is, we can regress firms' PEG ratios against firm betas in cross-section to estimate the loading on the firm betas at each time, and such estimated coefficient is a proxy for the price of beta risk, bearing out the expected market equity premium.

3. Data and Empirical Method

In this section we first describe the data and their summary statistics, and then we explain in details the empirical method used to conduct our analysis.

3.1 Data and Variable Constructions

We draw raw data other than macroeconomic variables from five sources. The Center for Research in Security Prices (CRSP) monthly stock file contains monthly prices, shares outstanding, dividends, and returns for NYSE, Amex, and Nasdaq common stocks. The COMPUSTAT annual research file provides the relevant accounting information for most publicly traded US stocks. We supplement the COMPUSTAT accounting information with the Moody's book equity information for industrial firms as collected by Davis, Fama and French (2000). Moreover, we require firms to have a one-year-ahead earnings-per-share (EPS) forecast and a long-term growth rate (LTG) forecast from the Institutional Brokers Estimates System (I/B/E/S) history summary file. We constrain our sample to firms with stock price greater than $2 per share and fiscal-year-ends in December, and we use I/B/E/S forecasts issued in May. (For robustness we also use the average of the forecasts in January, February, March, April, and May and obtain qualitatively similar results.) This constraint ensures that forecasted earnings correspond to the correct fiscal year, and our use of analysts' forecasts only up to May of each year helps avoid the look-ahead bias. We also winsorize the EPS forecasts from I/B/E/S and the accounting variables from COMPUSTAT at the top and bottom one percentiles to mitigate the potential influence of outliers. We further require data to be available in the last three consecutive years.

We follow the logic of PTV (2006) and construct risk-premium estimates in two steps. First, for each firm we calculate its PEG ratio as the P/E ratio divided by a growth rate measure, where P is the stock price per share at the end of May and E is the earnings per share in the last fiscal year end. To be consistent with Campbell and Shiller's log-linear framework, we use the present value of future growths in the PEG calculation.[2] We adopt a three-stage growth model similar to Pastor, Sinha, and Swaminathan (2008) and Da and Warachka (2009) to form growth rates for each future year. Specifically, in stage one, we calculate the growth rates in year 1 and year 2 based on current realized earnings, analysts' one-year-ahead and two-year-ahead earnings forecasts, and we use analysts' long-term growth forecasts (LTG) as the growth rates for year 3 to year 5. In stage two, we calculate the steady-state growth (SSG) as the cross-sectional average of LTGs and use it as a proxy for the growth rates for year 10 and beyond. In stage three, we apply a linear interpolation between LTG and SSG to calculate the growth rates from year 6 to year 9. Setting the discount rate to 0.95, we then compute the present value of future growth rates and use it in calculating a firm's PEG ratio. We proceed to construct an aggregate growth proxy, APVG, as the equal-weighted average of firms' present values of future growths. Furthermore, according to the logic of Graham and Dodd (1934) and the ensuing vast empirical findings, high PEG values typically correspond to high current prices and low expected future returns. We then rank in each year the cross section of negative PEG ratios from low to high and transform each raw measure

[2] There is no consensus on which growth rate proxy should be used in the PEG calculation. It appears that the use of long-term growth rates in the formulation is popular among practitioners. For example, Yahoo! Finance uses five-year expected growth rate in calculating PEG ratios. As a robustness check, we also use analysts' forecast of long-term growth rates (LTG) in the calculation. Results are similar and available upon request.

into an ordinal composite measure, $PEG\_rank_{i,t}$ so that a high value of *PEG_rank* mirrors a high expected return.

Second, for each firm and in each month we estimate the firm's beta, β, in an OLS regression that fits the past three years of monthly stock returns (a minimum of one year of data required) on a constant and the contemporaneous monthly returns on the value-weight NYSE-Amex-Nasdaq portfolio. Because sometimes we have only 12 observations to estimate betas, we censor each firm's individual monthly returns to the range (-50%, 100%) to limit the influence of extreme firm-specific outliers. We update our beta estimates month by month. Our results are insensitive to small variations in the beta-estimation method. We then align the monthly betas of each year with that year's annual ordinal PEG ratios for each firm, and we run cross-sectional regressions of *PEG_rank* on β month-by-month. The estimated coefficient on β, R_{PEG}, serves as our measure of the cross-section beta premium (up to one scale). We also follow PTV (2006) to construct their cross-section beta-premium estimate (R_{PTV}). That is, in each year, we first calculate the conventional valuation ratios such as dividend yield, earnings yield, book-to-market of equity, and cash-flow-to-price ratio and transform each ratio into an ordinal measure for each stock, and then we compute R_{PTV} as the cross-sectional correlations between the yearly averages of the four ranked valuation ratios and the firm betas.

Compared to R_{PTV}, the variable R_{PEG} incorporates analysts' growth forecasts as additional information content in estimating the cross-section beta premium. There is some controversy in using analysts' forecasts. On the one hand, Frankel and Lee (1998) and Lee, Myers and Swaminathan (1999) demonstrate that analysts' earnings forecasts contain more value-relevant information than historical earnings information does. On the other hand, researchers document that, likely due to conflicts of interests, analysts tend to be overly optimistic in their forecasts (see, e.g., the review by Kothari, 2001; Easton and Sommers, 2007). Motivated by these studies, Hou, van Dijk, and Zhang (2012, HVZ hereinafter), Li and Monharam (2013, LM hereinafter) propose a model-based approach to forecast future earnings using realized accounting numbers. They find that, compared to analysts' forecasts, model-based earnings forecasts are less biased albeit less accurate. To address the controversy on analysts' forecasts, we also construct two alternative cross-section beta-premium estimates, R_{PEG_HVZ} and R_{PEG_LM}, by following the above two-step approach and using the growth rates implied respectively from HVZ's and LM's model-based earnings forecasts.[3]

Easton (2004) and Ohlson and Juettner-Nauroth (2005) develop models to link the PEG ratio to the expected rate of return. Both models are static and imply that short-term growth rates in earnings should be used in the PEG calculation. We thus construct a fourth measure of the PEG ratio, using the growth rate in analysts' two-year-ahead earnings forecasts over one-year-ahead earnings forecasts in the PEG calculation; we repeat the above two-step approach to estimate the cross-section beta-premium estimates, R_{PEG_STG}.

The excess log return on the market (MKR) is the difference of the log return on the CRSP equal-weighted stock index over the log risk-free rate. We use the CRSP's rate on the Treasury bills with approximately three month maturity as the risk-free rate. Variables measuring macroeconomic activities come from the St. Louis Federal Reserve Bank. We select the following variables to represent broad categories of macroeconomic time series: coincident economic

[3] For the two alternative PEG ratios based on the model-implied earnings forecasts, we use the average of the three-year-ahead, four-year-ahead, and five-year-ahead growth rates as a proxy for the long-term growth forecasts (LTG).

activity index,[4] consumer price index, and unemployment rate (UNR),. We calculate the percentage changes in the two indices and label them as CIG and CPIG, respectively.

3.2 Summary Statistics

Our sample spans the period from June 1982 to December 2012, a total of 367 months. Panel A of Table 1 presents the summary statistics of the variables used in our study. It is important to point out that, given the way they are constructed, all the cross-section beta-premium estimates proxy for the *ex-ante* market risk premiums only up to one scale: they do not measure the risk premium in an exact magnitude, but they are able to capture the dynamics of the risk premium. Except for the variable MKR which has an autocorrelation of 0.26, all the other variables have quite high persistency. The first-order autocorrelations of the beta-premium estimates (R_{PEG}, R_{PEG_STG}, R_{PEG_HVZ}, R_{PEG_LM}, and R_{PTV}), the aggregate growth proxy (APVG), and aggregate PE ratio are higher than 0.91. The first-order autocorrelations of CIG and UNR are even higher, around 0.99 or above. The first-order autocorrelation of CPIG is at a moderate level of 0.42. Because the cross-section beta-premium estimates are the generic predictors in our study and it is well documented that highly persistent predictors can cause statistical issues for return predictive regressions (e.g., Stambaugh, 1999), we deal with this problem in our empirical analysis and elaborate on the details in Section 3.3.

