Risk Premia – The Analysts' Perspective

Pascal Büsing[†] Hannes Mohrschladt[‡]

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Abstract: We examine the time-series and cross-section of stock market risk premia from the perspective of financial analysts. Our novel approach is based on the notion that analysts' stock recommendations reflect both their subjective return expectations and their perceived stock risk. Thus, we can empirically infer presumed risk premia from recommendations and target price implied expected returns. We show that analysts' presumed risk premia are strongly countercyclical such that their correlation with the VIX is 72%. Moreover, they predict future stock market returns and are closely related to the price-dividend ratio and other cyclical state variables. In the cross-section, the presumed risk premia are comparably large for high-beta, small, and value stocks lending support to a risk-based interpretation of these characteristics.

Keywords: Risk Premia, Subjective Return Expectations, Financial Analysts.

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[†]Finance Center Münster, University of Münster, Universitätsstr. 14-16, 48143 Münster, Germany; Email: pascal.buesing@wiwi.uni-muenster.de.

[‡]Finance Center Münster, University of Münster, Universitätsstr. 14-16, 48143 Münster, Germany; Email: hannes.mohrschladt@wiwi.uni-muenster.de.

1. Introduction

How does the market risk premium vary over time? Which stocks do investors consider comparably risky such that they require higher expected returns? These questions have been at the core of many research papers during the past decades—without definite answers so far. Indeed, an empirical answer to these questions is difficult to provide: Observing significant time-variation in realized market returns or cross-sectional return premia for specific stocks might be due to risk premia or mispricing effects. Similarly, if researchers elicit return expectations for a group of investors, high subjective expectations might reflect a high risk premium or a perceived undervaluation and comparably optimistic beliefs. Ideally, to infer investors' risk premia, researchers would like to observe their stock preferences while holding subjective stock return expectations constant. This would allow to recover risk premia without the confounding impact of biased beliefs and could contribute to some of the most important open research questions about stock market risk premia.

Unfortunately, data on every investors' stock preferences for a fixed level of expected stock return is not available to academia (and will presumably never be). But at least, we take a small step in this direction by investigating the influential group of financial analysts. Our key idea is very simple and illustrated by the following cross-sectional example. Let's assume that an analyst issues a buy recommendation for a specific stock and that her corresponding target price implies a subjective expected return of 10%. At the same time, she recommends to sell another stock despite an identical subjective return expectation of 10%. Hence, she prefers the former stock over latter stock for reasons beyond expected return beliefs, that is, she seemingly considers the latter stock riskier and, consequently, applies a higher risk premium for this latter stock. Our time-series arguments are very similar: analysts' presumed risk premia are higher in times when a 10% return expectation implies a sell recommendation compared to times when a 10% return expectation suffices to issue a buy recommendation. Consequently, this new method allows us to infer cross-sectional differences and time-series fluctuations in analysts' presumed risk premia. Following this key idea, our estimation approach is thoroughly outlined in Section 2. In a nutshell, we use simple least squares optimization to infer which risk premia allow to best explain analyst recommendations based on their target price implied expected returns.

Referring to the time-series of analysts' presumed risk premia, our findings point toward strong countercyclicality, that is, analysts' required rate of return is substantially higher following down-markets, in recessions, and during high-volatility periods. For example, the correlation between the option-implied volatility index VIX and the analysts' presumed risk premia is 72%. Hence, analyst recommendations are in line with many standard rational asset pricing models that imply countercyclical risk premia (e.g., Campbell and Cochrane, 1999; Bansal and Yaron, 2004; Gârleanu and Panageas, 2015). In particular, analysts' presumed risk premia predict one-year-ahead market returns with a positive sign and partly capture well-known countercyclical return predictors. For example, the price-dividend ratio significantly predicts subsequent market returns in univariate regressions, but becomes insignificant after controlling for the time-series of analysts' presumed risk premia. Consequently, the presumed risk premia can explain substantial parts of the variation in the price-dividend ratio as well as its return predictability (also see De La O and Myers, 2021).

