The Value Premium and Beta Premium Sensitivity using a Direct Market Estimates Approach

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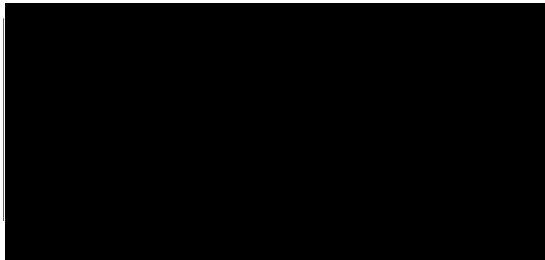
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ABSTRACT

I study the relative risk of value and growth stocks using beta premium sensitivities and find that, on average, value stocks are less risky than growth stocks based on this measure. I find that value stock betas tend to covary less with the expected market risk premium than growth stock betas. Value stocks are therefore less susceptible to time-varying risk during recessionary periods when the expected market risk premium is high. My finding does not offer support for a risk-based explanation of the value premium.

The beta premium sensitivity is a measure of the covariation between a stock's time-varying beta and the expected market risk premium. I derive expected stock returns, the expected market risk premium and expected market volatility using a direct market estimates approach. This is the first study, to my knowledge, that investigates the relative risk of value and growth stocks in this manner.

Under the direct market estimates approach I use professional stock analysts' forecasts and the CBOE VIX index to derive expected stock returns and the expected market volatility respectively. I also use an instrumental (conditioning) variables approach for comparison, as has been used in previous research, under which I derive expected returns using predictive regressions. My results using instrumental variables are in the opposite direction to those using direct market estimates, whereby I find that value stocks are riskier than growth stocks on average based on beta premium sensitivities. The divergent results do not appear to be caused by the tendency for professional stock analysts' forecasts to exhibit optimism, as both the direct market estimates and instrumental variables approaches exhibit more optimism for growth stock forecasts relative to value stock forecasts.

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1   INTRODUCTION

Possible causes of the value premium are the subject of continued debate. One prominent perspective favours a risk-based explanation, whereby the value premium arises as compensation for non-diversifiable sources of risk. Another popular perspective suggests that the value premium arises due to investor behaviour or other factors that do not have a risk-based explanation.

I explore causes of the value premium by studying the relative risk of value and growth stocks using beta premium sensitivities and a direct market estimates approach. I find that value stock betas covary less with the expected market risk premium than growth stock betas on average. From this perspective, I find that value stocks are less risky than growth stocks. My finding does not offer support for a risk-based explanation of the value premium. Rather, it accords with previous research that ascribes non-risk causes of the value premium (Lakonishok, Shleifer and Vishny 1994). My research contributes to perspectives on what causes the value premium and is the first study (to my knowledge) that applies a beta premium sensitivity framework using direct market estimates to this question.

A stock's beta premium sensitivity measures the sensitivity (degree of covariation) of its time-varying beta to the expected market risk premium. It is derived from its expected return premium, the expected market risk premium, its time-varying beta and the expected market variance. I estimate beta premium sensitivities for US value and growth stocks over the period March 1999 to July 2017. I find that the average beta premium sensitivity for value stocks is lower than that for growth stocks over the sample period. This is my central result.

A stock's average riskiness depends on its risk during recessionary periods (when the expected market risk premium is high) and expansionary periods (when the expected market risk premium is low). I estimate beta premium sensitivities separately for recessionary and

expansionary periods. I find that value stocks have lower average beta premium sensitivities than growth stocks during recessionary periods. Hence, value stock betas are less sensitive to changes in the expected market risk premium when the expected market risk premium high. I also find that value stocks have higher average beta premium sensitivities than growth stocks during expansionary periods, when the expected market risk premium is low. The combined effect is that value stocks have lower beta premium sensitivities than growth stocks on average.

I derive expected stock returns, the expected market risk premium and expected market variance using a direct market estimates approach. I employ professional stock analysts' forecasts (from the IBES[1] database) and the CBOE VIX index[2] for this purpose. I find that expected returns derived from analysts' forecasts tend to be optimistic, consistent with previous studies (Asquith, Mikhail and Au 2005, Brav and Lehavy 2005). I also find that growth return forecasts are more optimistic than value return forecasts on average.

Direct market estimates circumvent limitations associated with alternative approaches for deriving expected returns, such as instrumental variable approaches. In this thesis I use the term instrumental variables to refer to conditioning variables, as it is used in finance, not to be confused with its usage in econometrics. Instrumental variables have been used in previous studies (Gibbons and Ferson 1985, Harvey 1989, Petkova and Zhang 2005) and are subject to biases such as overfitting (Foster, Smith and Whaley 1997). For comparison with my central result, I derive beta premium sensitivities using an instrumental variables approach. I find that average beta premium sensitivities under this approach are in the opposite direction of my central result, according with previous research on beta premium sensitivities that uses instrumental variables (Petkova and Zhang 2005).

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[1] Institutional Brokers' Estimate System.
[2] Chicago Board Options Exchange Volatility Index.

The beta premium sensitivity is linear in expected returns, *ceteris paribus*. Hence, relative differences in optimism (which translate to expected return forecasts) can influence relative differences in beta premium sensitivities. I study forecast accuracies (degrees of optimism) associated with expected returns derived using both the direct market estimates and the instrumental variables approaches. I find that expected returns are optimistic under both approaches and expected growth returns are more optimistic than expected value returns under both approaches. I therefore do not find that the optimism associated with analysts' forecasts explains the divergence in my results between the direct market estimates and instrumental variable approaches.

The beta premium sensitivity is a useful measure for portfolio management practitioners. An improved understanding of its behaviour can assist with portfolio risk management decisions through the economic cycle. During periods when the expected market risk premium is rising, stocks with higher (positive) beta premium sensitivities are likely to experience larger increases in their risk exposure (beta) than stocks with lower beta premium sensitivities. This information can assist the portfolio manager in better allocating risk (due to a more complete depiction of risk) across the economic cycle.

This thesis proceeds as follows. In Section 2, I provide a brief survey of the relevant literature. In Section 3, I outline the theoretical and empirical frameworks for measuring the beta premium sensitivity which underpins my approach. In Section 4, I outline the sources and construction of data that I employ, and in Section 5, I present my results.

2 LITERATURE REVIEW

2.1 The value premium

Value investing in US stocks has been explored through the work of several researchers. In an early study, Basu (1983) uses earnings yield (E/P) as a metric for determining value and finds that shares with a higher E/P earn on average higher risk-adjusted returns compared with shares that have a lower E/P, providing support for a value premium. Similarly, using the ratio of book value of equity to the market value of equity (B/M), Rosenberg, Reid and Lanstein (1985) and later Fama and French (1992) also find evidence for a value premium due to higher average returns for firms with a higher B/M. Chan, Hamao and Lakonishok (1991) similarly find evidence for a value premium based on the B/M for Japanese stocks.

These and other studies have shown the value premium to be persistent, and its existence is now considered to be a well-established empirical fact (Asness et al 2015). Notwithstanding, the underlying causes of the value premium have been the subject of much debate. Two prominent perspectives on this debate are the risk-based and behavioural explanations. The risk-based explanation considers sources of systematic risk as drivers of the value premium. Examples include the higher degree of financial leverage risk associated with value firms (Garlappi and Yan 2011) and the increased sensitivity to time-varying market risk of value firms (Petkova and Zhang 2005). The behavioural explanation seeks to ascribe the value premium to investor behaviour rather than systematic risk. Such behaviour includes the under- and over-reaction to financial and economic news (Hwang and Rubesam 2013) and a tendency to extrapolate past returns in a manner inconsistent with rational expectations (Lakonishok, Shleifer and Vishny 1994). Neither the risk-based nor behavioural perspectives have yet drawn findings to put the debate to rest.

2.2 The CAPM and time-varying beta

A widely cited asset pricing model that is used for studying the value premium is the Sharpe-Lintner-Black Capital Asset Pricing Model (CAPM). This was developed by Sharpe (1964), Lintner (1965) and Black (1972) and expresses an asset's expected return as a linear function of its beta and the expected return of the market portfolio containing all assets in the economy. Here the asset's beta is assumed to be unvarying over the investment time horizon, hence this model may be referred to as the 'static CAPM'.

Albeit enjoying widespread popularity amongst academics and practitioners, the static CAPM has not performed well in explaining asset pricing anomalies such as the value premium. One possible cause is the assumption of static risk premia and static betas. This is highlighted in research from Ball and Kothari (1989) and Basu and Stremme (2007) amongst others who find evidence for the role of time-varying relative risks in influencing asset prices. Also, Choi (2013) finds that the betas of value firms increase when risk premiums are high while those of growth firms remain relatively stable (Choi 2013). The static CAPM may therefore provide an insufficient means for explaining asset pricing anomalies relative to models that allow for time variation in explanatory variables.

2.3 The conditional CAPM and the beta premium sensitivity

Petkova and Zhang (2005) employ the conditional CAPM in their study of the relative risk of value and growth stocks. The conditional CAPM expresses the expected return of a stock at time t in terms of its beta and the market risk premium that apply at t rather than in terms of static (average) values of these variables. The conditional CAPM therefore accounts for time-varying risk premia and can help to explain a larger proportion of the cross-sectional variation in average returns than the static CAPM (Jagannathan and Wang 1996). The role of time-varying beta in the conditional CAPM framework is examined in some detail by

Jagannathan and Wang (1996). They do not consider the assumption of static beta to be reasonable, given that the relative risk of a firm's cash flows is likely to vary over a business cycle and in general is dependent on information available at a given point in time. Allowing for time variation in expected returns and betas, Jagannathan and Wang (1996) derive the unconditional version of the CAPM implied by the conditional version. They find that unconditional average returns are jointly linear in an asset's average beta and a measure of sensitivity of the asset's beta to changes in the expected market risk premium. The authors refer to this sensitivity measure as the beta premium sensitivity.

Given that the framework proposed by Jagannathan and Wang (1996) portrays an asset's average return as related to both its average beta and the degree of variation in its beta over the business cycle, it follows that higher average returns serve as compensation for either higher average betas or a higher variation in betas. This motivates a useful perspective on the value premium and other asset pricing anomalies. Such premia may arise not only due to assets' betas, but also due to the degree of sensitivity of those betas to changes in the expected market risk premium.

Petkova and Zhang (2005) explore this perspective by considering beta premium sensitivities in respect of value and growth stocks. They propose that stocks with positive (or high) beta premium sensitivities have higher risk during recessionary periods when investors dislike risk, hence these stocks should earn higher average returns than stocks with negative (or low) beta premium sensitivities. The authors show that beta premium sensitivities tend to be positive for value stocks and negative for growth stocks and hence offer support for explaining the value premium.

2.4 Instrumental variables and predictive regressions

In their analysis of beta premium sensitivities, Petkova and Zhang (2005) note that the expected market risk premium and conditional betas are unobservable, hence they estimate these using instrumental (conditioning) variables and predictive regressions. They employ the default spread, the term spread, the short-term Treasury bill rate and the market dividend yield as conditioning variables, which they argue are common instruments used to model the expected market risk premium. Realised market excess returns are regressed against these instrumental variables, from which fitted (predicted) values for the expected market risk premium and conditional betas are derived.

The instrumental variables approach has also been used by several researchers for the purposes of estimating expected returns. Gibbons and Ferson (1985) introduce an instrumental variables model using two conditioning variables to estimate returns for the Dow Jones 30 stock index. Keim and Stambaugh (1986) employ three conditioning variables to estimate expected returns on NYSE stock portfolios, US corporate bonds and US government bonds. Harvey (1989) uses five conditioning variables to predict US stock portfolio returns with varying average market capitalisations, and Ferson and Harvey (1991) employ six conditioning variables to predict returns on US stock and bond portfolios. The choice of instrumental variables employed by these researchers has varied amongst studies but tends to contain some common elements including the short-term Treasury bill rate, the term premium and the default spread.