[4] The coincident economic activity index is a single summary statistic that tracks the current state of the economy. The index is computed from the following data series that move systematically with overall economic conditions: nonfarm payroll employment, average hours worked in manufacturing, the unemployment rate, and wage and salary disbursements deflated by the consumer price index. The long-term growth of the index matches the long-term growth of GDP. A rise (or decline) in the index indicates an expansion (or contraction) of the economic activity.

Panel B of Table 1 displays the cross correlations among these variables. We discuss a few patterns. First, the correlation of the two cross-section beta-premium estimates based on PEG ratios, R_{PEG} and R_{PEG_STG}, equals 0.647. Given that analysts' short-term growth forecasts is one component in calculating the present value of future growths, the moderate correlation suggests that the present value of future growth likely captures information that is not contained in the short-term growth. Second, the correlations of R_{PEG} with the two alternative measures based on model-based earnings forecasts, R_{PEG_HVZ} and R_{PEG_LM}, are positive but tiny in magnitudes. Both correlations are lower than 0.04, suggesting that the analysts' growth forecasts and the historical earnings, on which the model-based earnings forecasts are made, carry vastly different information contents. Third, the correlation between R_{PEG} and R_{PTV} is negative, equal to -0.117, signaling that the information contained in the PEG ratios and in the valuation ratios are considerably different from each other. Fourth, R_{PEG} is positively correlated with MKR with a coefficient of 0.128, while the correlations of R_{PEG_HVZ} and R_{PEG_LM} with MKR are respectively -0.156 and -0.132, foretelling the potentially opposite return-forecasting relations with the two different sets of PEG-based risk premium estimates as return predictors. Fifth, R_{PEG} is negatively correlated with the coincidence index growth, CIG, and is positively correlated with the unemployment rate, UNR. The correlation coefficients are respectively -0.357 and 0.347, echoing the evidence of counter-cyclical variations in risk premiums. Finally, consistent with economic intuition, the aggregate growth proxy, APVG, is correlated positively with CIG and negatively with UNR; the correlation coefficients are 0.219 and -0.476, respectively.

3.3 Empirical Method

We primarily use the ordinary least squares (OLS) estimator in our analysis. We calculate and report Newey-West's (1987) heteroscedasticity and autocorrelation consistent (HAC) *t*-statistics with 12 lags for parameter estimates. To deal with the statistical issue facing long-horizon regressions, we also calculate and report Hodrick's (1992) *t*-statistics. However, as well documented in the return predictability literature, predictive regressions have econometric issues beyond the above two (e.g., Nelson and Kim, 1993; Mark, 1995; Stambaugh, 1999). In particular, Stambaugh (1999) shows that there is a bias in the estimated predictive coefficient in a common empirical framework to study stock return predictability with price-scaled variables. The bias arises because innovations in these price-scaled variables are contemporaneously correlated (negatively oftentimes) with stock returns. This bias is more pronounced when the contemporaneous correlation between the innovation terms is strong, the persistence of the predictors is high, or the sample size is small. Our key predictors are the cross-section beta-premium estimates; they are not price-scaled variables, but they have quite high persistence level. Moreover, the multi-horizon market returns and macroeconomic time series typically have autocorrelation and (conditional) heteroskedasticity, which may invalidate the conventional residual-based bootstrap procedures that treat the regression error as *i.i.d* (Goncalves and Kilian, 2004). To address these statistical issues we adopt the wild bootstrap procedure per Goncalves and Kilian's suggestions, impose the null of no predictability in calculating the critical values, and report the bootstrap *p*-values for each parameter estimate.

This bootstrapping procedure consists of several steps. Step 1, we start estimating the following two equations jointly with OLS:

$$y_{t+k} = \alpha + \beta x_t + u_{1,t+k} \qquad (8)$$

$$x_{t+k} = \gamma + \rho x_t + u_{2,t+k} \qquad (9)$$

Here, equations (8) and (9) characterize the generic predictive regression used in our study and the dynamics of the predictor variable(s), respectively. Note that in the case of a multivariate regression the predictor x is a vector variable and equation (9) becomes a restricted vector-autoregressive (VAR) process with the off-diagonal terms of the transition matrix ρ all set to zeros. The residuals of the two equations, u_1 and u_2, have a variance-covariance matrix $\sum$. Given the OLS estimates for parameters in the two equations, we calculate and store the two residuals for sampling. Step 2, we randomly draw (with replacement) from the residuals ($\hat{u}_1, \hat{u}_2$), and we generate two bootstrapped time series ($\hat{y}, \hat{x}$) by using the OLS estimates obtained in Step 1 and imposing no predictability. Specifically, the data-generating process in this step is assumed to be as follows:

$$\hat{y}_{t+k} = \alpha + \eta_t \hat{u}_{1,t+k} \qquad (10)$$

$$\hat{x}_{t+k} = \gamma + \rho \hat{x}_t + \hat{u}_{2,t+k} \qquad (11).$$

Note that the error term in equation (10) is a product of $\hat{u}_{1,t+k}$ and η_t, where $\hat{u}_{1,t+k}$ is the regression residual from Step1 and η_t is a random variable with zero mean and unit variance. Per the wild bootstrap procedure, we include the random variable η_t in the error term of equation (10) to better address potential autocorrelation and (conditional) heteroskedasticity in the data.[5] Step 3, we re-estimate equations (8) and (9) jointly with OLS using the bootstrapped time series ($\hat{y}, \hat{x}$) to obtain the parameter estimates ($\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\rho}, \widehat{\sum}$). Step 4, we repeat Steps 2-3 for N times, and for each replication we store the bootstrapped parameter estimates. Finally, we calculate the bootstrapped p-value for each parameter estimate as the fraction of these N replications in which

[5] We also try the conventional bootstrapping procedure in the empirical exercise. That is, we generate the bootstrapped series of $\hat{y}$ as $\hat{y}_{t+k} = \alpha + \hat{u}_{1,t+k}$. The results are qualitatively similar and available upon request.

the absolute value of the particular parameter's bootstrapped estimate, which is obtained from Step 3, exceeds the absolute value of the corresponding parameter's OLS estimate, which is obtained from Step 1.

In regard to the Stambaugh's (1999) bias this bootstrap procedure has two merits: it not only preserves the autocorrelation structure of the predictor variable(s) but also retains the cross-correlation structure of the residuals of the two equations (Goyal and Welch, 2008). In addition, the wild bootstrap procedure takes into consideration the potential (conditional) heteroskedasticity of unknown form present in the data (Goncalves and Kilian, 2004). As a result, this bootstrapping method helps address the statistical issues associated with predictive regressions likely to face our empirical study. In implementing the bootstrapping procedure, we set the number of replications N to 10,000. We also set N to 25,000 or 50,000; the results are similar and are not reported for the sake of brevity.

4. Predicting Market Equity Premiums with Cross-Section Beta-Premium Estimates

In this section we analyze the power of the various cross-section beta-premium estimates to forecast realized market equity premiums both in-sample and out-of-sample. The cross-section beta-premium estimates are proxies for ex-ante market equity premiums, and we thus hypothesize that the estimates are able to predict future market equity premiums.

4.1 In-Sample Prediction: Univariate Analysis

Table 2 presents the in-sample prediction results by in turn using R_{PTV}, R_{PEG}, R_{PEG_STG}, R_{PEG_HVZ}, and R_{PEG_LM} as the sole return predictor over the full sample period. For each beta-premium estimate we conduct one-, three-, six-, and 12-month-ahead predictions, respectively. To save space, for each regression we only report the adjusted regression R^2s and the estimated predictive coefficients with their associated Newey-West (1987) *t*-statistics in parentheses, Hodrick (1992) t-statistics in brackets, and bootstrapped *p*-values in braces.

The first two columns of Table 2 list the results when the beta-premium estimate based on the cross-section of conventional valuation ratios, R_{PTV}, is the return predictor. It is clear that R_{PTV} has virtually no power in forecasting future market equity premiums. The estimated predictive coefficients are all statistically insignificant with *p*-values well above 0.60; and the regression R^2s at the four horizons are either negative or nearly zero. This result corroborates the PTV's (2006) finding that the cross-section beta-premium estimate based on conventional valuation ratios only has, if any, weak power in forecasting market equity premiums in the post-1965 period.