Referring to the cross-section, we find that analysts' presumed risk premia increase in a stock's market beta. More specifically, our cross-sectional analyses imply that the annual market price of risk applied by financial analysts equals approximately 5% such that it matches the historical market-wide equity premium quite well. Consequently, our findings support rational asset pricing models such as the CAPM that imply higher risk premia for stocks that show a positive covariance with the market. Moreover, we show that this cross-sectional market price of risk is positively correlated with the VIX. Hence, in line with economic intution, analysts use higher risk premia if overall economic risk is comparably high. Beyond market risk, we also examine size and book-to-market, the other two underlying characteristics of the Fama and French (1993) three-factor model. We find that analysts' average presumed price of risk is negative for size and positive for book-to-market. Hence, our findings qualitatively match size and value premium documented in the cross-section of realized stock returns and are in line with a risk-based interpretation of these two stock market phenomena.

Our overall findings extend the vast literature on beliefs and expectations in financial markets. Most of these studies show that market participants such as retail investors extrapolate recent returns when forming beliefs such that their return expectations tend to be procyclical (Greenwood and Shleifer, 2014; Amromin and Sharpe, 2014; Andonov and Rauh, 2022; Nagel and Xu, 2022a). On the contrary, the expected returns of economists seem to be countercyclical (Dahlquist and Ibert, 2022; also see their evidence on asset manager expectations). Given the different cyclicality patterns, we find that analysts' presumed risk premia are negatively correlated with the former group of survey expectations and positively with the latter. However, while these surveys and the corresponding studies focus on *beliefs*, our focus is on *preferences* (i.e., given a fixed set of beliefs, which assets do market participants prefer due to risk considerations?). Consequently, the presumed risk premia that we infer are conceptually different from the belief-based subjective risk premia as recently discussed by Nagel and Xu (2022b). Given that the surveyed investors set up subjective optimal portfolios in line with their stated beliefs, their subjective risk premia equal their subjective excess return expectations. Hence, an investor group's procyclical subjective return expectations imply that their subjective risk premia are procyclical, too. However, this observation does not necessarily imply that the surveyed investors consider the overall market riskier during booms than recessions; the observation might simply reflect overly optimistic beliefs during booms and overly pessimistic beliefs during recessions (for example, see corresponding model on extrapolative belief formation in Barberis et al., 2015). On the contrary, we show that the countercyclicality in analysts' presumed risk premia is not driven by countercyclicality in their optimism versus pessimism. Analysts tend to be more optimistic in up-markets as the proportion of favorable recommendations is higher compared to down-markets. Hence, their higher presumed risk premia in down-markets cannot be driven by excessive optimism. They are rather in line with rational considerations as they predict future returns with positive sign.

In addition, our findings add to the large literature on financial analysts. For example, Jegadeesh et al. (2004) and Lin et al. (2011) examine the relation between analyst recommendations and risk-related characteristics. Marston and Harris (1993), Gebhardt et al. (2001), Gode and Mohanram (2003), and Hail and Leuz (2006) derive expected returns and implied cost of capital from earnings forecasts while Francis et al. (2004), Botosan and Plumlee (2005), Brav et al. (2005), and McInnis (2010) examine target price implied expected returns. In this context, Wang (2021) documents that analysts' (excess) return expectations are countercyclical and Bastianello (2022) interprets these expectations as subjective risk premia. However, equivalent to our arguments in the previous paragraph, this does not necessarily imply countercyclicality in analysts' perceived overall market risk, but might rather reflect when analysts consider the market mispriced. On the contrary, our method of combining recommendation and target price data allows to examine risk-related preferences beyond analysts' beliefs. Combining these two pieces of analyst information, Bradshaw (2002) supports our methodological approach by showing that target prices are an important determinant of recommendations; Brav and Lehavy (2003) show that the publication of both target prices and recommendations induces stock market reactions.

Finally, instead of inferring subjective risk premia from subjective return expectations, only few researchers have directly elicited the level of perceived risk. In this context, Ben-David et al. (2013) show that CFOs' underestimation of S&P 500 return volatility is strongest in high-VIX quarters. Further, and in line with our findings, controlled experimental evidence based on financial professionals indicates that high-beta and small firms are considered riskier than their low-beta and large counterparts (Bloomfield and Michaely, 2004; Merkle and Sextroh, 2021). However, the experimental subjects do not deem value stocks comparably risky. Hence, our approach based on a large sample of real-world analyst reports tests the external validity of the experimental evidence. In particular, we add to the intense debate on the cross-sectional determinants of risk given that experimental evidence and realized cross-sectional return premia do not always align well.