Whilst useful for estimating expected returns, the instrumental variables approach can provide misleading results stemming from overfitting biases. Foster, Smith and Whaley (1997) show that spurious levels of explanatory power may result from choosing a few explanatory variables given the large pool of possible choices. Goyal and Welch (2008) find that commonly used instrumental variables have performed poorly out-of-sample and would

not have helped investors with market timing decisions in a practical sense. Chen and Zhao (2009) highlight the misspecification error that results from the use of predictive regressions that have low predictive power.

2.5 Direct market estimates

To circumvent the limitations of instrumental variable approaches, Chen, Da and Zhao (2013) employ methods that do not rely on predictive regressions. Rather, they use direct estimates of the required expectations provided by professional stock analysts. Drienko (2012) also adopts direct market estimates in his study of conditional asset pricing models by using analyst forecasts and the Chicago Board Options Exchange VIX index. He argues that direct estimates provide a superior alternative to the instrumental variables approach, due to a better fit between of these estimates and realised future stock returns.

The choice of stock analyst forecasts as a source of direct market estimates is a natural one for estimating US stock variables such as expected earnings or price targets. These forecasts are available for a large number of stocks and have been aggregated over a number of years. Nevertheless, they have been found to suffer from biases including a tendency for optimism (Dechow and Sloan 1997), a tendency to overreact and underreact to positive and negative news (Easterwood and Nutt 1999 cited in Anderson, Ghysels and Juergens 2005) and a tendency to herd (Trueman 1994). As highlighted by Chen, Da and Zhao (2013) however, these biases may not always have a material impact on results, depending on the study at hand.

2.6 Analyst target price forecasts

Whilst previous studies using analyst forecasts have tended to focus on earnings, since the 1990s a growing number of sell-side equity analysts have been publishing price targets in addition to earnings forecasts (Gleason, Johnson and Li 2013). These price targets are

typically for a 12-month horizon and have been found to be informative, even in the presence of contemporaneous buy-sell recommendations and earnings forecast revisions (Brav and Lehavy 2003).

In addition to the aforementioned biases, analyst forecasts may move away from consensus due to influences such as forecast horizon, prior accuracy, brokerage size and analyst experience (Clement and Tse 2005). Nevertheless, if the focus of the research is not on the levels of the forecasts but rather on the differences between forecasts, then the impact of such biases may be reduced, as noted by Anderson, Ghysels and Juergens (2005) who studied dispersions, rather than levels, of analyst forecasts.

2.7 Identifying value stocks

In their various studies of the value premium previous researchers have typically used historical measures to identify value stocks based on relative differences in the cross-section. Basu (1983) for instance constructs portfolios based on earnings yield, calculated as the historical 12-month earnings per share divided by the stock price at 31 December in each year of his investigation. He then ranks stocks by earnings yields and sorts them into quintiles for differentiation. Fama and French (1992) find that the ratio of book value of equity (BV) to the market value of equity (MV) plays an important role in differentiating stocks in the cross-section. They use MVs as at 31 December in each year and draw BVs from the preceding fiscal year's accounting data.

Once value stocks have been identified, researchers have formed portfolios that are differentiated by the chosen value metric in order to calculate and compare average returns. Fama and French (1992) construct portfolios at June of each year based on BV/MV stock rankings (quintiles, deciles or top and bottom 30 percent) and calculate average returns for each portfolio over their sample period. They use these portfolio average returns to draw

inferences about the explanatory power of the value metric in the cross-section of average returns.

2.8 Literature gap

To my knowledge, beta premium sensitivities have not been studied using a direct market estimates approach, nor has the combination of beta premium sensitivities and the direct market estimates approach been applied to the study of relative risks between value and growth stocks. Direct market estimates offer an alternative source of expectations for stock and market variables and draw upon a range of information sources employed by practitioners. They offer a different perspective to results derived through more traditional methods for deriving expectations, such as predictive regressions. With this research I contribute to the exploration of what causes the value premium through studying the relative risk of value and growth stocks using beta premium sensitivities and a direct market estimates approach, addressing this gap in the literature.

3 RESEARCH DESIGN

I study the relative risk of value and growth stocks using beta premium sensitivities. These measure the degree of covariation of stocks' time-varying betas with the expected market risk premium. In the following I outline the theoretical and empirical frameworks under which I measure beta premium sensitivities for the purposes of this study.

3.1 Beta Premium Sensitivity – Theoretical Framework

The beta premium sensitivity of asset i, φ_i, was introduced by Jagannathan and Wang (1996) within the framework of the conditional capital asset pricing model (conditional CAPM). In the following I adopt the specification of Petkova and Zhang (2005) in using excess returns to cash, based on which the beta premium sensitivity is given by,

$$\varphi_i \quad = \quad Cov[\beta_{it-1}, r_{mt}] / Var[r_{mt}] \tag{1}$$

Where, conditional on information available at $t-1$, β_{it-1} is the beta of asset i, r_{mt} is the excess return on the market (market risk premium) from $t-1$ to t, and $Var[r_{mt}]$ is the variance of the return on the market (market variance).

The beta premium sensitivity is derived from the conditional CAPM as follows: under the conditional CAPM, the expected excess return for asset i from $t-1$ to t, conditional on information available at $t-1$, is given by,

$$E_{t-1}[r_{it}] \quad = \quad E_{t-1}[r_{mt}]\beta_{it-1} \tag{2}$$

Where $E_{t-1}[r_{it}]$ is the expected excess return on asset i from $t-1$ to t, $E_{t-1}[r_{mt}]$ is the expected market risk premium from $t-1$ to t, and β_{it-1} is the beta of asset i, defined as $Cov_{t-1}[r_{it}, r_{mt}]/Var_{t-1}[r_{mt}]$.

Following Jagannathan and Wang (1996) and taking unconditional expectations on both sides of (2),

$$E[r_{it}] \qquad = \qquad E[r_{mt}]E[\beta_{it-1}] + Cov[r_{mt}, \beta_{it-1}] \qquad (3)$$

Equation (3) expresses a stock's expected return as being made up of two terms. The first term ($E[r_{mt}]E[\beta_{it-1}]$) relates to the stock's sensitivity to the expected market risk premium and the second term ($Cov[r_{mt}, \beta_{it-1}]$) relates to the covariance between its conditional beta and the conditional market risk premium. As noted by Jagannathan and Wang (1996), if the covariance in the second term is zero then equation (3) reduces to the first term and resembles the static CAPM. The extent of covariation between a stock's conditional beta and the conditional market risk premium therefore contributes to the stock's expected return under the conditional CAPM. This suggests a role for the beta premium sensitivity in explaining expected returns, given (1).

Substituting the expression for beta premium sensitivity, φ_i, in (3),

$$E[r_{it}] \qquad = \qquad E[r_{mt}]E[\beta_{it-1}] + \varphi_i Var[r_{mt}] \qquad (4)$$

According to (4), a stock's expected return is explained by a two-factor model where the factors are the expected market risk premium and the market variance. Under this specification a stock's beta premium sensitivity captures its sensitivity to the market variance, acting in addition to its sensitivity to the market risk premium (beta) in explaining its expected return.

3.2 Beta Premium Sensitivity – Empirical Framework

To estimate the beta premium sensitivity, I rearrange (4) as follows,

$$\widehat{\varphi_i} \qquad = \qquad (\,\widehat{E[r_{it}]} - \widehat{E[r_{mt}]}\widehat{E[\beta_{it-1}]}\,)\,/\,\widehat{Var[r_{mt}]} \qquad (5)$$

Equation (5) measures the beta premium sensitivity of a stock as the contribution from the second term in (4). It expresses this as the difference between the stock's unconditional expected return and the contribution from the first term in (4), scaled by the market variance. Alternatively, (5) measures a stock's beta premium sensitivity as the component of its unconditional expected return in excess of that provided by its expected beta exposure, per unit of market variance.

The expectations in (5) reflect investors' views about future stock returns and are essentially unobservable. One approach for estimating these expectations is the use of predictive regressions with instrumental (conditioning) variables. This approach is based on the notion that the instrumental variables, typically macro-economic or stock-market variables such as the prevailing levels of inflation, interest rates or the market dividend yield, have predictive power for the market return and for individual stock returns. This has been used in the literature although has been subject to criticism for overfitting (Foster, Smith and Whaley 1997). In this study I use an alternative approach based on reported professional stock analysts' forecasts obtained from the IBES database. These forecasts capture the views of market practitioners who use various sources of information and a variety of techniques in forming expectations about future stock variables such as price, earnings and dividends.

In order to arrive at an estimate for $\widehat{\varphi_i}$ I therefore obtain estimates for the terms on the RHS of (5) using the two approaches. I estimate the unconditional expectation of conditional excess returns for asset i, $\widehat{E[r_{it}]}$, the unconditional expectation of conditional excess returns for the market (the expected market risk premium), $\widehat{E[r_{mt}]}$, the unconditional variance of the market, $\widehat{Var[r_{mt}]}$, and the unconditional expectation of conditional betas for asset i, $\widehat{E[\beta_{it-1}]}$.

4   DATA SOURCES AND CONSTRUCTION

4.1 Expected Returns

The sample period that I use in this study is March 1999 to July 2017. I calculate beta premium sensitivities for US stocks over this period using two approaches for generating expected returns: direct market estimates and instrumental variables (IV). I will refer to the expected returns generated using these approaches as forecast returns and predicted returns respectively. Under both approaches I derive annual returns, updated monthly, for individual stocks and for the market.

4.2 Forecast Returns

4.2.1   Individual stocks

I calculate forecast returns (under the direct market estimates approach) for individual stocks using analysts' forecast price targets obtained from the Institutional Brokers' Estimate System (IBES). IBES provides a selection of analyst forecast data that has been widely used by researchers and considered to be a relatively superior source of such information (Call, Hewitt et al 2018). Analysts' earnings-per-share (EPS) and dividends-per-share (DPS) estimates, price targets and other forecasts are available from IBES for individual analysts or in consensus form across a broad cross-section of US and international shares.

In this study I use monthly consensus estimates for US stocks available on the IBES database (covering the majority of US publicly traded companies), using the median as the consensus measure and the IBES Statistical Period as the date at which I take the consensus each month. The IBES Statistical Period is the Thursday before the third Friday of each calendar month.

I derive forecast annual returns for each stock, at each month, by adopting an approach similar to that of Drienko (2012), using consensus analyst 12-month price targets and DPS forecasts sourced from the IBES database and then dividing by historical stock prices sourced

from the CRSP database. I use historical stock prices from the close-of-business on the day prior to the IBES Statistical Period. I calculate returns as the logarithm of excess returns over the risk-free rate. The forecast return for stock i at month t, $\widehat{r_{it}}$, is therefore given by,

$$\widehat{r_{it}} = \widehat{R_{it}} - r_{ft}$$

Where $\widehat{R_{it}}$ is derived from the analyst consensus (median) forecast annual return for stock i at month t, and $r_{ft} = \ln(1 + R_{ft})$, where R_{ft} is the risk-free rate (1-year US Treasury rate) at month t.