We obtain dramatically different results when we use the various beta-premium estimates based on the cross-section PEG ratios as the sole return predictor. The beta-premium estimate, R_{PEG}, is able to forecast future market equity premiums with a positive and highly significant predictive coefficient. The signs of the coefficient estimates are intuitive. For the one-month-ahead forecasting, R_{PEG} can predict 1.7% of the variations in market equity premiums; the predictive coefficient estimate has a Newey-West *t*-statistic of 2.34, a Hodrick *t*-statistic of 2.92, and a bootstrapped *p*-value of 0.039. For the three-month-ahead forecasting, the explaining power increases to 4.4% and the predictive coefficient estimate has a Newey-West *t*-statistic of 2.60, a Hodrick *t*-statistic of 3.03, and a bootstrapped *p*-value of 0.024. For the six-month-ahead prediction, 9.4% of the variations in market equity premiums are predictable with the predictive coefficient estimate significant at the 2% level (Newey-West *t*-statistic = 2.91, Hodrick *t*-statistic = 3.20, and *p*-value = 0.013). For the one-year-ahead prediction, R_{PEG} can predict 12.2% of the variations in market equity premiums; the predictive coefficient estimate has a Newey-West *t*-statistic of 2.98, a Hodrick *t*-statistic of 2.57, and a bootstrapped *p*-value of 0.009. These results indicate that the beta-premium estimate based on the cross-section PEG ratios, R_{PEG}, is able to consistently forecast realized market risk premium in different horizons from one-month-ahead to one-year-ahead.

The present-value growth rate used for the calculation of the PEG ratio is derived from a combination of the analysts' long-term growth forecasts with short-term growth rates. Also, the static models of Easton (2004) and Ohlson and Juettner-Nauroth (2005), linking the PEG ratio to the expected rate of return, call for the use of the short-term growth rates in the PEG calculations. Thus, we predict future returns with R_{PEG_STG} to further investigate whether the short-term growth has return forecasting power. As shown in the middle two columns of Table 2, R_{PEG_STG} has somewhat return forecasting power, but its power is considerably weaker than R_{PEG}. The regression R^2s for the one-, three-, six-, and 12-month-ahead horizons are 0.009, 0.024, 0.044, and 0.042, respectively; the predictive coefficients are all positive but in most cases are not significant except that we look at the Hodrick *t*-statistics. Consistent with the moderate correlation between R_{PEG_STG} and R_{PEG}, the information contents of the two ex-ante risk-premium are likely different, and the incremental return forecasting power of R_{PEG} appears to derive mainly from the analysts' long-term growth forecasts.

We further use as the return predictor the two alternative cross-section beta-premium estimates based on PEG ratios, whereas we derive growth rates from the model-based earnings forecasts per HVZ (2012) and LM (2013), respectively. Both predictors have decent power in forecasting future returns. When RPEG_HVZ is the return predictor, the regression R^2s for the one-, three-, six-, and 12-month horizons are 0.020, 0.051, 0.071, and 0.031, respectively. When

R_{PEG_LM} is the return predictor, the regression R^2s for the four forecasting horizons are respectively 0.016, 0.034, 0.041, and 0.021. Noticeably, although the predictive coefficients with either predictor are highly significant with small *p*-values, their signs are negative, which is counterintuitive. The anomalous negative signs on the predictive coefficient seem to mirror the particular finding reported by both HVZ (2012, Table 7) and LM (2013, Table 7): the implied costs of capital derived from various model-based earnings forecasts load significantly negatively on firm betas in cross-section.

4.2 In-Sample Prediction: Bivariate Analysis

We run several horse races between R_{PEG} and other cross-section beta-premium estimates in term of their return forecasting power. Table 3 reports the bivariate regression results.

When we throw both R_{PEG} and R_{PTV} into the predictive regression, across the four forecast horizons the loadings on R_{PEG} are all positive and highly significant (often better than the 1% level with *p*-values all below 0.02) while the loadings on R_{PTV} are not significant at all. We also include both R_{PEG} and R_{PEG_STG} into the predictive regression. Across the four forecast horizons the estimated coefficients on R_{PEG} remain positive and highly significant, especially at the horizons of six months or longer. In contrast, the estimated coefficients on R_{PEG_STG} are not significant at all at any of the four horizons.

Our main interest is in the horse races between R_{PEG} and R_{PEG_HVZ} (or R_{PEG_LM}). All the three beta-premium estimates are based on cross-sectional PEG ratios. In constructing the PEG ratios, we use two different sources to calculate growth rates: one is based on analysts' forecasts with the LTG forecasts as the underlying source, and the other on model-based earnings forecasts with historical earnings as the underlying source. To check whether the information contents of the two sets of sources subsume each other, we run two sets of bivariate regressions.

We first include R_{PEG} and R_{PEG_HVZ} in the predictive regression. Across the four forecasting horizons, the estimated coefficients on R_{PEG} are positive and significant with *p*-values smaller than 0.1, and the estimated coefficients on R_{PEG_HVZ} remain to be negative and higly significant, with *p*-values smaller than 0.01, except at the one-year-ahead horizon. The explaining power of the bivariate regression improves dramatically, almost twice of the explaining power of the univariate regression in three horizons: the regression R^2s for the one-, three-, six-, and 12-month horizons are 0.037, 0.0902 0.156, and 0.144, respectively. We then include R_{PEG} and R_{PEG_LM} in the predictive regression and obtain similar results. Across the four forecasting horizons, R_{PEG} retains positive and significant loadings, with *p*-values all smaller than 0.01; R_{PEG_LM} carries consistently negative loadings and except for the one-year horizon, the loadings are statistically significant, with *p*-values smaller than 0.1. The explaining power of the bivariate regression also increases substantially relative to that of the univariate regression, albeit slightly weaker than that of the first bivariate regression: the regression R^2s for the one-, three-, six-, and 12-month horizons are 0.034, 0.078, 0.129, and 0.135, respectively. Overall, the results of the two sets of the bivariate regressions show unequivocally that the two information sources, analysts' forecasts (of earnings and long-term growths) versus historical earnings, contain different information contents that are supplementary to each other.

4.3. Out-of-Sample Prediction

Heeding Goyal and Welch's (2008) concern about in-sample predictions, we follow their advice to conduct the out-of-sample (OOS) test using one-month-ahead OOS forecasting with nested-model comparisons.[6] We conduct the initial estimation over the period from June 1982 to December 1997 and then recursively do the model re-estimation out-of-sample until December 2012.

We use the Clark-McGracken's (2001) test to carry out the nested-model OOS forecasting analysis. We specify two restricted models commonly used in the literature, the constant-mean model and the AR(1) model. The constant-mean model has only one regressor, i.e., the constant, and the AR(1) model includes two regressors, the constant and the one-period lagged stock market returns. Given each restricted model, the corresponding unrestricted model includes one additional return predictor in the restricted model. Clark and McCracken (2001) enlist two types of OOS tests: the equal forecast accuracy test and the forecast encompassing test. For the equal forecast accuracy test, the null hypothesis is that the restricted and unrestricted models have equal mean-squared errors (MSE), and the alternative is that the restricted model has higher MSE. "MSE-F" and "MSE-t" respectively provide the results of the equal forecast accuracy *F*-test and *t*-test. For the encompassing test, the null hypothesis is that the restricted model forecast encompasses the unrestricted model, and the alternative is that the unrestricted model contains information that can significantly improve the restricted model's forecast. "ENC-F" and "ENC-t" provide the modified Harvey, Leybourne, and Newbold (1997) test statistics on forecast encompassing tests.