2. Conceptual Framework and Methodology

2.1. Conceptual Framework

Financial analysts frequently issue recommendations to stock market investors. As these recommendations are publicly available, we assume that the target audience is a typical representative investor (e.g., this representative investor holds the market portfolio as the set of risky assets). The analyst will issue a favorable recommendation with respect to a specific stock ($rec = 1$) if she thinks that investors would benefit from overweighing this stock in their portfolios. Otherwise she will issue an unfavorable stock recommendation ($rec = 0$). Consequently, she will issue a favorable recommendation if (and only if) she believes that the stock's expected return ER exceeds the representative investor's required rate of return RRR for that stock.[1] More formally, for any recommendation of analyst k with respect to stock i issued at time t, it should hold that

$$rec_{ikt} = Ind(ER_{ikt} > RRR_{ikt}). \tag{1}$$

The required rate of return RRR_{ikt} can be decomposed into risk-free rate RF_t and the risk premium RP_{ikt} that analyst k deems reasonable for the representative investor. Consequently,

$$rec_{ikt} = Ind(ER_{ikt} - RF_t > RP_{ikt}). \tag{2}$$

This equation perfectly complies with standard intuition on analyst behavior: if, for example, the analyst expects an excess return of 10% for a specific stock and thinks that the average investor will require a risk premium of 5%, she will issue a "buy" recommendation because the typical investor could increase the expected utility by increasing the portfolio weight of that stock. Stated differently, the "buy" recommendation shows that the analyst considers the stock undervalued such that she expects a positive risk-adjusted return.

Given that analyst recommendations rec are readily available and that analysts' one-year expected returns ER can be easily retrieved from target prices, Equation (2) can be used

[1] This conclusion directly follows from optimal portfolio choice: an investor should always increase investments in assets with $ER > RRR$ until she obtains the optimal portfolio which is characterized by $ER = RRR$.

to empirically examine the time-series and cross-sectional dynamics of RP_{ikt} (the specific estimation procedures are introduced in the next subsection). Hence, this conceptual framework allows to identify *when* analysts consider risk premia to be particularly high and also *which* stocks they consider most risky.

As directly illustrated by the k-subscript in RP_{ikt}, we infer presumed rather than objective risk premia since RP_{ikt} depends on what analyst k considers a reasonable risk premium for a typical investor. Importantly, these presumed risk premia RP_{ikt} are conceptually very different from the subjective risk premia examined in the literature (for example, see Nagel and Xu, 2022b). These subjective risk premia of a specific investor are subjective in the sense that they reflect the required rate of return given the person's individual portfolio. Referring to the previous example, if an analyst believes in an expected excess return of 10%, standard portfolio optimization implies that she will increase the weight of this stock in her portfolio until the stock's required rate of excess return equals 10%, i.e., the analyst will only hold a subjective optimal portfolio if her subjective risk premium equals her subjective expected return. Given this portfolio optimization argument, the literature has directly inferred subjective risk premia from subjective expected excess returns.[2]

The example illustrates that the high subjective risk premium of 10% is caused by the perceived undervaluation of the stock: as the analyst considers the stock undervalued, she strongly tilts her portfolio toward this stock until her subjective risk premium equals 10%. However, while these 10% might be a perfect estimate for her subjective risk premium, its

[2]The implicit assumptions underlying this literature (e.g., Bastianello, 2022 in the context of financial analysts) are that analysts indeed trade in the stocks they cover, that they set up an optimal portfolio in line with their stated return expectations, and that constraints (e.g., short-sell constraints) do not prevent them from holding such a portfolio. While the latter two assumptions are standard in asset pricing models, the empirically documented pass-through of beliefs to actual portfolio choices seems fairly weak (Giglio et al., 2021). However, if these assumptions are not met, it is unclear whether the subjective return expectation equals the analyst's subjective risk premium. Note that our approach to recover the presumed risk premium from Equation (2) does not depend on any of these assumptions.

high magnitude simply results from the strong portfolio tilt of the analyst such that the 10% substantially differ from the risk premium of a representative investor. Consequently, previous evidence on time-series and cross-sectional patterns in analysts' subjective risk premia might simply reflect patterns in analysts' perceived mispricing—in particular as the identification of under- versus overvalued stocks is one of analysts' key tasks.