I calculate $\widehat{R_{it}}$ as,

$$\widehat{R_{it}} = \ln\left(\frac{\widehat{Pf}_{it} + \widehat{Div_{it}}}{P^c{}_{it}}\right)$$

Where $\widehat{Pf}_{it}$ is the IBES consensus (median) 12-month price target for stock i at month t, $\widehat{Div_{it}}$ is the sum of IBES consensus (median) forecast dividends over the next 12 months for stock i at month t, and $P^c{}_{it}$ is the realised (closing) price for stock i at month t (on the day prior to the IBES Statistical Period) from the CRSP database.

4.2.2 Market risk premium

I derive the forecast market risk premium as the weighted average of the forecast returns generated for individual stocks, where the weights are the market capitalisations of the individual stocks. I obtain market capitalisations by multiplying the stock price and the number of shares outstanding for each stock at each month, sourced from the CRSP database. The forecast annual market risk premium at month t, $\widehat{r_{mt}}$, is therefore given by,

$$\widehat{r_{mt}} = \widehat{R_{mt}} - r_{ft}$$

Where $\widehat{R_{mt}}$ is the forecast annual market return at month t, and $r_{ft} = \ln(1 + R_{ft})$, with R_{ft} being the risk-free rate (1-year US Treasury rate) at month t. I calculate $\widehat{R_{mt}}$ as,

$$\widehat{R_{mt}} = \ln\left(1 + \Sigma\, w_{it}\widehat{FCST}_{it}\right)$$

Where $\widehat{FCST}_{it}$ is the forecast annual return for stock i at month t, and w_{it} is the market capitalisation of stock i as a proportion of the aggregate market capitalisation of all stocks available at month t ($\Sigma\, w_{it} = 1\ \forall\ i$ at each month t, where the market capitalisation of stock i is given by the price of stock i multiplied by the number of shares outstanding for stock i at month t, sourced from the CRSP database). I calculate $\widehat{FCST}_{it}$ as,

$$\widehat{FCST}_{it} = \left(\frac{\widehat{Pf}_{it} + \widehat{Div}_{it}}{P^c{}_{it}}\right) - 1$$

Where $\widehat{Pf}_{it}$ is the IBES consensus (median) 12-month price target for stock i at month t, $\widehat{Div}_{it}$ is the sum of IBES consensus (median) forecast dividends over the next 12 months for stock i at month t, and $P^c{}_{it}$ is the realised (closing) price for stock i at month t (on the day prior to the IBES Statistical Period) from the CRSP database.

4.3 Predicted Returns

4.3.1 Individual stocks

For comparison with my results under the direct market estimates approach, I calculate predicted returns under an IV approach in a manner similar to that of Petkova and Zhang (2005). Under this approach I generate expected returns through predictive regressions and a set of instrumental (conditioning) variables rather than through direct estimates from market practitioners.

For individual stocks I predict annual returns for each stock i at each month t. My choice of instrumental variables adopts those used by Petkova and Zhang (2005), which are based on standard choices from the literature on time-series predictability. Accordingly, I use the T-bill rate (TB_t), the term spread ($TERM_t$), the default spread (DEF_t) and the dividend yield (DY_t)

as instrumental variables. I include details on the sources and construction of these variables in Appendix 1.

Following Petkova and Zhang (2005), I use conditional market regressions to predict stock returns. For a given stock i at month t, I assume,

$$r^P{}_{it} \quad = \quad \alpha_i + \beta_{it-1} r^P{}_{mt} + \epsilon_{it}$$

Where $r^P{}_{it}$ is the excess annual return on asset i at month t, $r^P{}_{mt}$ is the excess annual return on the market (market risk premium) at month t, β_{it-1} is the conditional beta of asset i at month t, and ϵ_{it} are IID error terms, all based on information available at the end of month $t-1$.

I express the conditional betas for asset i in terms of the instrumental variables as follows,

$$\beta_{it-1} \quad = \quad b_{i0} + b_{i1} TB_{t-1} + b_{i2} TERM_{t-1} + b_{i3} DEF_{t-1} + b_{i4} DY_{t-1} + \partial_{it}$$

Where ∂_{it} are IID error terms.

From which,

$$r^P{}_{it} \quad = \quad \alpha_i + (b_{i0} + b_{i1} TB_{t-1} + b_{i2} TERM_{t-1} + b_{i3} DEF_{t-1} + b_{i4} DY_{t-1})\, r^P{}_{mt} + \epsilon_{it} \quad (6)$$

Using this approach, for each stock i, I regress the realised annual excess returns for the stock, rolling monthly, against the realised annual market risk premium and the instrumental variables over the sample period. The excess returns are over 1-year US Treasury rates and the realised stock returns and the market return are sourced from the CRSP database. From these I obtain estimates for the coefficients in (6), namely $\widehat{a}_\iota$, $\widehat{b_{\iota 0}}$, $\widehat{b_{\iota 1}}$, $\widehat{b_{\iota 2}}$, $\widehat{b_{\iota 3}}$ and $\widehat{b_{\iota 4}}$, and use these to derive predicted annual excess returns for each stock i, rolling monthly.

4.3.2   *Market risk premium*

I derive the predicted market risk premium by regressing the realised market risk premium and the set of instrumental variables as follows,

$$r^P{}_{mt} = \alpha_m + b_{m1}TB_{t-1} + b_{m2}TERM_{t-1} + b_{m3}DEF_{t-1} + b_{m4}DY_{t-1} + \epsilon_{mt} \quad (7)$$

Where ϵ_{mt} are IID error terms. Using (7), I obtain estimates for the coefficients $\widehat{a_m}$, $\widehat{b_{m1}}$, $\widehat{b_{m2}}$, $\widehat{b_{m3}}$ and $\widehat{b_{m4}}$, and from these I obtain the predicted annual market risk premium, rolling monthly, from the instrumental variables and using (7).

I show the expected market risk premium over the whole sample period using forecast returns and predicted returns, and the realised market risk premium using the CRSP historical market return, in Chart 1. I set out further details on the distributions of expected returns and the expected market risk premium using the direct market estimates and IV approaches in Appendix 2.

4.4 Value and Growth Returns

To compare the beta premium sensitivities of value and growth stocks, I need to identify which stocks are value and which stocks are growth. Whilst various measures have been used for this purpose in previous research (such as the book value of equity to market value of equity used by Rosenberg, Reid and Lanstein 1985 and Fama and French 1992), the measure that I use in this study is the earnings yield. This has also been used in previous research (Basu 1983). The earnings yield can be constructed from both direct market estimates and historical data, hence I use the earnings yield derived from direct market estimates for forecast returns and the earnings yield derived from historical data for predicted returns.

I identify value and growth for each stock based on point-in-time observations on a relative basis (in the cross-section). Using the earnings yield, I deem each stock as value or growth (or neither) in any given month relative to the earnings yields of all other stocks at that month. I refer to months in which the stock is deemed value as value stock-months for that stock, and months in which the stock is deemed growth as growth stock-months for that

stock. A given stock can therefore move in and out of the value, growth (or neither) categories from month-to-month over its sample history.

If I were to classify a stock as value or growth with that classification applying for the whole sample period, then I would need to decide how many value stock-months or how many growth stock-months are required as a proportion of all months in its sample history for the stock to be deemed as a value or growth stock respectively. Moreover, I can only calculate these proportions on a look-back basis for each stock, at the end of the sample period. To avoid the need for such arbitrary ex-post decisions on value and growth stock-month proportions, I construct value and growth return series for each stock consisting exclusively of the ex-ante identified value and growth stock-months respectively. I use these constructed return series to represent value and growth stock returns in this study. The return series for value and growth stocks are therefore subsets of each stock's original return series.

I calculate the earnings yield as the earnings-per-share (EPS) for each stock i over the next 12-months (for forecast returns) or trailing 12-months (for predicted returns), divided by its historical stock price at month t. The EPS applies at the date of the IBES Statistical Period in each month and the historical stock price is at the close-of-business the day prior. For forecast returns I use analyst forecast EPS and for predicted returns I use reported (historical) EPS for each stock.

Hence, for each stock i, at each month t, I calculate the earnings yield as,
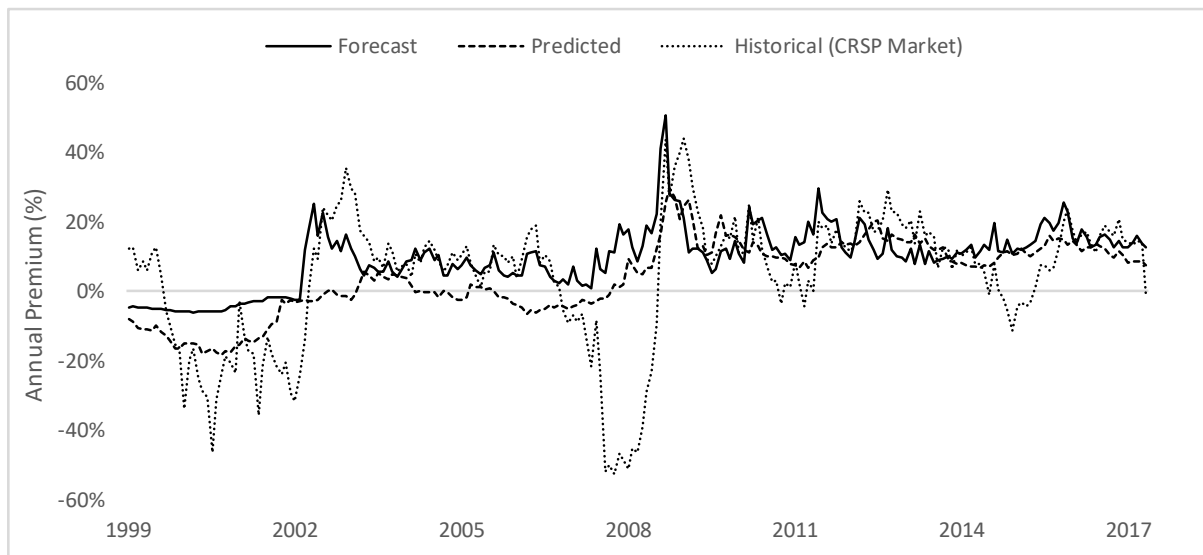
$$\widehat{EY_{it}} \qquad = \qquad \widehat{EPS_{it}} / P^c{}_{it}$$

Where $\widehat{EY_{it}}$ is the estimated earnings yield for stock i at month t, $\widehat{EPS_{it}}$ is the IBES consensus (median) EPS over the next 12 months (for forecast returns) or the reported EPS over the trailing 12 months (for predicted returns) for stock i at month t, and $P^c{}_{it}$ is the

realised closing price for stock i at month t (on the day prior to the IBES Statistical Period) from the CRSP database.

Chart 1: Market Risk Premium using Forecast, Predicted and Historical Returns

Rolling annual market risk premium using forecast returns, predicted returns and historical returns over the whole sample period (March 1999 to July 2017). All returns are excess over the 1-year Treasury rate, assume continuous compounding and are updated monthly. Forecast returns are derived using analyst 12-month price targets and dividend forecasts from the IBES database, dividing by historical stock prices from the CRSP database. Predicted returns are derived using linear regressions between realised returns from the CRSP database and a set of instrumental variables (the T-bill rate, the term spread, the default spread and the dividend yield). The market risk premium using forecast returns is derived each month as the weighted average of annual forecast returns for individual stocks where the weights are the historical market capitalisations of the stocks. The historical market risk premium is derived from historical annual CRSP market returns.

I identify value and growth based on percentile-ranking the earnings yields across all stocks at each month, arriving at the percentile rank PR_{it} for each stock i at each month t. I deem a stock as being a value stock at month t (value stock-month) if it is in the top 30% of percentile ranks across all stocks for the month (ranked 0.3 or higher) and as being a growth stock at month t (growth stock-month) if it is in the bottom 30% for the month (ranked 0.7 or lower). That is,

If, PR_{it} $<$ 0.3   ⎤   Value
               $>$ 0.7   ⎥   Growth
               Else   ⎦   Neither

Where PR_{it} is the percentile rank for stock i at month t.