Table 4 reports the nested-model comparison results for the case of using R_{PEG} as the comparison predictor. The values for "MSE-F" and "MSE-t" suggest that we generally cannot reject the null that the restricted model, i.e., either the constant-mean model or the AR(1) model,

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[6] We focus on one-month-ahead OOS forecasting because, as argued by Clark and McCracken (2001), the asymptotic distributions of the tests generally depend on the parameters of the data-generating process for multi-month-ahead forecasting, which invalidates using asymptotically pivotal approximations to test for equal accuracy or forecast encompassing.

and the unrestricted model have equal forecast accuracy with one exception. There is some evidence that the unrestricted model outperforms the constant-mean model in terms of forecast accuracy, with the "MSE-F" test statistic indicating significance at the 10% level. The forecast encompassing test tells a more clear-cut story: the values for "ENC-F" and "ENC-t" imply that the null of the test is soundly rejected at either the 1% or 5% level. The results on the encompassing test clearly show that the beta-premium estimate based on the cross-sectional PEG ratios, R_{PEG}, has predictive content for market equity premiums. Relative to the AR(1) mode, there is also some evidence that the unrestricted model outperforms: Although the forecast accuracy test statistics are smaller than the critical values, the forecast encompassing test statistics leads to rejection of the null at the 10% or 5% level. It is worthy pointing out that the equal forecast accuracy test and the forecast encompassing test can yield different results, as evidenced here on using R_{PEG} as one additional return predictor. Clark and McCracken (2001) find that the power of the forecast encompassing test is generally superior to the power of other OOS tests like the equal forecast accuracy test. In our case, the equal forecast accuracy test appears to be not powerful enough to single out the predictive content of R_{PEG} for market equity premiums, yielding the discrepancy in inference between the two nested-model-comparison tests.

4.4 Discussion: R_{PEG} versus Alternative Beta-Premium Estimates

In the above analysis we essentially run horse races of the beta-premium estimate based on the cross-sectional PEG ratios, R_{PEG}, versus the beta-premium estimate based on the cross-sectional valuation multiples, R_{PTV}, or the two risk premium measures based on alternative PEG ratios, R_{PEG_LM} and R_{PEG_HVZ}. Overall, the in-sample prediction analysis shows that R_{PEG} outperforms the alternative beta-premium estimates by a large margin in predicting future market equity premiums and that the degree of the superior performance of R_{PEG} relative to these other predictors intensifies as the forecasting horizon increases from one month to one year. Although a bit weak, the out-of-sample testing evidence confirms that R_{PEG} has forecasting power for market equity premiums. These results have several ramifications, on which we elaborate below.

First, the cross-section data do contain useful information about the aggregate market, but the choice of information source is of ultimate importance to the performance of cross-section information extraction. Note that the three PEG-based risk premium estimates, R_{PEG}, R_{PEG_HVZ}, and R_{PEG_LM}, all have decent in-sample return forecasting power while the valuation-ratio-based risk premium estimate, R_{PTV}, lacks such power. As shown in Section 2, the PEG ratio is linked to the stock's expected future return only; in contrast, the conventional valuation multiples are jointly determined by both the expected future return and the expected future growth. According to Menzly, Santos, and Veronesi (2004), time-varying expected dividend growth offsets the standard positive relation between the dividend yield and expected returns, thereby reducing the ability of the dividend yield to forecast returns. Our finding that the PEG-based risk premium estimates outperform the valuation-ratio-based risk premium estimate in forecasting future returns echoes their logic.[7] Appropriately controlling for time-varying growth is of relevance to the return predictability with cross-section beta-premium estimates.

Second, our result suggests that analysts' forecasts (of earnings and growths) and historical earnings contain different dimensions of information about market risk premiums. The two dimensions of information contents are supplementary to each other. When analysts assess a firm's

[7] To address this issue, PTV (2006) add a growth proxy in the cross-section regression to purge the effect of growth from the beta-premium estimation, but the results change little. The PEG model appears to provide a more direct and more effective way to control for the time-varying growth. Also our analytical derivation is different from PTV's (2006), although in similar spirits: PTV's is built on the Gordon's constant growth model for stock valuations while ours is developed on the basis of Campbell and Shiller's log-linear present-value model.

(long-term) growth prospect they likely take into consideration the expected changes in the market-wide risk premium. The finding that R_{PEG} tops R_{PEG_HVZ} and R_{PEG_LM} in predicting future market equity premiums both in-sample and out-of-sample shows that analysts' forecasts are forward-looking measures and contain more precise information than historical earnings, an ex-post measure, about future movements in aggregate market returns.

Third, the CAPM, despite the lack of empirical success in explaining cross-section return variations in the post-War period, remains a useful theoretic tool to guide empirical exercises. Both PTV's (2006) study and our work derive motivations from the CAPM logic. Our cross-section beta-premium estimate R_{PTV} essentially replicates PTV's measure and has very weak power, if any, in forecasting stock market returns in the 1983-2011 period, thereby corroborating the PTV's (2006) finding. In a sharp contrast, the various beta-premium estimates based on cross-sectional PEG ratios, R_{PEG} in particular, exhibit considerable return forecasting power in the 1983-2011 period. This result implies that the PTV's finding is mainly driven by the use of conventional valuation ratios as noisy measures of expected returns but not by the poor empirical performance of the CAPM in the post-1960 period.

5. Two Applications

Given the superior return forecasting power of R_{PEG} over alternative cross-section beta-premium estimates, we extend our analysis to two applications, return predictability with the PE ratio and macroeconomic activity forecasting.

5.1 Dissecting Return Predictability with the PE ratio

The empirical asset pricing literature had mixed evidence on stock return predictability with valuation ratios like the PE ratio (see, e.g., references cited in Campbell and Thompson (2008) and Goyal and Welch (2008)). The loglinear present-value framework as shown in equation (5) implies that a valuation ratio comprises two components, expected return and expected growth. We thus infer that, at the *aggregate* level, the PE ratio also consists of two components, the long-term expected return and the long-term expected fundamental growth. We measure the return component by the cross-section beta-premium estimate, R_{PEG}, and the growth component by the present value of future growth rates, APVG, respectively. As it's well known that both the discount rate and the fundamental growth drive stock returns (Campbell, 1991), we use the two measures in univariate and bivariate predictive regressions. By doing so, we can dissect the return predictability with the PE ratio and assess the relative importance of R_{PEG} versus APVG in predicting future market excess returns with the PE ratio.

Table 5 reports the results. Panel A respectively list the results when we use the PE ratio, R_{PEG}, and APVG as the sole return predictor. Panel B presents the bivariate regression results with the two components of the PE ratio as predictors. We discuss several observations below. First, the PE ratio has power in forecasting market returns with positive and significant predictive coefficients. This result mirrors the evidence on stock return predictability with valuation ratios (see, e.g., references cited in Campbell and Thompson (2008) and Goyal and Welch (2008)). The regression R^2s increase monotonically from 1.2% at the one-month horizon to 7.5% at the one-year horizon. Second, in univariate regressions, R_{PEG} retains positive and significant loadings across the four forecasting horizons; in contrast, APVG carries negative and statistically insignificant loadings. While R_{PEG} has considerable return forecasting power, APVG has virtually no power. Third, the patterns in the loadings on R_{PEG} and APVG from the univariate regressions carry over to bivariate regressions. Compared to the univariate regression with R_{PEG} as the return predictor, the inclusion of APVG in the bivariate regression does not increase the forecasting power much: the regression R^2s for the one-, three-, six-, and 12-month horizons are 0.018, 0.056, 0.113, and 0.129, respectively. It is clear that the expected-return component, R_{PEG}, dominates the growth component, APVG, in forecasting market returns at each forecast horizon. This evidence suggests that the return forecasting power of the PE ratio is mainly from its expected return component rather than its expected growth component.

Taken together, the results of the univariate and bivariate regressions, suggest that the growth component of the PE ratio attenuates the forecasting power of the PE ratio, corroborating the finding of Menzly, Santos, and Veronesi (2004). After controlling for the time-varying growth in the predictive regression the valuation ratio can be a robust return predictor.