On the contrary, differences in the presumed risk premium RP cannot be related to differences in perceived mispricing in such a mechanical way since perceived mispricing is reflected in both rec and ER such that its effects cancel out when estimating RP in Equation (2). To illustrate this, consider that the analyst issues a "buy" recommendation for the exemplary stock with a subjective expected excess return of 10%. Based on Equation (2), we merely conclude that the stock's presumed risk premium is below 10%. In addition, consider that the analyst assigns a "sell" recommendation to a second stock with an identical subjective expected excess return of 10%. Hence, this second stock's presumed risk premium is above 10%. Consequently, we can conclude that the second stock has a higher presumed risk premium than the first. In this case, the higher risk premium associated with the second stock cannot stem from a perceived undervaluation as such an undervaluation should have resulted in a "buy" recommendation. In conclusion, our approach allows to identify analysts' perceived stock risk beyond their personal portfolio point of view and beyond a mechanical impact of under- versus overvaluation beliefs.

2.2. Methodology

The empirical implementation of Equation (2) to estimate the presumed risk premia RP_{ikt} requires data for ER_{ikt} and rec_{ikt}. Referring to the former, we calculate the subjective expected return as the relative difference between the analyst's one-year-horizon target price and the current stock price. Referring to the latter, we categorize the recommendations "strong sell", "sell", and "hold" as unfavorable ($rec = 0$) and the recommendations "buy" and "strong buy" as favorable ($rec = 1$). Of course, the categorization of "hold" is somewhat arbitrary such that we provide corresponding robustness tests in the Online Appendix. But given analysts' strong tendency to avoid sell recommendations (Bradshaw, 2002), treating "hold" as unfavorable leads to a better balance in the number of favorable versus unfavorable observations. Moreover, the asymmetry in analyst recommendations also implies that "hold" is indeed frequently interpreted as negative signal by the market (Lin and McNichols, 1998; Corredor et al., 2013). If an analyst provides both target price and recommendation for a given stock on the same day, we use this observation in our estimation.

2.2.1. Estimating the Time-Series of Presumed Risk Premia

Given that the indicator function in Equation (2) is based on an inequality, a combined observation of rec_{ikt} and ER_{ikt} only allows to estimate an upper or lower bound for RP_{ikt}, but no precise value for each single stock. Consequently, in order to examine time-series fluctuations in RP, we do not explicitly model stock-level differences in RP in this part of our analysis, but delegate these differences to the model's error term instead. Moreover, we aggregate observations on the monthly level such that the number of observations allows to substantially narrow down the possible range of the presumed risk premium. Hence, for each month t and each analyst k, we estimate the risk premium RP_{kt} from

$$rec_{ikt} = Ind(ER_{ikt} - RF_t > RP_{kt}) + \epsilon_{ikt} \tag{3}$$

by minimizing the sum of squared error terms ϵ_{ikt}^2.[3] To provide intuition on this optimization, assume that an analyst issues several unfavorable recommendations with 5% as the highest expected excess return. Moreover, she issues favorable recommendations where the lowest expected excess return is 7%. In this case, any value of RP_{kt} from the interval [5%, 7%) results in the optimum with a sum of squared error terms equal to zero. Hence, using the interval's midpoint, we would conclude that the analyst's presumed risk premium (i.e., her required rate of excess return to issue a favorable recommendation) is 6%.

2.2.2. Estimating the Cross-Section of Presumed Risk Premia

Our intuition on the estimation of cross-sectional differences in RP is as follows. Consider a stock with an unfavorable recommendation that has a higher subjective expected return than a stock with a favorable recommendation. Following Equation (2), this directly implies that the analyst considers the unfavorable stock more risky than the favorable stock (i.e., given that the unfavorable stock has a higher expected return, its worse recommendation must be due to a higher level of risk). In the following, we formalize this intuition to estimate which stocks are considered comparably risky by analysts.

As the inequality in Equation (2) does not allow to precisely estimate RP_{ikt} based on rec_{ikt} and ER_{ikt}, we do not explicitly model analyst heterogeneity in our main cross-sectional analyses, i.e., we drop the k-index from RP. Moreover, Equation (2) still does not allow to estimate RP_{it} for each individual stock. Hence, to further reduce the number of unknown parameters, we assume

$$RP_{it} = \lambda_t + \beta_{it}\gamma_t. \tag{4}$$

[3] Given the inequality in Equation (3), the optimization typically results in a range of RP_{kt}-values that yield the lowest sum of squared error terms. If the optimization results in a finite interval of optimal RP_{kt}-values, we use the interval's midpoint as RP_{kt}-estimate. Otherwise, we drop the analyst-month-observation.