I apply the 30 percent criteria ex-ante at each month. My choice of the 30 percent level, albeit arbitrary, is motivated by Fama and French (1992) who construct portfolios at June of each year and identify value and growth stocks based on the top and bottom 30 percent rankings of stocks' book value of equity to the market value of equity respectively. The Fama and French (1992) approach has been adopted by several researchers and practitioners in forming value portfolios.

I discuss further details on comparing average expected value and growth returns in Appendix 2.

4.5 Variance of the Market Risk Premium

4.5.1 Forecast returns

I estimate the expected variance of the market risk premium under the direct market estimates approach using a market-based estimate. I use the Chicago Board Options Exchange Volatility Index (VIX) for this purpose. The VIX is described by the CBOE as a measure of "constant, 30-day expected volatility of the US stock market, derived from real-time, mid-quote prices of S&P500 Index call and put options"[3]. It can be interpreted as the annualised, implied volatility on a hypothetical option on the S&P500 index with 30 days to expiration.

The range of options included in the VIX calculation can vary over time, but only those with non-zero bid values, which are at-the-money or out-of-the-money and with expirations between 23 and 37 days are included. I obtain estimates of the 1-year conditional variance for the market in any given month as the square of the VIX index for the month (as at the IBES Statistical Period date).

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[3] ref: www.cboe.com/vix accessed 1.06 pm Sydney time 6th September 2018

Whilst limited by the assumptions that the S&P500 index constitutes the market, that the selection of index options used in the VIX calculation is sufficiently representative of the market and that the annualising approach is appropriate, the VIX index is a widely used measure for providing estimates of market variance amongst practitioners.

As an alternative, I could directly calculate the variance of the forecast market risk premium (derived from the forecast returns). This however results in low (unrealistic) estimates for the market variance. This is likely due to the analysts' forecasts which underpin the market risk premium, which tend to be updated relatively infrequently and with typically small increments, resulting in unrealistically low levels of variability in returns constructed from these forecasts.

4.5.2 *Predicted returns*

Under the IV approach, I estimate the variance of the predicted market risk premium using the realised market variance calculated from annual CRSP market returns for months that coincide with the available IV return data for each stock. I exclude stocks that have less than 20 data points. Where there are consecutive months of data for a stock, the variance is calculated based on annual returns, rolling monthly, hence there is likely to be a degree of serial correlation in the return series underlying the variance calculations. Nevertheless, the pattern of annual returns, rolling monthly, is consistent with all return series used in this study.

As an alternative, I could calculate the variance of the predicted market risk premium directly from the series of annual, rolling monthly, predicted market risk premium returns. Similar to the situation for the forecast market risk premium however, this results in low estimates of market variance which are inconsistent with the levels of variance observed for the VIX

index (which is used for forecast returns). This may be due to the averaging effect of the linear regression approach used to generate the predicted returns.

4.6 Economic States

As a stock's average risk sensitivity depends on its riskiness during good times (expansionary periods) and bad times (recessionary periods), I separate the sample period into expansionary and recessionary states and analyse the risk sensitivity in each state. Given that the beta premium sensitivity is defined in terms of the expected market risk premium, I identify expansionary and recessionary states based on my estimates of the expected market risk premium. Petkova and Zhang (2005) argue that this approach is consistent with modern asset pricing theories and that the expected market risk premium is countercyclical. Hence, I classify the expansionary state as including months in which the expected market risk premium is below its whole-of-sample average and the recessionary state as including months in which it is above its whole-of-sample average. I use forecast estimates of the expected market risk premium in respect of forecast returns and predicted estimates of the expected market risk premium in respect of predicted returns for this purpose.

Of the total 221 months in the sample period used for this study, I find that 98 months are in the expansion state and 123 months are in the recession state when using the forecast market risk premium, and 101 months are in the expansion state and 120 months are in the recession state when using the predicted market risk premium. I estimate beta premium sensitivities for value and growth stocks over the whole sample period and in each of the expansion and recession states.

As the beta premium sensitivity measures the degree of covariation between a stock's time-varying beta and the market risk premium based on expected measures, it is also instructive

to observe the betas derived from realised returns (realised betas) during different economic

states. I discuss these in Appendix 2.

5 RESULTS

Here I present my central result, that value stocks are less risky than growth stocks on average based on beta premium sensitivities and using a direct market estimates approach. I also present a result in the opposite direction, that value stocks are riskier than growth stocks on average when predictive regressions and instrumental (conditioning) variables are used. Analysts' forecast optimism does not appear to explain the divergence in these results. Instrumental variable approaches are characterised by a tendency for overfitting and limited information sets, whilst analysts' forecasts are drawn from practitioner assessments based on a myriad of information sources. Analysts' forecasts may therefore provide a more effective means of deriving expected returns and this may be contributing to the divergent results. Further research is warranted in this area.

5.1 Beta Premium Sensitivities

5.1.1   Using direct market estimates (forecast returns)

Chart 2 shows the distributions of beta premium sensitivities derived using direct market estimates (forecast returns) for value and growth stocks over the whole sample period. Table 1 reports the same information through a set of distribution percentiles and summary statistics (Table 1 also reports on beta premium sensitivities derived using instrumental variables).

The average beta premium sensitivity when using forecast returns is lower for value stocks than for growth stocks (5.2 and 6.2 respectively). The difference is significant, as reported in Table 2. The beta premium sensitivity measures the degree of covariation between a stock's time-varying beta and the expected market risk premium, hence my results indicate that value stock betas covary less with the expected market risk premium than growth stock betas and hence value stocks are less sensitive to time-varying risk than growth stocks on average.

As a stock's average risk sensitivity depends on its riskiness during good times (expansionary periods) and bad times (recessionary periods), I report expansionary and recessionary beta premium sensitivities in Table 3. During expansionary periods the average beta premium sensitivity for value stocks (4.4) is higher than that for growth stocks (3.0). During recessionary periods the reverse is true, with the average beta premium sensitivity for value stocks (5.2) being lower than that for growth stocks (6.9). The difference is significant in both cases. This suggests that value stocks are less susceptible to time-varying risk during recessionary periods when the expected market risk premium is high, and vice-versa during expansionary periods. The average result over all periods is that value stocks are less sensitive to time-varying risk than growth stocks.

My results are not consistent with risk-based explanations of the value premium, such as the one provided by Zhang (2005). He differentiates value from growth stocks in terms of assets in place (associated with value stocks) and growth options (associated with growth stocks) and argues that assets in place are riskier than growth options during bad times. Value stocks are hence riskier than growth stocks during bad times while in good times the reverse is true (although not to the same extent). This provides a basis for the value premium according to Zhang (2005).

Lakonishok, Shleifer and Vishny (1994) propose an alternative view, that value stocks outperform growth (glamour) stocks due to suboptimal investor behaviour rather than being riskier. They find that value stocks outperform growth stocks on average during bad times (market downturns) and conclude that value stocks are not fundamentally riskier than growth stocks. They consider that "value stocks could be described as having higher up-market betas and lower down-market betas than glamour stocks with respect to economic conditions" (Lakonishok, Shleifer and Vishny 1994, p. 1569). My beta premium sensitivity results using direct market estimates are consistent with this perspective.

5.1.2   Using instrumental variables (predicted returns)

For comparison with my beta premium sensitivity results using direct market estimates, I also calculate beta premium sensitivities using instrumental variables (predicted returns). My beta premium sensitivity results using this approach are reported in Table 1 (beta premium sensitivity distribution percentiles and summary statistics). I set out further details on comparing the beta premium sensitivity distributions in Appendix 3.

Using instrumental variables, the average beta premium sensitivity is higher for value stocks than for growth stocks (4.6 and 2.4 respectively) with a difference that is significant (Table 2). I report expansionary and recessionary beta premium sensitivities in Table 3. Here the average beta premium sensitivity for value stocks is lower than for growth stocks during expansionary periods (-0.5 and 0.5 respectively) and higher during recessionary periods (17.2 and 11.9 respectively). The difference is significant in both cases. Value stocks are therefore more susceptible to time-varying risk during recessionary periods when the expected market risk premium is high and overall are riskier than growth stocks based on this measure. These results are in the opposite direction to my results using direct market estimates and accord with those of Petkova and Zhang (2005).

5.2 Comparing Expected Returns

In the following I consider possible contributors to the divergence in my results by comparing the expected returns derived under each of the direct market estimates and instrumental variable approaches. Differing characteristics of these derivations may be of relevance for the divergence in my results. In particular I report on the optimism typically associated with analysts' forecasts and the limitations of using instrumental variables for return prediction.

5.2.1   Forecast optimism

Analysts' forecasts have been shown to exhibit optimism (Asquith, Mikhail and Au 2005,

Brav and Lehavy 2005). From the equation for estimating beta premium sensitivity (6) we

observe that a given stock's beta premium sensitivity is positively related to its expected

**Chart 2: Beta Premium Sensitivities: Forecast Returns over Whole of Period – Value
and Growth**

Distribution of beta premium sensitivities across stocks identified as value and growth using forecast
returns over the whole sample period (March 1999 to July 2017). Forecast returns are derived using
analyst 12-month price targets and dividend forecasts from the IBES database and historical stock
prices from the CRSP database. Stocks are evaluated as being either value or growth based on ranking
earnings yields across all available stocks' earnings yields for each month. A stock is deemed value if
its earnings yield ranks in the top 30% across all stocks for the month and deemed growth if it ranks
in the bottom 30%. For each stock, the beta premium sensitivity $\widehat{\varphi_i}$ is estimated using ($\widehat{E[r_{it}]}$ −
$\widehat{E[r_{mt}]}\widehat{E[\beta_{it-1}]}$) / $\widehat{Var[r_{mt}]}$ and: (i) Its average excess return $\widehat{E[r_{it}]}$, (ii) the average market excess
return $\widehat{E[r_{mt}]}$, (iii) its average betas $\widehat{E[\beta_{it-1}]}$, and (iv) the market variance $\widehat{Var[r_{mt}]}$, calculated using
monthly VIX forecasts.
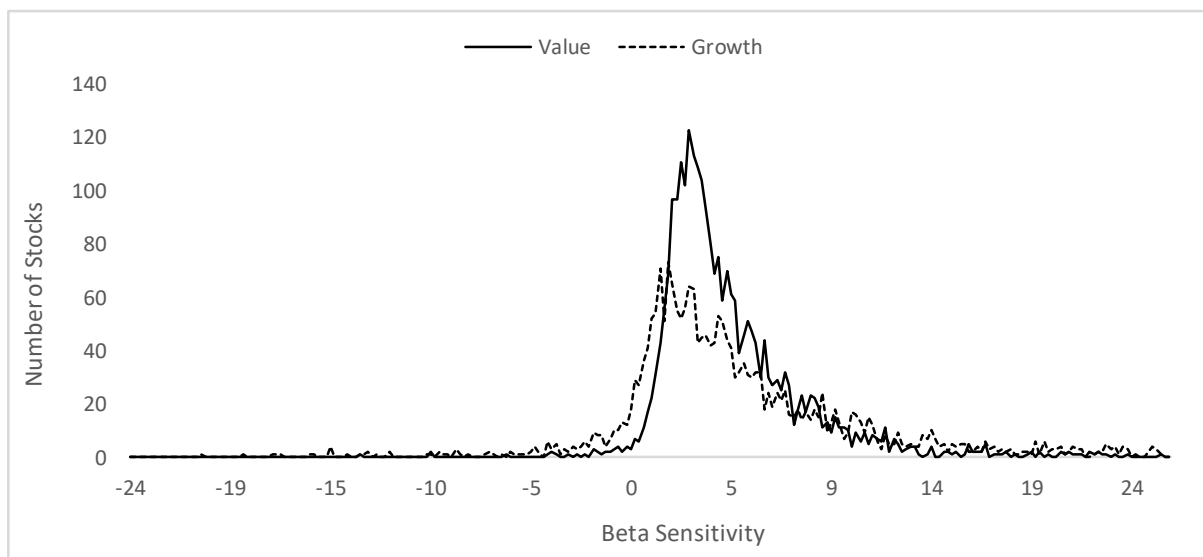
return. More optimistic forecasts translate to higher estimates of expected return and vice

versa for less optimistic forecasts. Relative differences in optimism associated with value and

growth stock returns, and the way these differences manifest in forecast and predicted

returns, may therefore influence relative differences in beta premium sensitivity results.