5.2 Predicting Macroeconomic Activities

The market equity premium is a compensation for the market risk. As well recognized in the asset pricing literature, both the pricing and the fundamental sources of risk in the stock market are inevitably linked to fundamental features of the underlying economic environment (Cochrane, 2001). In this subsection we use the cross-section beta-premium estimates and the aggregate fundamentals proxy to predict various macroeconomic activities such as growth rate in coincident economic activity index (CIG), unemployment rate (UNR), and inflation rate as measured by growth rate in consumer price index (CPIG). In general, both CIG and CPIG are pro-cyclical measures, and UNR is a countercyclical measure. The forecast horizon ranges from one month to one year.

Table 6, Panels A, B, and C, display the univariate regression results, with CIG, UNR, and CPIG as the dependent variable, respectively. We first look at the analysis regarding CIG predictions. R_{PEG} has considerable power in predicting CIG: the regression R^2s equal to 0.102 for one-month ahead, 0.084 for three-month ahead, 0.059 for six-month ahead, and 0.022 for one-year ahead. The associated predictive coefficients are all negative and highly significant, with *p*-values often smaller than 0.07 except at the one-year horizon. Although quite a few Newey-West (1987) *t*-statistics and Hodrick (1992) *t*-statistics indicate significance of the predictive coefficient estimates, the bootstrap *p*-values are large enough to nullify the statistical significance when we use R_{PTV}, R_{PEG_HVZ} or R_{PEG_LM} as the sole predictor.

We proceed with predicting UNR. Again, R_{PEG} alone has considerable forecasting power: the regression R^2s equal to 0.125 for one-month ahead, 0.130 for three-month ahead, 0.134 for six-month ahead, and 0.130 for one-year ahead. The associated predictive coefficients are all negative and highly significant, with *p*-values often smaller than 0.06. R_{PTV}, R_{PEG_HVZ}, and R_{PEG_LM} appear to have somewhat power in forecasting UNR. The regression R^2s range around 2%-3% for R_{PTV}, 6%-8% for R_{PEG_HVZ}, and 5%-6% for R_{PEG_LM} at the four horizons, but the bootstrap *p*-values of coefficient estimates exceed 0.14.

We then assess the forecasting of CPIG. Generally, except for R_{PTV}, there isn't a strong predictive relation between any of the predictors and the inflation rate as all the regression R^2s are either negative or positive but below 0.020 at the four horizons. R_{PTV} is significantly and negative related to future CPIG.

We further conduct bivariate regressions to assess whether the information contents of the risk-premium estimates, if any, are subsumable. Table 7 reports the results that are largely similar to the univariate regressions. When we use both R_{PEG} and APVG as predictors, the estimated coefficients on R_{PEG} are significantly negative in forecasting CIG or CPIG, and are significantly positive in forecasting UNR. The aggregate fundamentals proxy, APVG, also has strikingly strong power in predicting UNR. Across the four forecast horizons, its associated coefficient estimates are all significant, with Newey-West *t*-statistics above 4.6, Hodrick *t*-statistics above 13.9, and *p*-values of 0.000 in magnitudes. Moreover, the estimated coefficients on APVG are all negative in forecasting UNR and positive in forecasting CIG. The case of predicting UNR deserves some discussions. The estimated coefficients on R_{PEG} and APVG all have highly significant *t*-statistics, Newey-West-type and Hodrick-type alike, and low bootstrapped *p*-values (all at or below 0.01). Notably, the adjusted R^2s of the bivariate regressions are quite high and increase substantially from the univariate regressions with R_{PEG} as the predictor; the R^2s equal 0.348, 0.359, 0.373, and 0.368 at the one-month, three-month, six-month and twelve-month horizons, respectively. It is clear that the forecasting power of R_{PEG} for the three macro series is not subsumed by APVG, and the power of APVG in forecasting UNR is not subsumed by R_{PEG}.

When we include R_{PEG} and R_{PEG_HVZ} or R_{PEG_LM} in the bivariate regressions, R_{PEG} always predicts CIG and CPIG with a negative sign, and it always predicts UNR with a positive sign. Most the loadings on R_{PEG} are significant at the 10% level in forecasting CIG and CPIG. In contrast, the majority of the loadings on R_{PEG_HVZ} or R_{PEG_LM} have high *p*-values.

Combining the results of Table 6 and Table 7, we have the following observations. First, R_{PEG} has consistent and robust power in forecasting the three macro series; the signs of the loadings on R_{PEG} indicate that a higher market equity premium forecasts a higher unemployment rate or a weaker economy in the future, in line with the economic rationale that the market equity premium varies counter-cyclically (e.g., Fama and French, 1989; Campbell and Cochrane, 1999; Lettau and Ludvigson, 2001). Second, APVG has considerable power in forecasting UNR; the signs on the estimated coefficients on APVG are all significantly negative, bearing an intuitive economic implication that a proxy for stronger economic fundamentals foretells a lower unemployment rate in the future. Third, although the two alternative measures based on PEG ratios have some power in forecasting one of the three macro series individually, they do not behave consistently, especially when we use them together with R_{PEG} in regressions.

5.3 Discussion: R_{PEG} vs. APVG

Using the loglinear present value model, we decompose a valuation ratio like the PE ratio into a return component and a fundamentals component. We respectively use the cross-section beta-premium estimate, R_{PEG}, and the present value of forecasted growth rates, APVG, as proxies for the two components and we apply the two components in forecasting market returns and macroeconomic activity. The beta-premium estimate R_{PEG} is found to have considerable power to forecast both market equity premiums and macro growths and unemployment rates; instead, the aggregate fundamentals proxy APVG has strong power in forecasting unemployment rates, and macro growth rate to a much less extent. Here we discuss likely interpretations of the results.

First, the different levels of importance of R_{PEG} and APVG in various forecasting exercises suggest that the two components have different information contents. The cross-section risk-premium estimate primarily contains information about future stock returns while the fundamentals component contains information on economic activity growth. The two sets of information contents are supplementary to each other and are not subsumable by the other.

Second, the evidence that the return component dominates the fundamentals component in predicting future market returns has a say about the weak return predictability with the PE ratio. Mirroring the findings of Menzly, Santos, and Veronesi (2004), the existence of the fundamentals component in the PE ratio disguises the fact that the ratio contains a bunch of information about market returns; controlling for the fundamentals in the predictive regression helps recover the return predictability with the PE ratio.

Third, the evidence that both of the two components have strong power in forecasting future unemployment rates pinpoints to the importance of the labor market movements to both the stock market and the analysts. When making growth forecasts, the analysts pay much attention to the labor market news as a vital information source. Further, because the PE ratio is the sum of the two components we naturally infer that the PE ratio should contain substantial information about the future movements in the labor market as well.

6. Conclusions

In this paper, by combining the loglinear present value model and the CAPM logic we derive a PEG model to establish a theoretic link between PEG ratios and expected returns of stocks. We then capitalize on this theoretic link to conduct various empirical tests. We construct several PEG ratios by separately using analysts' forecasts and model-based earnings forecasts. We extract information contained in the cross-sectional PEG ratios to form estimates of the market's expectations for aggregate returns and economic fundamentals. The estimates constructed on the basis of analysts' forecasts have robust power in forecasting future market equity premium and macroeconomic activity.

By using a theory-guided empirical approach to extract aggregate-level information from cross-section data on analysts' forecasts and accounting information, our study has several implications. First, cross-section data contain useful information about future movements in both the aggregate stock market and the underlying economy. Imposing theoretic restrictions on cross-section data provides an alternative approach to aggregating firm-level information. Moreover, choosing what cross-section data to work with is critical to the empirical performance of such information extraction.

Second, compared to the model-based earnings forecasts using historic earnings as the underlying information source, analysts' forecasts of earnings and long-term growth forecasts contain more salient information about future movements in both the aggregate stock market and the underlying economy. Analysts appear to take into account the aggregate-level information in forming forecasts and making recommendations. Therefore, analysts' forecasts and/or recommendations at the aggregate level can serve as an informative measure of the aggregate stock market and overall business conditions.

Third, economic theory provides relevant guidance, with which researchers are able to extract information from cross-section data and take it to real-world tests. To this extent, despite the difficulty in explaining cross-sectional return variations in the post-War period, the CAPM is still vital in providing such theoretic guidance for empirical works. The evidence from our analysis thus echoes Campbell's (2008) argument:

"The lesson I draw from this experience is that one is more likely to predict stock returns successfully if one uses finance theory to reduce the number of parameters that must be

freely estimated from the data, and to restrict estimates of the equity premium to a reasonable range".