β_{it} refers to a characteristic of stock i in month t which might be associated with risk (e.g., a stock's market beta). γ_t is the price of risk that the analysts associate with this characteristic (e.g., the analysts' presumed market risk premium).[4] λ_t reflects the part of the presumed risk premium beyond characteristic-related risk (e.g., if the analysts universally apply the same presumed risk premium to all stocks, this is reflected by λ_t since γ_t equals zero).

Combining Equations (2) and (4), for each month, we minimize the sum of squared error terms in

$$rec_{ikt} = Ind(ER_{ikt} - RF_t > \lambda_t + \beta_{it}\gamma_t) + \epsilon_{ikt}. \tag{5}$$

Based on this optimization, we obtain the analysts' presumed price of risk γ_t. First, we will provide the proportion of months that imply a positive versus negative price of risk for a potential risk characteristic. Second, we will estimate the magnitude of the price of risk that fits analyst recommendations best.[5] In summary, we can draw conclusions on whether analysts charge a higher risk premium for high-market beta, small, or value stocks in comparison to low-market beta, big, or growth stocks, and we can estimate the corresponding prices of risk.

3. Data and Variables

Our analyses are based on analyst announcements with respect to common ordinary stocks trading on NYSE, AMEX, or NASDAQ.[6] Stock prices, stock returns, and the one-year

[4]For simplicity, these explanations are based on one risk characteristic such that β_{it} and γ_t are simple scalars. However, β_{it} and γ_t can also be interpreted as vectors to jointly account for several risk characteristics (as we will also do in our empirical analysis).

[5]Again, given the inequality structure in Equation (4), the optimization yields a range of optimal coefficients rather than precise estimates such that we use the average of these optimal γ_t-values as estimate.

[6]In the Online Appendix, we provide similar results from analyses where we only use S&P 500 stocks.

U.S. Treasury rate (RF_t) are sourced from the Center for Research in Security Prices (CRSP). Data on analyst recommendations and target prices is obtained from I/B/E/S. Target prices must be denominated in U.S. dollar and have a 12-month horizon. The option-implied volatility index VIX is obtained from the Chicago Board Options Exchange. For the cyclical state variables, we retrieve the S&P 500 dividend yield and corporate bond yields from Amit Goyal's website and the cyclically adjusted price-earnings ratio (CAPE) from Robert Shiller's website. Data on industrial production is downloaded from the Federal Reserve Bank of Philadelphia. Further, we compare analysts' presumed risk premia to the following surveys on subjective return expectations: the Livingston survey from the Federal Reserve Bank of Philadelphia, the Graham-Harvey CFO survey from the Duke CFO Global Business Outlook, and an aggregated time-series of individual investor surveys from Stefan Nagel's website. For the cross-sectional analyses, we use accounting data from COMPUSTAT.

We consider analyst announcements between January 2003 and December 2020. The start of the sample period is restricted by the availability of analyst data. Even though I/B/E/S provides target prices starting in 1999, coverage is comparably low in early years. Moreover, variation in recommendations is also low during the early 2000s as it was very uncommon for analysts to provide "sell" recommendations then (Bradshaw, 2002).

We examine analyst announcements where an analyst issues both target price and recommendation with respect to a specific stock on the same day. We adjust target prices and stock prices for stock splits and exclude data from the three days surrounding a stock split. We calculate the target price implied expected return (ER) as the stock's target price plus the expected dividend, all divided by the prior-day closing price minus one.[7] We

[7] We use the past year's cumulative dividend per share as an estimate for the expected dividend. In the Online Appendix, we also provide analyses where we use the analyst's dividend per share forecast (which reduces our sample size due to the lower availability of dividend expectations). Moreover, we present analyses where we simply ignore dividends. The results are qualitatively the same.