To investigate, I measure the degree of optimism for value and growth stocks under both

approaches using accuracy ratios. For each stock, at each month, I calculate the accuracy

ratio as $\frac{1+r}{1+h}$ where r is the stock's annual forecast or predicted return and h is its historical (realised) return over the same period (sourced from the CRSP data base). I calculate the average accuracy ratio for each stock as the average of its monthly accuracy ratios. The closer that the stock's accuracy ratio is to 1, the more accurate are its forecast or predicted returns. Ratios above 1 indicate optimism, whereas ratios below 1 indicate pessimism.

Table 1: Beta Premium Sensitivities – Whole of Period

Distribution of beta sensitivities across stocks identified as value and growth over the whole sample period (March 1999 to July 2017). Beta sensitivities are derived using analyst forecast returns, *Forecast*, or predicted returns, *Predicted*. Stocks are evaluated as being either value or growth based on ranking earnings yields, calculated using either analysts' forecast earnings-per-share, *Forecast EY*, or historically reported earnings-per-share, *Historical EY*, and dividing by historical stock prices. Refer notes for Chart 2. The distributions of beta sensitivities amongst value and growth stocks, using forecast or predicted returns, is summarised using the set of percentiles shown. The summary statistics reported are the *Average*, which is the average of each distribution, the standard error of the average, *SE Average*, the skew of the distribution of beta sensitivities, *Skew*, the standard error of the skew, *SE Skew*, and the resulting probability values, *P-Value*.

DISTRIBUTION OF BETA SENSITIVITIES	Forecast (Forecast EY)		Predicted (Historical EY)	
	Beta Sensitivities			
	Value	*Growth*	*Value*	*Growth*
90th	9.0	15.0	15.0	15.3
75th	5.9	7.9	6.7	7.5
67th	5.1	6.1	4.9	5.1
50th	3.7	3.9	2.7	2.2
33rd	2.8	2.3	0.7	-0.8
25th	2.5	1.7	-0.4	-2.7
10th	1.7	0.3	-4.4	-9.3
AVERAGE	**5.2**	**6.2**	**4.6**	**2.4**
SE AVERAGE	**0.14**	**0.18**	**0.31**	**0.43**
P-VALUE	**0.000**	**0.000**	**0.000**	**0.000**
SKEW	**8.00**	**2.06**	**3.86**	**-2.64**
SE SKEW	**0.05**	**0.05**	**0.06**	**0.06**
P-VALUE	**0.000**	**0.000**	**0.000**	**0.000**

The leftmost label column for the percentile rows reads **PERCENTILES** (printed vertically).

The distributions of accuracy ratios for value and growth stocks using forecast and predicted returns, including percentiles and summary statistics, are set out in Appendix 2. Consistent

with the literature I find that forecast returns are optimistic, both in an absolute sense and relative to predicted returns. I also find that growth returns are more optimistic than value returns under both approaches (accuracy ratios of 1.40 and 2.10 for value and growth forecast returns relative to 1.02 and 1.08 for value and growth predicted returns respectively). The

Table 2: Difference in Average Beta Premium Sensitivity: Value *less* Growth – Whole of Period

Difference in average beta premium sensitivity between value and growth stocks over the whole sample period (March 1999 to July 2017). Refer notes for Table 1.The summary statistics reported are the difference in average beta premium sensitivity between value and growth stocks, *Difference*, the standard error of the difference, *SE Difference*, and the resulting probability value, *P-Value*.

DIFFERENCE IN AVERAGE BETA PREMIUM SENSITIVITY: VALUE *less* GROWTH	Forecast (Forecast EY)	Predicted (Historical EY)
DIFFERENCE	-1.0	2.2
SE DIFFERENCE	0.23	0.53
P-VALUE	1.000	0.000

differences are significant in all cases (refer Appendix 2).

Despite excess optimism for growth stocks under both approaches, my beta premium sensitivity results are higher for growth stocks in the case of forecast returns but not in the case of predicted returns. Hence, differences in forecast optimism do not appear to explain the divergence in my beta premium sensitivity results between the two approaches.

5.2.2   Comparing the instrumental variables and direct market approaches

Although instrumental variables are widely used for predicting stock returns (Gibbons and Ferson 1985, Keim and Stambaugh 1986, Harvey 1989), they are subject to limitations such as a bias resulting from overfitting (Foster, Smith and Whaley 1997). Goyal and Welch

(2008) comprehensively examine predictive regression models, including those using instrumental variables, and find that most of these models are unstable and have performed poorly both in-sample and out-of-sample. In my results, the relative degree of overfitting for predicted returns is evident from Appendix 2 which shows that the standard errors of average accuracy ratios are an order-of-magnitude smaller for predicted returns compared with forecast returns (less than 0.005 versus greater than 0.036 respectively).

Table 3: Difference in Average Beta Premium Sensitivity: Value *less* Growth – Expansion and Recession States

Difference in average beta premium sensitivity between value and growth stocks during the expansion and recession states. Refer notes for Table 1. The expansion state corresponds to months in which the expected market return premium is less than the average premium over the sample period (March 1999 to July 2017), and the recession state corresponds to months in which the expected market return premium is more than the average premium. The summary statistics reported are the beta premium sensitivity for value and growth stocks, *Value* and *Growth* respectively, the difference in average beta premium sensitivities between value and growth stocks, *Difference*, the standard error of the difference, *SE Difference*, and the resulting probability value, *P-Value (Diff)*.

DIFFERENCE IN AVERAGE BETA PREMIUM SENSITIVITY: VALUE *less* GROWTH	Expansion State	Recession State
	FORECAST RETURNS	
VALUE	4.4	5.2
GROWTH	3.0	6.9
DIFFERENCE	1.4	-1.7
SE DIFFERENCE	0.34	0.25
P-VALUE (DIFF)	0.000	1.000
	PREDICTED RETURNS	
VALUE	-0.5	17.2
GROWTH	0.5	11.9
DIFFERENCE	-1.0	5.3
SE DIFFERENCE	0.40	1.30
P-VALUE (DIFF)	0.996	0.000

Instrumental variable approaches use a relatively small set of variables to predict expected returns. This contrasts with analysts' forecasts which are based on a large number of information sources of both a quantitative and qualitative nature. The business of forecasting stock returns is a competitive one, pursued by practitioners who are commercially motivated to produce forecasts that are superior to their peers. In this competitive landscape it is difficult to imagine that a small number of variables, with fixed coefficients for a given dataset, could effectively characterise return expectations.

Drienko (2012) compares the instrumental variable and analyst forecast approaches by conducting a test of the fit between estimated and realised future stock returns under both approaches. He finds that analysts' forecasts provide a better fit and concludes that these are more efficient at predicting stock returns than instrumental variables. Analysts' forecasts therefore appear to be a more realistic and effective source of return prediction than instrumental variable approaches. Further research is warranted, however, to better understand the differences between expected returns generated using analysts' forecasts and predictive regressions and the potential advantages and limitations of each approach.

APPENDIX 1: INSTRUMENTAL VARIABLES

A1.1   Data sources

I adopt the approach of Petkova and Zhang (2005) in selecting the instrumental (conditioning) variables that I use for generating predicted stock returns. Their data sources, construction and references from the time-series predictability literature (refer Petkova and Zhang 2005) are summarised in Table A1.1.

Table A1.1: Instrumental Variables

Instrumental variables used in deriving predicted returns: T-bill rate, term spread, default spread and dividend yield.

Instrumental Variable	Description / Data Source (as at the IBES Statistical Period date each month)	Construction References (Petkova and Zhang 2005, p. 189)
T-bill rate	3-month US T-bill rate (annualised) / US Federal Reserve Statistical Release	$\ln(1 + \frac{TB}{100})$ TB is the annualised 3-month US T-bill rate Fama and Schwert (1977) and Fama (1981)
Term spread	Difference in annualised yield between US 10-year and US 1-year government bond rates / US Federal Reserve Statistical Release	$\ln\left(1 + \frac{US_{10yr}}{100}\right) - \ln\left(1 + \frac{US_{1yr}}{100}\right)$ US_{10yr} and US_{1yr} are the annualised US 10-year and US 1-year government bond rates respectively Campbell (1987) and Fama and French (1989)
Default spread	Difference in average annualised yield between Moody's Baa-rated and Aaa-rated corporate bonds / US Federal Reserve Statistical Release	$\ln\left(1 + \frac{Corp_{Baa}}{100}\right)$ $- \ln\left(1 + \frac{Corp_{Aaa}}{100}\right)$ $Corp_{Baa}$ and $Corp_{Aaa}$ are the annualised average Moody's Baa-rated and Aaa-rated corporate bond rates respectively Keim and Stambaugh (1986)

Table A1.1: Instrumental Variables (Cont.)

Instrumental variables used in deriving predicted returns: T-bill rate, term spread, default spread and dividend yield. (Cont.)

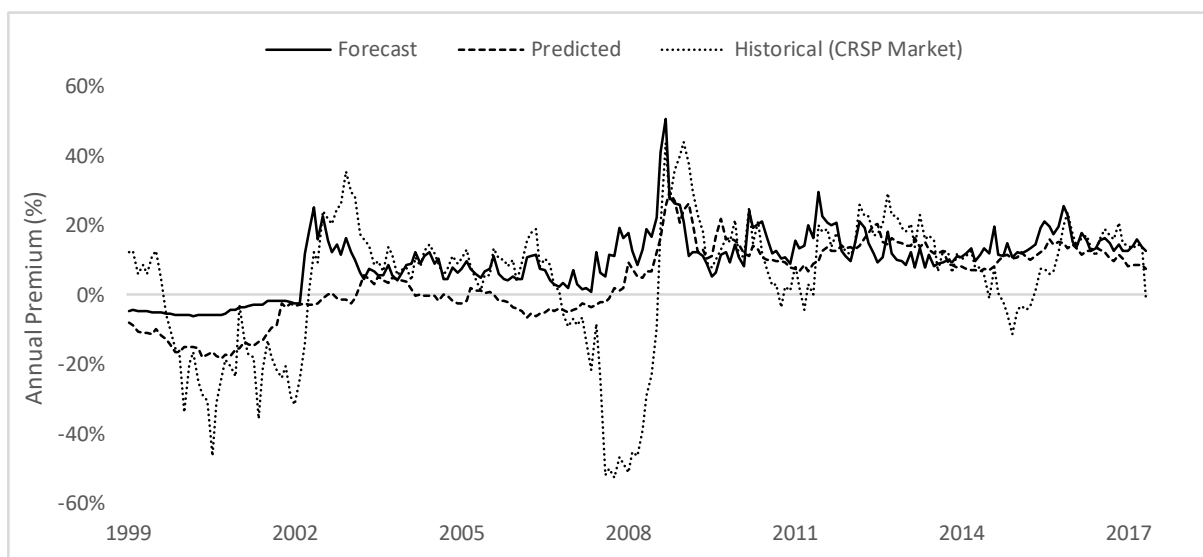| Instrumental Variable	Description / Data Source (as at the IBES Statistical Period date each month)	Construction References (Petkova and Zhang 2005, p. 189)
Dividend yield	Annual dividend yield on the market, proxied by the difference in trailing 251-day returns on the value-weighted CRSP market index with and without distributions	$\ln\left(\prod_{j}^{251} 1 + R_j^{INC} - \prod_{j}^{251} 1 + R_j^{EX}\right)$ R_j^{INC} and R_j^{EX} are the CRSP value-weighted market return on business day j with and without distributions respectively, where $j = 1$ is the business day occurring 251 business days prior to the IBES Statistical Period date for the month Fama and French (1988)

APPENDIX 2: EXPECTED RETURNS

A2.1 Expected and realised market risk premium

In Chart A2.1, I show the market risk premium over the whole sample period using forecast returns, predicted returns and CRSP historical (realised) market returns. The premium at each month represents the annual expected premium in the case of forecast and predicted returns and the annual realised premium in the case of CRSP market returns.