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Table 1. Descriptive Statistics

The table shows the descriptive statistics of estimated proxies of market risk premium, aggregate growth, market excess returns, and macro activities from the full sample period 1982:6-2012:12 with 367 monthly observations. R_{PEG} is the cross-section regression coefficient of PEG ratio ranks on stock betas, where we calculate a firm's PEG ratio as the firm's price-earnings ratio divided by its present value of future growth rates. In computing the present value of future growth rates, we set the discount rate to 0.95 and use a three-stage growth model similar to Pastor, Sinha, and Swaminathan (2008) and Da and Warachka (2009) to form growth rates for each future year. R_{PEG_STG} is estimated in the same way as R_{PEG} except that we use the growth rate in analysts' two-year-ahead earnings forecasts over one-year-ahead earnings forecasts in the PEG calculation. R_{PEG_HVZ} (or R_{PEG_LM}) is estimated in the same way as R_{PEG} except that we compute future growth rates using the model-based earnings forecasts obtained per Hou, Van DijK, and Zhang (2012) (or Li and Mohanram (2013)) in the PEG calculation. R_{PTV} is the cross-sectional correlation coefficient between valuation ratio ranks and stock betas per Polk, Thompson, and Vuolteenaho (2006). APVG is the equal-weighted average of firms' present values of future growth rates. PE is the price-earnings ratio of the S&P500 Index, where we use the 10-year moving average of earnings in calculating the PE ratios. MKR is the logged return on the Center for Research in Securities Prices (CRSP) equal-weighted index in excess of the logged three-month T-Bill rate. CIG is the monthly percentage change in coincident economic activity index. UNR is the unemployment rate. CPIG is the monthly percentage change in consumer price index. We obtain the three macroeconomic variables from the St. Louis Federal Reserve Bank. The column of "AR1" lists the first-order autocorrelation coefficients.

Panel A: Summary Statistics

Variables	Obs	Mean	Std	Min	Max	AR1
R_{PEG}	367	0.040	0.037	-0.031	0.160	0.950
R_{PEG_STG}	367	0.088	0.034	0.024	0.176	0.953
R_{PEG_HVZ}	367	0.025	0.099	-0.408	0.268	0.913
R_{PEG_LM}	367	-0.015	0.097	-0.449	0.120	0.964
R_{PTV}	367	-0.145	0.100	-0.442	-0.013	0.976
APVG	367	4.181	0.491	3.441	5.394	0.961
PE	367	22.198	14.871	7.742	123.731	0.971
MKR	367	0.007	0.055	-0.281	0.218	0.259
CIG	367	0.002	0.002	-0.005	0.006	0.989
UNR	367	0.063	0.017	0.038	0.108	0.995
CPIG	367	0.002	0.003	-0.018	0.014	0.421

Panel B: Pairwise Correlations

Variables	R_{PTV_STG}	R_{PEG_HVZ}	R_{PEG_LM}	R_{PTV}	APVG	PE	MKR	CIG	UNR	CPIG
R_{PEG}	0.647	0.006	0.037	-0.117	-0.047	0.257	0.128	-0.357	0.347	-0.098
R_{PEG_STG}		-0.151	-0.205	-0.725	-0.222	-0.049	0.060	-0.121	0.375	0.043
R_{PEG_HVZ}			0.520	0.259	0.278	0.090	-0.156	0.161	-0.235	0.002
R_{PEG_LM}				0.475	-0.105	0.031	-0.132	-0.017	-0.223	0.005
R_{PTV}					0.144	0.235	-0.012	-0.103	-0.160	-0.167
APVG						0.073	-0.070	0.219	-0.476	-0.060
PE							0.156	-0.621	0.041	-0.116
MKR								-0.048	0.136	-0.003
CIG									-0.114	0.211

UNR	-0.080

Table 2. Univariate Forecasting of Market Risk Premium

This table reports the estimated slope coefficients β, Newey-West (1987) *t*-statistics (12 lags) in parentheses, Hodrick (1992) *t*-statistics in brackets, wild bootstrap *p*-values in braces, and adjusted R^2s of the following predictive regressions, $R_{m,t+k} = \alpha + \beta X_t + \varepsilon_{t+k}$, where $R_{m,\,t+k}$ is the t+k month ahead market excess return, and X_t contains the predictors (listed in the column headings) in month t. See Table 1 for variable definitions. The sample period covers 1982:06 through 2012:12.

k	$X=R_{PTV}$	R^2	$X=R_{PEG}$	R^2	$X=R_{PEG\_STG}$	R^2	$X=R_{PEG\_HVZ}$	R^2	$X=R_{PEG\_LM}$	R^2
1	-0.020	-0.001	0.215	0.017	0.172	0.009	-0.084	0.020	-0.078	0.016
	(-0.506)		(2.343)		(1.430)		(-2.983)		(-2.517)	
	[-0.763]		[2.921]		[2.202]		[-3.896]		[-3.215]	
	{0.650}		{0.039}		{0.197}		{0.018}		{0.036}	
3	-0.054	0.000	0.685	0.044	0.544	0.024	-0.261	0.051	-0.223	0.034
	(-0.440)		(2.595)		(1.556)		(-3.529)		(-2.210)	
	[-0.697]		[3.025]		[2.363]		[-4.130]		[-3.112]	
	{0.690}		{0.024}		{0.163}		{0.006}		{0.060}	
6	-0.073	-0.001	1.549	0.094	1.093	0.044	-0.459	0.071	-0.365	0.041
	(-0.308)		(2.907)		(1.735)		(-3.132)		(-1.673)	
	[-0.518]		[3.200]		[2.425]		[-4.314]		[-2.754]	
	{0.778}		{0.013}		{0.120}		{0.017}		{0.159}	
12	0.036	-0.003	2.525	0.122	1.503	0.042	-0.433	0.031	-0.380	0.021
	(0.106)		(2.977)		(1.598)		(-1.723)		(-1.054)	
	[0.141]		[2.573]		[1.728]		[-2.395]		[-1.447]	
	{0.923}		{0.009}		{0.149}		{0.191}		{0.401}	

Table 3. Bivariate Forecasting of Market Risk Premium

This table summarizes the results from predictive regressions, $R_{m,t+k} = \alpha + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \varepsilon_{t+k}$, where where $R_{m,\,t+k}$ is the t+k month ahead market excess return, and X_{it} contains the predictors (listed in the column headings) in month t. See Table 1 for variable definitions. The sample period covers 1982:06 through 2012:12. The table reports the estimated slope coefficients β, Newey-West (1987) *t*-statistics (12 lags) in parentheses, Hodrick (1992) *t*-statistics in brackets, bootstrap *p*-values in braces, and adjusted R^2s.

k	X_1=R_{PEG}	X_2=R_{PTV}	R^2	X_1=R_{PEG}	X_2=R_{PEG_STG}	R^2	X_1=R_{PEG}	X_2=R_{PEG_H}	R^2	X_1=R_{PEG}	X_2=R_{PEG_LM}	R^2
1	0.211	-0.010	0.015	0.189	0.042	0.015	0.212	-0.084	0.037	0.218	-0.079	0.034
	(2.373)	(-0.292)		(1.795)	(0.289)		(2.811)	(-4.098)		(2.610)	(-3.424)	
	[2.828]	[-0.399]		[1.960]	[0.410]		[2.980]	[-4.045]		[3.027]	[-3.500]	
	{0.017}	{0.766}		{0.074}	{0.775}		{0.004}	{0.000}		{0.009}	{0.000}	
3	0.676	-0.021	0.041	0.594	0.150	0.042	0.665	-0.254	0.092	0.680	-0.221	0.078
	(2.650)	(-0.190)		(1.951)	(0.353)		(3.113)	(-4.659)		(2.936)	(-2.917)	
	[2.928]	[-0.269]		[1.989]	[0.489]		[3.004]	[-4.213]		[3.070]	[-3.336]	
	{0.008}	{0.847}		{0.050}	{0.724}		{0.002}	{0.000}		{0.003}	{0.004}	
6	1.554	0.010	0.091	1.427	0.202	0.092	1.477	-0.430	0.156	1.503	-0.340	0.129
	(2.997)	(0.051)		(2.460)	(0.287)		(3.217)	(-3.396)		(3.237)	(-1.999)	
	[3.129]	[0.075]		[2.306]	[0.352]		[3.061]	[-4.109]		[3.151]	[-2.764]	
	{0.004}	{0.960}		{0.014}	{0.767}		{0.002}	{0.003}		{0.001}	{0.054}	
12	2.634	0.194	0.126	2.554	-0.047	0.120	2.436	-0.367	0.144	2.451	-0.308	0.135
	(3.094)	(0.653)		(2.761)	(-0.050)		(2.935)	(-1.519)		(3.132)	(-0.988)	
	[2.599]	[0.763]		[2.060]	[-0.044]		[2.445]	[-1.970]		[2.511]	[-1.298]	
	{0.003}	{0.558}		{0.006}	{0.964}		{0.004}	{0.256}		{0.003}	{0.448}	