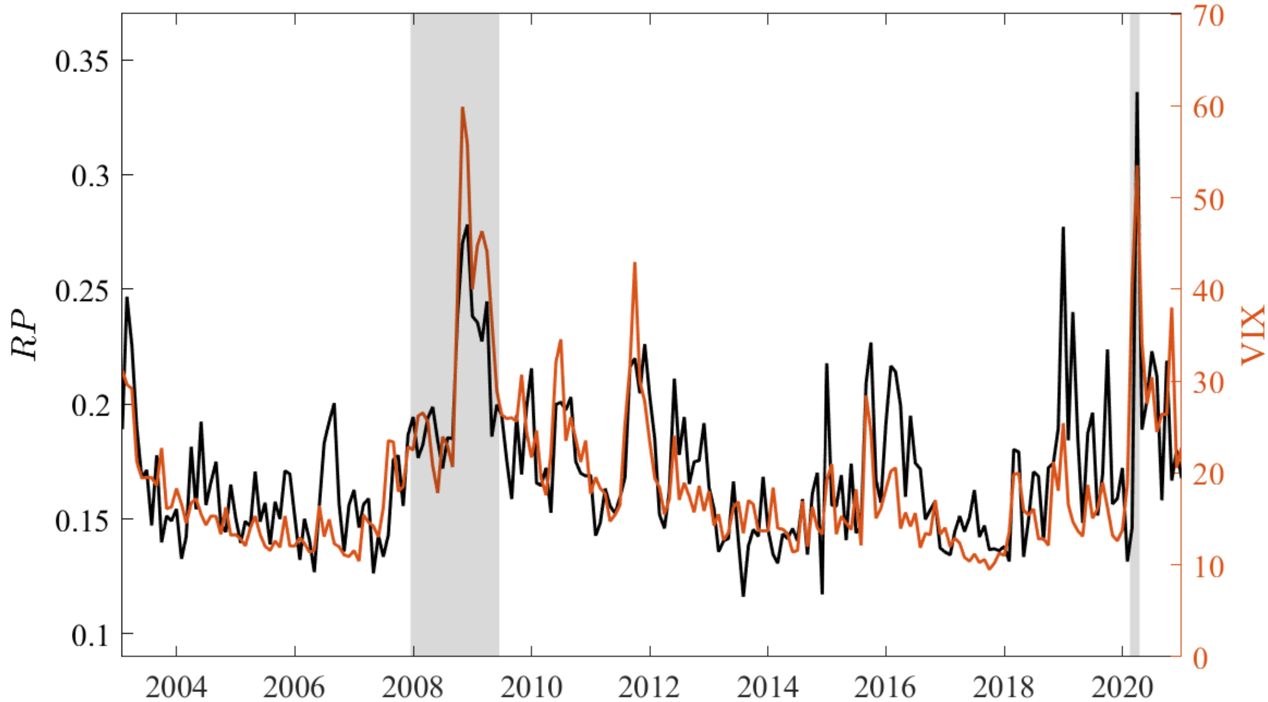
add the expected dividend to the target price, as recommendations should be based on total expected returns. We trim these expected returns at the 1st and at the 99th percentile. Each target price implied expected return is matched with a recommendation ($rec = 1$ for "strong buy" and "buy" and $rec = 0$ for "hold", "sell", and "strong sell'). After this matching procedure, our sample in the time-series analyses consists of 211,909 analyst announcements (target price and recommendation).

In our cross-sectional analyses, we consider three stock characteristics which might reflect a stock's risk. They are motivated by the three factors of Fama and French (1993). We use a stock's market beta ($BETA$) following Frazzini and Pedersen (2014), the log market capitalization ($SIZE$), and the book-to-market ratio (BM) following Fama and French (1993). To ensure that we do not include any forward looking information in our analyses that has not been available to the analyst at the announcement date, we match the previous month's stock characteristics with the analyst announcements. We only keep observations with data available for all three characteristics. This procedure reduces our sample size to 162,431 analyst announcements for the cross-sectional analyses.

4. The Time-Series of Presumed Risk Premia

We start our empirical analysis by examining the time-series variation in the presumed risk premium (RP_t) that the average analyst deems reasonable for a representative investor. As described in Subsection 2.2.1, we can estimate RP_{kt} by minimizing the sum of squared residuals in Equation (3) for each analyst in every month. We then compute the monthly average RP_t over all analysts to obtain a time-series of presumed risk premia. This time-series is displayed in Figure 1.