From Chart A2.1 we observe a tendency for the forecast and predicted market risk premia to rise during periods when the CRSP market premium falls, such as during 2001-2002, 2007-

Chart A2.1: Market Risk Premium using Forecast, Predicted and Historical Returns

Rolling annual market risk premium using forecast returns, predicted returns and historical returns over the whole sample period (March 1999 to July 2017). All returns are excess over the 1-year Treasury rate, assume continuous compounding and are updated monthly. Forecast returns are derived using analyst 12-month price targets and dividend forecasts from the IBES database, dividing by historical stock prices from the CRSP database. Predicted returns are derived using linear regressions between realised returns from the CRSP database and a set of instrumental variables (the T-bill rate, the term spread, the default spread and the dividend yield). The market risk premium using forecast returns is derived each month as the weighted average of annual forecast returns for individual stocks where the weights are the historical market capitalisations of the stocks. The historical market risk premium is derived from historical annual CRSP market returns.

2009 and 2014-2015. This reflects the forward-looking nature of the expected forecast and predicted premia relative to the realised premium. It also reflects the difficulty in foreseeing turning points through expectations measures such as the forecast and predicted premia.

The average premium over the sample period in each case, along with the associated standard errors and p-values, are shown in Table A2.1. Here we observe that all three premia are significant and positive. The size of the average predicted premium is consistent with that of the average realised premium (both at 4.0 per cent per annum), a result that is not surprising given that the predicted premium is derived from the historical premium. The size of the average forecast premium is significantly higher (9.6 per cent per annum), which is consistent with the relative optimism associated with the analyst forecasts that underpin the construction of the forecast premium.

Table A2.1: Average Market Risk Premia

Average annual market risk premium using forecast returns, predicted returns and historical returns over the whole sample period (March 1999 to July 2017). Refer notes for Chart A2.1. The summary statistics reported are the *Average Annual*, which is the average of each premium, the standard error of the average, *SE Average Annual*, and the resulting probability values, *P-Value*.

	Forecast	Predicted	Historical
AVERAGE ANNUAL (%)	9.6	4.0	4.0
SE AVERAGE ANNUAL (%)	0.6	0.7	1.3
P-VALUE	0.000	0.000	0.002

A2.2 Average expected returns

Chart A2.2 shows the distributions of average annual returns across all stocks over the whole sample period (March 1999 to July 2017) using forecast and predicted returns. Since the derived forecast and predicted returns for a given stock are annual, calculated each month, each stock's return series is therefore a set of annual returns, rolling monthly, for months in which the stock has data. The average annual return for a given stock is the average of its

Chart A2.2: Average Annual Returns – Forecast and Predicted Returns over Whole of Period – All Stocks

Distribution of average annual returns using forecast and predicted returns over the whole sample period (March 1999 to July 2017). All returns are excess over the 1-year Treasury rate, assume continuous compounding and are updated monthly. Average annual returns are based on analyst forecast returns or predicted returns. Forecast returns for each stock, for each month, are derived using analyst 12-month price targets and dividend forecasts from the IBES database and dividing by historical stock prices from the CRSP database. Predicted returns are derived using linear regressions between the historical annual market premium, based on monthly rolling annual returns from the CRSP database and a set of instrumental variables (the T-bill rate, the term spread, the default spread and the dividend yield). The average return for each stock, using forecast or predicted returns, is the average of its return series, that is, the average of its monthly annual excess returns.
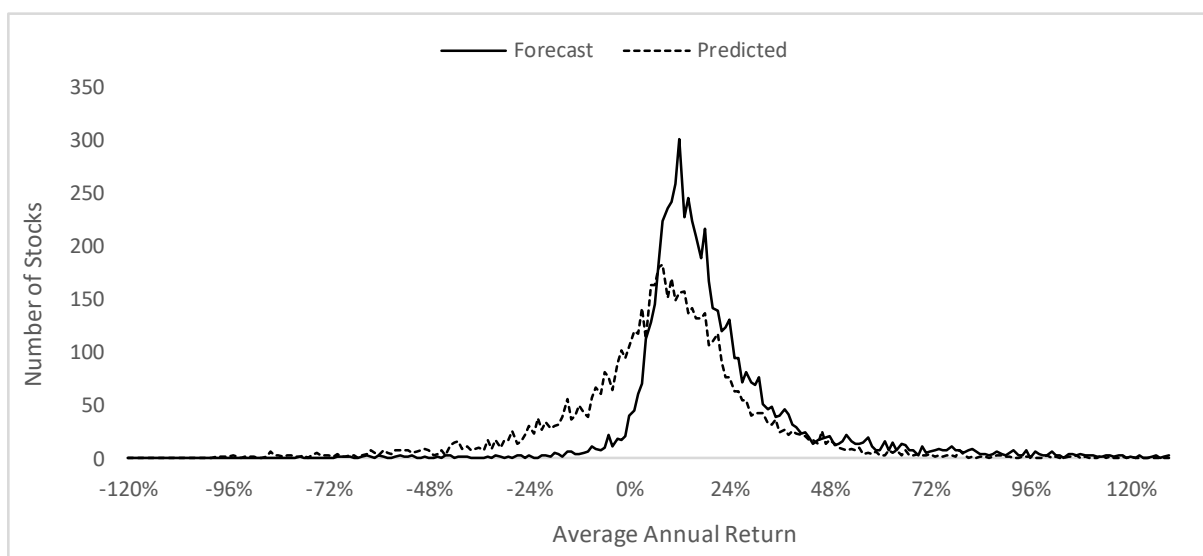

return series, that is, the average of its monthly rolling annual returns.

Charts A2.3 and A2.4 show the distributions of average annual returns for value and growth stocks using forecast and predicted returns respectively. The return series for a value stock contains only those months in which it is deemed value and the return series for a growth stock contains only those months in which it is deemed growth. Table A2.2 summarises the information in Charts A2.2, A2.3 and A2.4, representing the distributions by a set of percentiles and summary statistics. Each value in the distribution represents the average annual return for a given value or growth stock. Table A2.3 shows the difference in average annual returns between value and growth stocks for forecast and predicted returns.

Chart A2.3: Average Annual Returns – Forecast Returns over Whole of Period – Value and Growth

Distribution of average annual returns across stocks identified as value and growth using forecast returns over the whole sample period (March 1999 to July 2017). All returns are excess over the 1-year Treasury rate, assume continuous compounding and are updated monthly. Refer notes for Chart A2.2. Stocks are evaluated as being either value or growth based on ranking earnings yields across all available stocks' earnings yields for each month. A stock is deemed value if its earnings yield ranks in the top 30% across all stocks for the month and deemed growth if it ranks in the bottom 30%. Earnings yields are calculated using analysts' forecast earnings-per-share (in the case of forecast returns) and dividing by historical stock prices. The return series for a value stock contains only those months in which it is deemed value, whilst the return series for a growth stock contains only those months in which it is deemed growth.
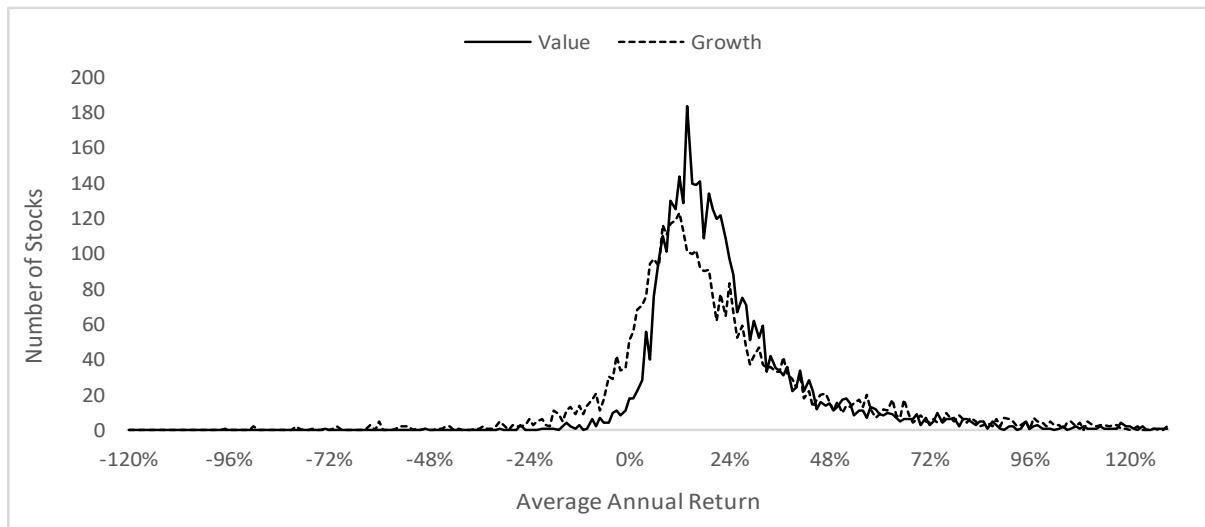
Chart A2.4: Average Annual Returns – Predicted Returns over Whole of Period – Value and Growth