Table 4. Out-of-Sample Forecast

The table reports the results of nested-model forecast comparisons of predicting one-month-ahead equal-weighted CRSP index returns in excess of three-month T-bill rates. We conduct the initial estimation over the period from 1982:06 to 1997:12, and then recursively estimate the model out-of-sample until 2012:12. The restricted model is either the constant mean model or the AR(1) model. The unrestricted model adds a comparison predictor in the restricted model. "MSE-F" and "MSE-t" respectively provide the results of the out-of-sample equal forecast accuracy *F*-test and *t*-test. The null hypothesis is that the restricted and unrestricted models have equal mean-squared errors (MSE); the alternative is that the restricted model has higher MSE. "ENC-F" and "ENC-t" provide the modified Harvey, Leybourne, and Newbold (1997) test statistics on forecast encompassing tests. The null hypothesis is that the restricted model forecast encompasses the unrestricted model; the alternative is that the unrestricted model contains information that can significantly improve the restricted model's forecast. The column labeled "Asymptotic Critical values (1-sided)" gives the asymptotic distribution of the statistic as derived in McCracken (1999).

		Asymptotic Critical values (1-sided)		
Rpeg vs Constant	Test value	0.100	0.05	0.01
MSF-F	1.474	0.760	1.552	3.561
MSF-t	0.302	0.456	0.788	1.441
ENC-F	4.453	0.973	1.562	3.152
ENC-t	1.837	0.957	1.335	2.052
Rpeg vs AR(1)	Test value	0.100	0.05	0.01
MSF-F	0.303	0.760	1.552	3.561
MSF-t	0.072	0.456	0.788	1.441
ENC-F	2.761	0.973	1.562	3.152
ENC-t	1.326	0.957	1.335	2.052

Table 5. Return Predictability with PE ratios: R_{PEG} versus APVG.

This table reports the estimated slope coefficients β, Newey-West (1987) *t*-statistics (12 lags) in parentheses, Hodrick (1992) *t*-statistics in brackets, wild bootstrap *p*-values in braces, and adjusted R^2s of the following predictive regressions, $R_{m,t+k} = \alpha + \beta X_t + \varepsilon_{t+k}$ and $R_{m,t+k} = \alpha + \beta_1 X_{1,t} + \beta_2 X_{2.t} + \varepsilon_{t+k}$ where $R_{m,\,t+k}$ is the t+k month ahead market excess return, and X_t contains the predictors (listed in the column headings) in month t. See Table 1 for variable definitions. The sample period covers 1982:06 through 2012:12.

k	X=PE	R^2	X=R_{PEG}	R^2	X=APVG	R^2	X_1=R_{PEG}	X_2=APVG	R^2
1	4.54e-4	0.012	0.215	0.017	-0.007	0.001	0.211	-0.006	0.018
	(1.988)		(2.343)		(-1.097)		(2.328)	(-1.071)	
	[1.820]		[2.921]		[-0.998]		[2.855]	[-0.904]	
	{0.088}		{0.039}		{0.000}		{0.020}	{0.290}	
3	0.001	0.030	0.685	0.044	-0.029	0.014	0.675	-0.028	0.056
	(2.001)		(2.595)		(-1.473)		(2.563)	(-1.522)	
	[2.130]		[3.025]		[-1.408]		[2.974]	[-1.353]	
	{0.084}		{0.024}		{0.000}		{0.011}	{0.125}	
6	0.003	0.048	1.549	0.094	-0.050	0.019	1.554	-0.051	0.113
	(2.134)		(2.907)		(-1.359)		(2.887)	(-1.529)	
	[2.329]		[3.200]		[-1.249]		[3.215]	[-1.271]	
	{0.065}		{0.013}		{0.000}		{0.005}	{0.134}	
12	0.004	0.075	2.525	0.122	-0.041	0.004	2.549	-0.047	0.129
	(2.732)		(2.977)		(-0.647)		(2.979)	(-0.843)	
	[2.351]		[2.573]		[-0.514]		[2.609]	[-0.590]	
	{0.021}		{0.009}		{0.000}		{0.004}	{0.420}	

Table 6. Univariate Forecasting of Macroeconomic Activity

This table reports the estimated slope coefficients β, Newey-West (1987) *t*-statistics (12 lags) in parentheses, Hodrick (1992) *t*-statistics in brackets, wild bootstrap *p*-values in braces, and adjusted R^2s of the following predictive regressions, $Y_{t+k} = \alpha + \beta X_t + \varepsilon_{t+k}$, where Y_{t+k} is the t+k month ahead macro activities, and X_t contains the predictors (listed in the column headings) in month t. See Table 1 for variable definitions. The sample period covers 1982:06 through 2011:12.

Panel A: Y = CIG

k	X=R_{PTV}	R^2	X=R_{PEG}	R^2	X=R_{PEG_HVZ}	R^2	X=R_{PEG_LM}	R^2
1	-0.002	0.010	-0.016	0.102	0.002	0.015	0.001	0.000
	(-0.683)		(-2.643)		(1.254)		(-0.307)	
	[-1.875]		[-6.465]		[2.103]		[-0.743]	
	{0.555}		{0.022}		{0.322}		{0.791}	
3	-0.007	0.015	-0.043	0.084	0.004	0.004	-0.006	0.008
	(-0.859)		(-2.538)		(0.739)		(-0.683)	
	[-2.479]		[-6.515]		[1.384]		[-1.833]	
	{0.444}		{0.025}		{0.552}		{0.557}	
6	-0.017	0.025	-0.075	0.059	-0.003	0.000	-0.020	0.032
	(-1.108)		(-2.112)		(-0.051)		(-1.299)	
	[-3.256]		[-5.809]		[-0.102]		[-3.400]	
	{0.329}		{0.062}		{0.967}		{0.271}	
12	-0.039	0.039	-0.091	0.022	-0.030	0.022	-0.063	0.094
	(-1.330)		(-1.130)		(-1.315)		(-2.510)	
	[-3.663]		[-3.478]		[-3.774]		[-4.692]	
	{0.247}		{0.308}		{0.286}		{0.035}	

Panel B: Y = UNR

k	X=R_{PTV}	R^2	X=R_{PEG}	R^2	X=R_{PEG_HVZ}	R^2	X=R_{PEG_LM}	R^2
1	-0.028	0.026	0.166	0.125	-0.045	0.069	-0.041	0.054
	(-0.787)		(2.476)		(-1.635)		(-1.185)	
	[-2.549]		[7.339]		[-4.087]		[-3.784]	
	{0.476}		{0.031}		{0.191}		{0.307}	
3	-0.096	0.026	0.591	0.130	-0.163	0.078	-0.146	0.058
	(-0.780)		(2.447)		(-1.730)		(-1.228)	
	[-2.982]		[8.536]		[-5.274]		[-4.625]	
	{0.485}		{0.029}		{0.182}		{0.301}	
6	-0.227	0.025	1.520	0.134	-0.416	0.087	-0.359	0.060
	(-0.762)		(2.357)		(-1.841)		(-1.260)	
	[-3.886]		[10.590]		[-7.594]		[-6.489]	
	{0.489}		{0.039}		{0.156}		{0.286}	
12	-0.610	0.021	4.401	0.130	-1.176	0.084	-0.963	0.051
	(-0.738)		(2.183)		(-1.888)		(-1.217)	