Figure 1. Time-Series of Analysts' Presumed Risk Premia and the VIX
This figure depicts analysts' presumed risk premia RP_t and the option-implied volatility index VIX across time. RP_t is the monthly average of RP_{kt} among all analysts. RP_{kt} is the risk premium that analyst k deems reasonable for a representative investor in month t and is estimated based on Equation (3). The grey bars indicate NBER recessions. The sample period is from January 2003 to December 2020.



RP_t is clearly not stable over time but rather volatile. Furthermore, this variation does not merely reflect estimation noise, but is systematically connected to the market state. We highlight the two NBER recessions in our sample period, the global financial crisis and the COVID-19 crisis, with grey bars in Figure 1. During these recessions, RP_t rises sharply and peaks. As soon as the recessions are over, RP_t returns to moderate levels again. We also display the VIX as a measure of market uncertainty in Figure 1. It follows a remarkably similar pattern as RP_t. In fact, the correlation between both time-series is 72.12% ($t = 15.23$). Hence, analysts presume higher risk premia when the market is expected to be comparably volatile. This observation shows that analyst recommendations take into account a typical risk-return tradeoff: in order to bear an increased level of volatility and uncertainty, analysts presume higher risk premia for the representative investor.

Figure 1 also shows that the average level of RP_t (17.08%) is quite high compared to standard estimates of the annual equity premium (e.g., Pástor and Stambaugh (2001) provide an estimate between 4% and 6%). However, this high level is mechanically driven by the unconditional upward-bias in analysts' target prices (Brav and Lehavy, 2003). This well-documented analyst bias increases the expected excess returns for stocks with both favorable and unfavorable recommendations such that the required rate of return separating these two groups increases as well. Hence, we cannot interpret the absolute magnitude of RP_t, but only its time-series changes and its cross-sectional differences.[8]

4.1. Countercyclical Risk Premia

The strong comovement of the presumed risk premia and the VIX indicates that RP is countercyclical. To get a better understanding of the cyclicality of RP, we regress it on several cyclical state variables following Nagel and Xu (2022b). These state variables are the 12-month log growth in the U.S. industrial production index (IP), the cyclically adjusted price-earnings ratio (CAPE; Campbell and Shiller, 1998), the price-dividend ratio (P/D) as the level of the S&P 500 index divided by the past year's cumulated dividends of its constituents, the default yield spread (DYS) as the difference between corporate bond yields from BAA and AAA-rated bonds, and the VIX. We further control for the value-weighted CRSP return of the previous year (R_{past}). IP, CAPE, and P/D are known to be procyclical, while DYS and the VIX are countercyclical (Campbell and Shiller, 1988, 1998;

[8]To further illustrate that the absolute level of RP_t is somewhat arbitrary, consider our robustness tests where we label "hold" recommendations as favorable instead of unfavorable. In these robustness tests, the average level of RP_t is only 1.23%. However, the time-series fluctuations in RP_t look very similar than those depicted in Figure 1.

Fama and French, 1989; Nagel and Xu, 2022b). For ease of interpretation, we standardize all independent variables to zero mean and unit standard deviation. The regression results are provided in Table 1.

Table 1. Cyclicality of Analysts' Presumed Risk Premia

This table reports results from time-series regressions with RP_t as the dependent variable. RP_t is the monthly average of RP_{kt} among all analysts. RP_{kt} is the risk premium that analyst k deems reasonable for a representative investor in month t and is estimated based on Equation (3). The independent variables refer to month t and are as follows. IP is the 12-month log change in industrial production, CAPE is Shiller's cyclically adjusted price-earnings ratio, P/D is the log price-dividend ratio as in Welch and Goyal (2008), DYS is the default yield spread as in Welch and Goyal (2008), VIX is the CBOE option-implied volatility index, and R_{past} is the value-weighted CRSP market excess return over the previous year. All independent variables are standardized to zero mean and unit standard deviation. The reported coefficients and the constant are multiplied by 100. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags. The sample period is from January 2003 to December 2020.