Distribution of average annual returns across stocks identified as value and growth using predicted returns over the whole sample period. Refer notes for Charts A2.2 and A2.3.
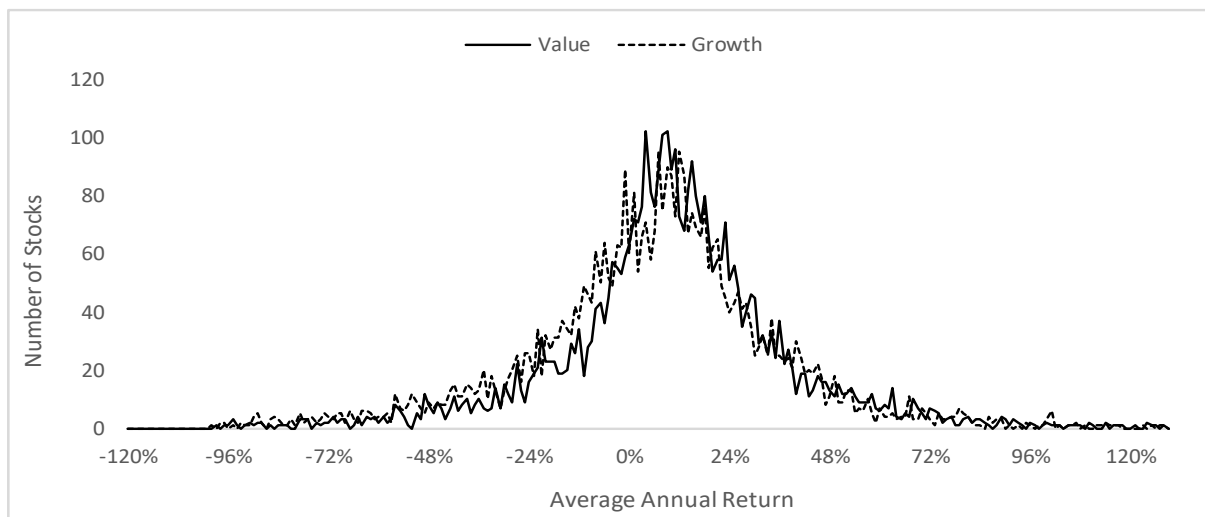
From the charts and tables, we observe a higher skew associated with forecast returns relative to predicted returns (0.4 and -0.3 respectively) and similarly for kurtosis (60.7 and 3.6 respectively). The average of the distribution is also higher for forecast returns (22.1 per cent per annum) relative to predicted returns (7.9 per cent per annum), consistent with previous research which has shown that forecast returns tend to be optimistic. Asquith, Mikhail and Au (2005) and Brav and Lehavy (2005) are examples of such research, which show an average implied analyst forecast return of 32.9% for the period 1997 to 1999, as is Bradshaw, Brown and Huang (2012) which shows an implied return of 24.0% for the period 2000 to 2009 (cited in Bradshaw, Huang and Tan 2012). This contrasts with estimates of real US equity returns, such as Mehra (2003) who finds a real annual US equity return of 7.0% over the period 1802 to 1998 (cited in Bradshaw, Huang and Tan 2012).

Considering value and growth stocks, we observe that when using forecast returns, value stocks are more positively skewed than growth stocks (3.5 and -0.4 respectively) albeit with less kurtosis (18.5 and 44.6 respectively). Value stocks also earn a higher average return than growth stocks over the sample period (25.4 and 22.7 per cent per annum respectively) by a margin which is significant as shown in Table A2.3 (2.8 per cent per annum with p-value 0.000). This is consistent with the historically observed value premium whereby average returns on value stocks are higher than those for growth stocks, as documented by several researchers (Basu 1983, Rosenberg, Reid and Lanstein 1985, Chan, Hamao and Lakonishok 1991 and Fama and French 1992 amongst others).

When using predicted returns, we also observe a higher skew associated with value stocks compared to growth stocks (0.4 and 0.0 respectively) and a higher kurtosis (4.4 and 1.8 respectively). Value stocks here too earn a higher average return than growth stocks over the sample period (11.2 and 6.4 per cent per annum respectively) with a significant margin as

Table A2.2: Average Annual Returns – Whole of Period

Distribution of average annual returns across stocks identified as value and growth over the whole sample period (March 1999 to July 2017). All returns are excess over the 1-year Treasury rate, assume continuous compounding and are updated monthly. Average annual returns are based on analyst forecast returns, *Forecast*, or predicted returns, *Predicted*. Refer notes for Chart A2.2 and A2.3. Earnings yields are calculated using either analysts' forecast earnings-per-share, *Forecast EY*, or historically reported earnings-per-share, *Historical EY*, and dividing by historical stock prices. The distributions of average returns amongst value and growth stocks, using forecast or predicted returns, is summarised using the set of percentiles shown. The summary statistics reported are the *Average*, which is the average of each distribution (that is, the average of the distribution of average annual returns for value and growth stocks), the standard error of the average, *SE Average*, the skew of the distribution of average returns, *Skew*, the standard error of the skew, *SE Skew*, the kurtosis of the distribution of average returns, *Kurtosis*, and the resulting probability values, *P-Value*.

DISTRIBUTION OF AVERAGE RETURNS	Forecast (Forecast EY)		Predicted (Historical EY)	
	Average Annual Returns (%)			
	Value	*Growth*	*Value*	*Growth*
90th	48.9	56.1	42.3	39.9
75th	30.0	31.2	24.3	21.8
67th	25.5	24.9	19.0	16.5
50th	19.6	16.7	10.7	7.8
33rd	14.8	10.5	3.1	-2.4
25th	12.7	7.6	-1.9	-8.5
10th	7.6	-0.7	-20.6	-29.1
AVERAGE	**25.4**	**22.7**	**11.2**	**6.4**
SE AVERAGE	**0.39**	**0.48**	**0.46**	**0.46**
P-VALUE	**0.000**	**0.000**	**0.000**	**0.000**
SKEW	**3.46**	**-0.44**	**0.42**	**-0.05**
SE SKEW	**0.04**	**0.04**	**0.04**	**0.04**
P-VALUE	**0.000**	**0.000**	**0.000**	**0.207**
KURTOSIS	**18.5**	**44.6**	**4.4**	**1.8**
P-VALUE	**0.000**	**0.000**	**0.000**	**0.000**

shown in Table A2.3 (4.8 per cent per annum with p-value 0.000). The distributions of value and growth stocks however appear less differentiated than for forecast returns, which is consistent with the estimates for standard error, skew and kurtosis being closer in value between value and growth for predicted returns than for forecast returns.

Table A2.4 shows the difference in average annual returns between value and growth stocks for forecast and predicted returns during the expansion and recession states. Here too we

Table A2.3: Difference in Average Annual Returns: Value *less* Growth – Whole of Period

Difference in average annual returns between value and growth stocks over the whole sample period (March 1999 to July 2017). Refer notes for Charts A2.2 and A2.3 and Table A2.2. The summary statistics reported are the difference in average annual returns between value and growth stocks, *Difference*, the standard error of the difference, *SE Difference*, and the resulting probability value, *P-Value*.

DIFFERENCE IN AVERAGE RETURNS: VALUE *less* GROWTH	Forecast (Forecast EY)	Predicted (Historical EY)
	Difference in Average Annual Returns between Value and Growth (%)	
DIFFERENCE	2.8	4.8
SE DIFFERENCE	0.6	0.6
P-VALUE	0.000	0.000

observe that value stocks earn a higher average return than growth stocks over both the expansion and recession states when using either forecast or predicted returns.

A2.3   Accuracy ratios

I measure the optimism of forecast and predicted returns relative to realised returns by using accuracy ratios. For each stock, at each month, I calculate the accuracy ratio as $\frac{1+r}{1+h}$, where r is the stock's annual forecast or predicted return and h is its historical return for the stock over the same period (from the CRSP data base). Charts A2.5 and A2.6 show the distributions of accuracy ratios for value and growth stocks using forecast and predicted returns respectively, with percentiles of the distributions and summary statistics shown in Table A2.5. We observe that forecast returns are more optimistic than predicted returns (accuracy ratios of 1.40 and 2.10 for value and growth forecast returns, relative to 1.02 and 1.08 for value and growth predicted returns respectively) and in both cases growth is more optimistic than value (accuracy ratios of 2.10 and 1.08 for growth forecast and predicted returns, relative to 1.40 and 1.02 for value forecast and predicted returns respectively).

Table A2.4: Difference in Average Annual Returns: Value *less* Growth – Expansion and Recession States

Difference in average annual returns between value and growth stocks during the expansion and recession states. Refer notes for Charts A2.2 and A2.3 and Table A2.2. The expansion state corresponds to months in which the expected market risk premium is less than the average premium over the sample period (March 1999 to July 2017) and the recession state corresponds to months in which the expected market risk premium is more than the average premium over the sample period. The summary statistics reported are the difference in average annual returns between value and growth stocks, *Difference*, the standard error of the difference, *SE Difference*, and the resulting probability value, *P-Value*.

DIFFERENCE IN AVERAGE RETURNS: VALUE *less* GROWTH	Forecast (using Forecast EY and Forecast Market Premium)	Predicted (using Historical EY and Predicted Market Premium)
	Difference in Average Annual Returns between Value and Growth (%)	
	EXPANSION State	
DIFFERENCE	3.2	2.6
P-VALUE	0.000	0.000
	RECESSION State	
DIFFERENCE	2.2	6.2
P-VALUE	0.000	0.000

Overall, predicted returns are more accurate than forecast returns, a result which is not surprising given that predicted returns are derived from historical returns (through linear regression using instrumental variables) whereas forecast returns are derived from consensus analysts' forecasts which are based on various qualitative and quantitative sources of information.

A2.4 Realised betas

I report the realised betas during different economic states (expansion and recession) in Table A2.6. I show the realised betas (calculated using realised returns) for value and growth stocks under both the forecast and historical value-growth classifications. We observe that value stocks have lower realised betas in both states (with significant differences) when using the
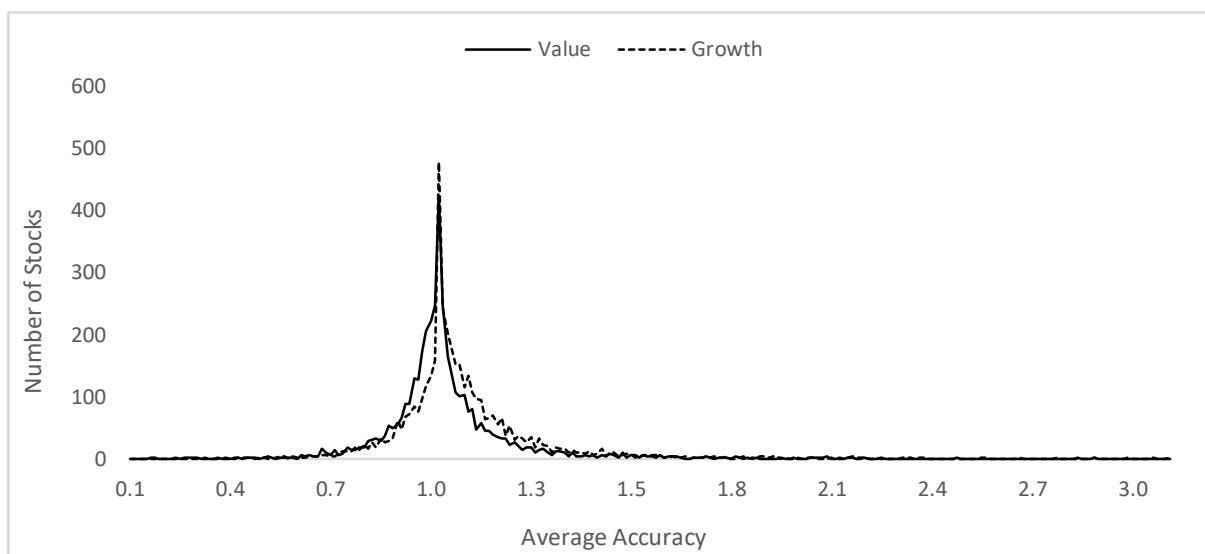
Chart A2.5: Accuracy of Forecast Returns – Value and Growth over Whole of Period