	[-6.651]		[15.956]		[-12.207]		[-11.045]	
	{0.510}		{0.054}		{0.145}		{0.322}	

Panel C: Y = CPIG

k	X=R_{PTV}	R^2	X=R_{PEG}	R^2	X=R_{PEG_HVZ}	R^2	X=R_{PEG_LM}	R^2
1	-0.004	0.022	-0.007	0.008	0.000	-0.003	0.000	-0.003
	(-2.179)		(-2.086)		(0.034)		(0.009)	
	[-3.161]		[-2.282]		[0.035]		[0.010]	
	{0.052}		{0.062}		{0.978}		{0.993}	
3	-0.012	0.043	-0.019	0.012	0.001	-0.002	0.001	-0.002
	(-2.217)		(-1.747)		(0.416)		(0.248)	
	[-3.270]		[-2.069]		[0.366]		[0.279]	
	{0.045}		{0.112}		{0.730}		{0.834}	
6	-0.026	0.095	-0.039	0.021	0.003	-0.002	0.001	-0.003
	(-2.690)		(-1.682)		(0.462)		(0.107)	
	[-4.203]		[-2.086]		[0.459]		[0.139]	
	{0.018}		{0.131}		{0.702}		{0.925}	
12	-0.064	0.253	-0.022	0.001	-0.007	0.000	-0.009	0.001
	(-4.194)		(-0.435)		(-0.698)		(-0.535)	
	[-5.572]		[-0.563]		[-0.948]		[-0.651]	
	{0.000}		{0.697}		{0.552}		{0.638}	

Table 7. Bivariate Forecasting of Macroeconomic Activity

This table summarizes the results from predictive regressions, $Y_{t+k} = \alpha + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \varepsilon_{t+k}$, where where Y_{t+k} is the t+k month ahead macro activities, and X_{it} contains the predictors (listed in the column headings) in month t. See Table 1 for variable definitions. The sample period covers 1982:06 through 2012:12. The table reports the estimated slope coefficients β, Newey-West (1987) *t*-statistics (12 lags) in parentheses, Hodrick (1992) *t*-statistics in brackets, bootstrap *p*-values in braces, and adjusted R^2s.

Panel A: Y = CIG

k	X_1=R_{PEG}	X_2=APVG	R^2	X_1=R_{PEG}	X_2=R_{PEG_HVZ}	R^2	X_1=R_{PEG}	X_2=R_{PEG_LM}	R^2
1	-0.015	0.001	0.133	-0.015	0.002	0.117	-0.015	-0.001	0.101
	(-2.456)	(1.460)		(-2.837)	(1.464)		(-2.609)	(-0.311)	
	[-6.176]	[3.894]		[-6.825]	[2.184]		[-6.396]	[-0.723]	
	{0.017}	{0.167}		{0.005}	{0.201}		{0.011}	{0.782}	
3	-0.043	0.002	0.105	-0.043	0.004	0.087	-0.043	-0.006	0.093
	(-2.412)	(1.258)		(-2.620)	(0.770)		(-2.491)	(-0.774)	
	[-6.291]	[3.625]		[-6.785]	[1.297]		[-6.508]	[-2.022]	
	{0.021}	{0.219}		{0.013}	{0.523}		{0.017}	{0.483}	
6	-0.075	0.002	0.068	-0.075	-0.002	0.057	-0.078	-0.021	0.096
	(-2.087)	(0.879)		(-2.119)	(-0.199)		(-2.189)	(-1.501)	
	[-5.768]	[2.735]		[-6.010]	[-0.365]		[-6.088]	[-3.939]	
	{0.044}	{0.385}		{0.039}	{0.862}		{0.034}	{0.167}	
12	-0.092	0.001	0.020	-0.099	-0.033	0.048	-0.107	-0.066	0.126
	(-1.144)	(0.187)		(-1.219)	(-1.588)		(-1.408)	(-2.785)	
	[-3.546]	[0.630]		[-3.870]	[-5.240]		[-4.142]	[-6.405]	
	{0.283}	{0.847}		{0.248}	{0.140}		{0.187}	{0.008}	

Panel B: Y = UNR

k	X_1=R_{PEG}	X_2=APVG	R^2	X_1=R_{PEG}	X_2=R_{PEG_HVZ}	R^2	X_1=R_{PEG}	X_2=R_{PEG_LM}	R^2
1	0.156	-0.016	0.348	0.164	-0.045	0.193	0.168	-0.042	0.183
	(2.646)	(-4.656)		(2.251)	(-1.643)		(2.459)	(-1.496)	
	[7.434]	[-13.989]		[6.818]	[-4.093]		[7.671]	[-4.848]	
	{0.010}	{0.000}		{0.027}	{0.156}		{0.016}	{0.174}	
3	0.572	-0.056	0.359	0.578	-0.157	0.202	0.588	-0.144	0.187
	(2.761)	(-4.791)		(2.209)	(-1.701)		(2.370)	(-1.476)	
	[8.762]	[-16.445]		[7.898]	[-5.103]		[8.609]	[-5.289]	
	{0.008}	{0.000}		{0.032}	{0.145}		{0.021}	{0.183}	
6	1.533	-0.138	0.373	1.455	-0.388	0.209	1.475	-0.334	0.186
	(2.887)	(-4.966)		(2.097)	(-1.740)		(2.193)	(-1.384)	
	[11.044]	[-21.159]		[9.514]	[-6.702]		[9.888]	[-6.090]	
	{0.005}	{0.000}		{0.037}	{0.146}		{0.032}	{0.222}	
12	4.603	-0.398	0.368	4.142	-1.065	0.199	4.197	-0.841	0.169
	(2.810)	(-5.072)		(1.921)	(-1.700)		(1.967)	(-1.211)	

	[16.322]	[-31.351]		[13.696]	[-9.730]		[13.458]	[-7.779]	
	{0.008}	{0.000}		{0.069}	{0.167}		{0.065}	{0.309}	

Panel C: Y = CPIG

k	X_1=R_{PEG}	X_2=APVG	R^2	X_1=R_{PEG}	X_2=R_{PEG_HVZ}	R^2	X_1=R_{PEG}	X_2=R_{PEG_LM}	R^2
1	-0.008	0.000	0.009	-0.007	0.000	0.005	-0.007	0.000	0.005
	(-2.155)	(-0.977)		(-2.087)	(0.015)		(-2.081)	(0.038)	
	[-2.347]	[-1.344]		[-2.285]	[0.012]		[-2.272]	[0.039]	
	{0.034}	{0.320}		{0.041}	{0.988}		{0.043}	{0.972}	
3	-0.020	-0.001	0.014	-0.019	0.001	0.010	-0.019	0.001	0.010
	(-1.787)	(-0.831)		(-1.750)	(0.435)		(-1.743)	(0.257)	
	[-2.117]	[-1.112]		[-2.068]	[0.320]		[-2.074]	[0.270]	
	{0.073}	{0.402}		{0.078}	{0.636}		{0.082}	{0.789}	
6	-0.038	-0.002	0.028	-0.038	0.002	0.019	-0.038	0.000	0.018
	(-1.668)	(-0.982)		(-1.662)	(0.372)		(-1.682)	(0.041)	
	[-2.093]	[-1.369]		[-2.073]	[0.330]		[-2.117]	[0.052]	
	{0.115}	{0.333}		{0.115}	{0.705}		{0.113}	{0.969}	
12	-0.020	-0.005	0.033	-0.024	-0.007	0.001	-0.025	-0.009	0.003
	(-0.377)	(-1.467)		(-0.471)	(-0.781)		(-0.494)	(-0.583)	
	[-0.507]	[-1.983]		[-0.605]	[-1.053]		[-0.635]	[-0.752]	
	{0.718}	{0.142}		{0.650}	{0.411}		{0.636}	{0.546}	