Distribution of average accuracy ratios using forecast returns across stocks identified as value and growth over the whole sample period (March 1999 to July 2017). All returns are excess over the 1-year Treasury rate, assume continuous compounding and are updated monthly. Forecast returns are derived using analyst 12-month price targets and dividend forecasts from the IBES database and historical stock prices from the CRSP database. Refer notes for Chart A2.3. For each stock, for each month, the accuracy ratio is calculated as $\frac{1+r}{1+h}$, where r is its annual forecast return and h is its historical return for the same period (CRSP data base). The average accuracy ratio for each stock is then calculated as the average of its monthly accuracy ratios corresponding with its return series. The closer the accuracy ratio is to 1, the more accurate the forecast return.
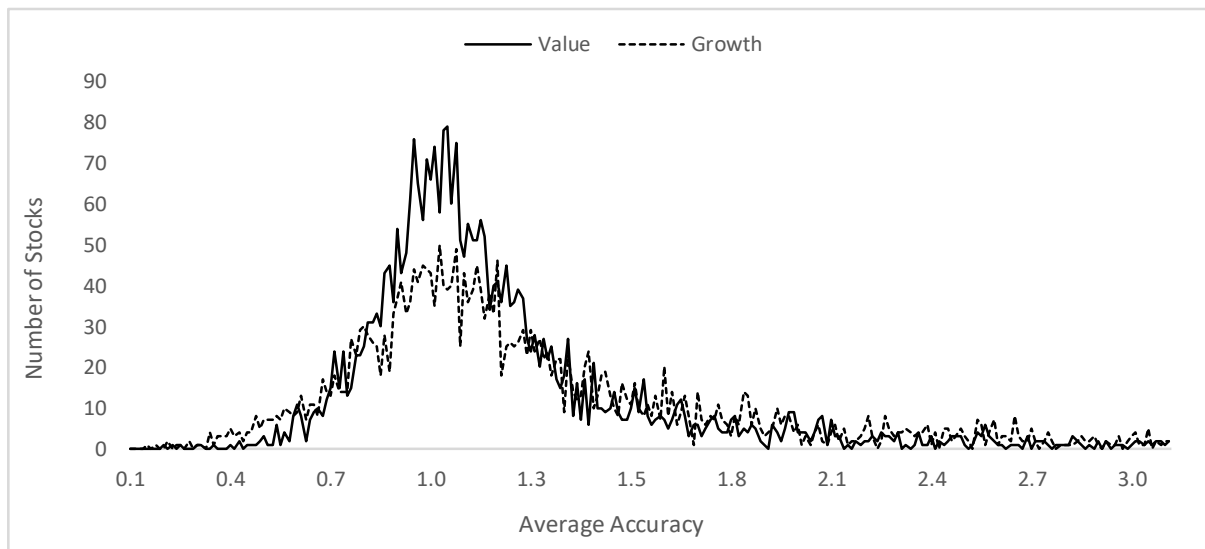
Chart A2.6: Accuracy of Predicted Returns – Value and Growth over Whole of Period

Distribution of average accuracy ratios using predicted returns across stocks identified as value and growth over the whole sample period. Predicted returns are derived using linear regressions between realised returns from the CRSP database and a set of instrumental variables (the T-bill rate, the term spread, the default spread and the dividend yield). Refer notes for Charts A2.3 and A2.5.

Table A2.5: Accuracy of Forecast and Predicted Returns – Value and Growth over Whole of Period

Distribution of accuracy ratios for forecast and predicted returns across stocks identified as value and growth over the whole sample period. Refer notes for Charts A2.3 and A2.5. Accuracy ratios are calculated for analyst forecast returns, *Forecast*, or predicted returns, *Predicted*. Earnings yields are calculated using either analysts' forecast earnings-per-share, *Forecast EY*, or historically reported earnings-per-share, *Historical EY*, and dividing by historical stock prices. The distributions of accuracy ratios amongst value and growth stocks, using forecast or predicted returns, is summarised using the set of percentiles shown. The summary statistics reported are the *Average*, which is the average of each distribution, the standard error of the average, *SE Average*, the skew of the distribution of beta sensitivities, *Skew*, the standard error of the skew, *SE Skew*, and the resulting probability values, *P-Value*.

DISTRIBUTION OF ACCURACY RATIOS	Forecast (Forecast EY)		Predicted (Historical EY)	
	Value	*Growth*	*Value*	*Growth*
	Average Accuracy Ratios			
90th	2.0	2.9	1.2	1.3
75th	1.3	1.7	1.1	1.1
67th	1.2	1.4	1.0	1.1
50th	1.1	1.2	1.0	1.0
33rd	1.0	1.0	1.0	1.0
25th	0.9	0.9	0.9	1.0
10th	0.8	0.7	0.9	0.9
AVERAGE	**1.40**	**2.10**	**1.02**	**1.08**
SE AVERAGE	**0.036**	**0.207**	**0.004**	**0.005**
P-VALUE (cf. 1)	**0.000**	**0.000**	**0.000**	**0.000**
SKEW	**24.3**	**32.6**	**11.3**	**12.6**
SE SKEW	**0.04**	**0.04**	**0.04**	**0.04**
P-VALUE	**0.000**	**0.000**	**0.000**	**0.000**

(Note: the leftmost header column is labelled **PERCENTILES** spanning the percentile rows 90th through 10th.)

forecast value-growth classification and in the expansion state when using the historical

value-growth classification (the recession state provides no significant difference in realised

betas under this classification). This has synergy with my central result which suggests that

value stocks are less risky than growth stocks on average.

Table A2.6: Realised Betas

Realised betas for stocks identified as value and growth during the expansion and recession states. Realised betas are calculated using realised stock and market returns sourced from the CRSP database. The expansion state corresponds to months in which the expected market risk premium is less than the average premium over the sample period (March 1999 to July 2017) and the recession state corresponds to months in which the expected market risk premium is more than the average premium over the sample period. The summary statistics reported are the realised betas, *Realised Beta*, and the standard error of the calculated realised beta, *SE*.

|	Forecast EY Classification		Historical EY Classification	
	Realised Betas			
	Value	*Growth*	*Value*	*Growth*
EXPANSION State				
REALISED BETA	0.13	0.72	0.14	0.69
SE	0.055	0.033	0.033	0.084
RECESSION State				
REALISED BETA	0.44	0.54	0.45	0.44
SE	0.015	0.028	0.015	0.018

APPENDIX 3: COMPARING BETA PREMIUM SENSITIVITIES

A3.1 Comparing forecast and predicted returns

Chart A3.1 shows the distributions of beta premium sensitivities across all stocks over the whole sample period using forecast and predicted returns. We observe that the beta premium sensitivities appear to be centred around a single-digit positive value, with forecast returns appearing to have more positively skewed beta premium sensitivities than predicted returns.

Chart A3.1: Beta Premium Sensitivities – Forecast and Predicted Returns over Whole of Period – All Stocks

Distribution of beta sensitivities across all stocks using forecast and predicted returns over the whole sample period (March 1999 to July 2017). All returns are excess over the 1-year Treasury rate, assume continuous compounding and are updated monthly. Forecast returns are derived using analyst 12-month price targets and dividend forecasts from the IBES database and historical stock prices from the CRSP database. Predicted returns are derived using linear regressions between realised returns from the CRSP database and a set of instrumental variables (the T-bill rate, the term spread, the default spread and the dividend yield). For each stock, the beta sensitivity $\hat{\varphi}_i$ is estimated using ($\widehat{E[r_{it}]} - \widehat{E[r_{mt}]}\widehat{E[\beta_{it-1}]}$) / $\widehat{Var[r_{mt}]}$ and: (i) The average of its conditional excess returns $\widehat{E[r_{it}]}$, using forecast or predicted returns, (ii) the average of market conditional excess returns for months that coincide with its return series $\widehat{E[r_{mt}]}$, using forecast or predicted market returns, (iii) the average of its conditional betas $\widehat{E[\beta_{it-1}]}$ based on regressing its conditional excess returns against conditional excess market returns for months that coincide with its return series, using forecast or predicted returns, and (iv) the variance of market conditional excess returns $\widehat{Var[r_{mt}]}$, calculated using monthly VIX values in the case of forecast returns or realised market variance in the case of predicted returns, based on months that coincide with its return series.
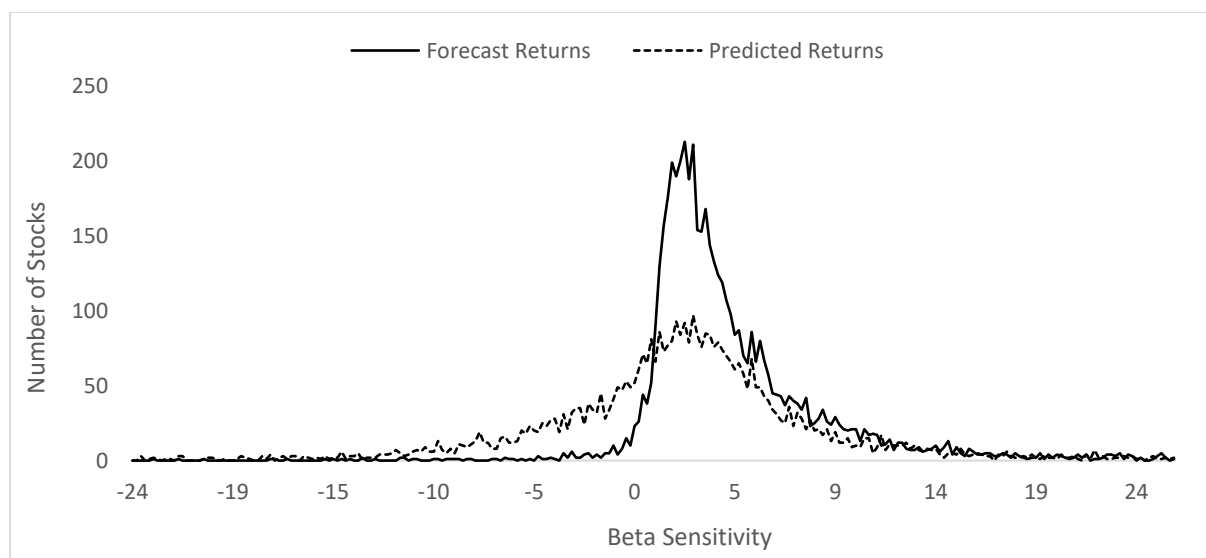
A3.2 Comparing value and growth beta premium sensitivity distributions

The extent to which the distributions of beta premium sensitivities differ between value and growth stocks, using both forecast and predicted returns, can be assessed using the Kolmogorov-Smirnov (KS) two-sample test. I show the results of this in Table A3.1. The KS test is a nonparametric test that compares two samples for differences against a null hypothesis that the samples are drawn from the same distribution. The empirical distribution functions of the two samples are used for comparison on the basis that they are reasonable estimates of their respective population CDFs (Chakraborti and Gibbons 2003). Using the KS test, we observe from Table A3.1 that the distributions of value and growth beta premium sensitivities are significantly different from each other, using either forecast or predicted returns.

Table A3.1: Comparing Beta Sensitivity Distributions: Value *vs* Growth

Comparison of beta sensitivity distributions for value and growth stocks over the whole sample period (March 1999 to July 2017). All returns are excess over the 1-year Treasury rate, assume continuous compounding and are updated monthly. Beta sensitivities are derived using analyst forecast returns, *Forecast*, or predicted returns, *Predicted*. Refer notes for Charts A2.3 and A3.1. Earnings yields are calculated using either analysts' forecast earnings-per-share, *Forecast EY*, or historically reported earnings-per-share, *Historical EY*, and dividing by historical stock prices. The distributions of beta premium sensitivities amongst value and growth stocks are compared using the Kolmogorov-Smirnov two-sample test. The summary statistics reported are the Kolmogorov-Smirnov statistic, *KS Statistic*, and the resulting probability value, *P-Value*.

COMPARISON OF BETA SENSITIVITY DISTRIBUTIONS: VALUE *vs* GROWTH	Forecast (Forecast EY)	Predicted (Historical EY)
	Value vs Growth Beta Sensitivity Distributions using Kolmogorov-Smirnov two-sample test	
KS STATISTIC	0.110	0.112
P-VALUE	0.000	0.000

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