	IP		CAPE		P/D		DYS		VIX	
Constant	17.08	17.92	17.08	17.88	17.08	17.60	17.08	17.28	17.08	17.46
	(49.65)	(51.25)	(40.86)	(43.17)	(47.48)	(48.55)	(69.48)	(47.53)	(78.44)	(55.95)
Coeff	-1.24	-0.37	-1.27	-0.71	-1.70	-1.15	1.91	1.66	2.31	2.02
	(-3.85)	(-1.13)	(-3.05)	(-1.90)	(-7.25)	(-3.14)	(6.09)	(4.11)	(18.73)	(13.10)
R_{past}		-1.35		-1.28		-0.83		-0.33		-0.61
		(-3.44)		(-3.25)		(-1.76)		(-0.79)		(-2.24)
Adj. R^2	0.15	0.25	0.15	0.28	0.28	0.31	0.35	0.35	0.52	0.54
n	216	216	216	216	216	216	216	216	216	216

We find that the coefficients of the independent state variables indicate a countercyclical RP in all regression specifications. While the procyclical variables IP, CAPE, and P/D have negative coefficients, the countercyclical variables DYS and VIX have positive coefficients. When R_{past} is included as additional independent variable, the coefficients of IP and CAPE are insignificant but still negative. At the same time, the coefficient of R_{past} is negative in all specifications. These results confirm that analysts' presumed risk premia are countercyclical. The high values of the adjusted R^2 that go up to 54% further underline that RP and the cyclical state variables are systematically related. Hence, analysts' presumed risk premia are in line with rational models arguing that countercyclical state variables proxy for time-varying risk premia that are highest in down-markets (e.g., Campbell and Cochrane, 1999; Bansal and Yaron, 2004; Gârleanu and Panageas, 2015).

4.2. Predicting Future Returns

The cyclical state variables from Subsection 4.1 do not only covary with RP but have also been shown to be good predictors of future excess returns—potentially because they reflect variation in risk premia. To the extent that RP captures this risk premia variation, it should also predict subsequent returns and might partly subsume the return predictability associated with the state variables. To test these hypotheses, we regress the next year's (months $t+1$ to $t+12$) value-weighted CRSP excess return on RP and the cyclical state variables, both in univariate and multivariate OLS regressions.[9] The regression results are provided in Table 2.

Panel A provides the results of the univariate regressions. In line with the previous literature, countercyclical (procyclical) state variables predict subsequent returns with positive (negative) sign. Except for CAPE and R_{past}, this return predictability is also statistically significant. Since the independent variables are standardized to zero mean and unit standard deviation, the coefficients are easily comparable: in the univariate regressions, IP and VIX show the strongest predictability and the highest adjusted R^2. Beyond the established state variables, RP significantly predicts future stock returns, too. An increase in RP of one standard deviation leads to an increase in the next year's value-weighted CRSP excess return of 4.81% ($t = 2.76$). The adjusted R^2 of 8% is comparable to the performance of the other predictors.

[9] We provide similar results for equally-weighted returns in the Online Appendix.

Table 2. Predicting Future Returns
This table reports results from time-series regressions, where the next year's value-weighted CRSP excess return from month $t+1$ to $t+12$ is the dependent variable. Panel A reports results from univariate regressions and Panel B results from multivariate regressions with the following independent variables. IP is the 12-month log change in industrial production, CAPE is Shiller's cyclically adjusted price-earnings ratio, P/D is the log price-dividend ratio as in Welch and Goyal (2008), DYS is the default yield spread as in Welch and Goyal (2008), VIX is the CBOE option-implied volatility index, and R_{past} is the value-weighted CRSP market excess return over the previous year. RP_t is the monthly average of RP_{kt} among all analysts. RP_{kt} is the risk premium that analyst k deems reasonable for a representative investor in month t and is estimated based on Equation (3). All independent variables are standardized to zero mean and unit standard deviation. The reported coefficients are multiplied by 100. An intercept is estimated but not reported. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags. The sample period is from January 2003 to December 2020.

Panel A: Univariate Regressions Explaining Future Returns							
	IP	CAPE	P/D	DYS	VIX	R_{past}	RP
Coefficient	-5.75	-3.25	-4.48	4.44	5.58	-3.29	4.81
	(-3.20)	(-1.52)	(-2.76)	(2.88)	(2.56)	(-1.59)	(2.76)
Adj. R^2	0.12	0.03	0.07	0.07	0.11	0.03	0.08
n	216	216	216	216	216	216	216
Panel B: Multivariate Regressions Explaining Future Returns							
RP	3.04	4.18	3.39	3.36	1.64	4.21	2.39
	(1.67)	(1.87)	(1.43)	(1.69)	(1.28)	(2.50)	(2.20)
IP	-4.57						-5.98
	(-2.49)						(-1.77)
CAPE		-1.60					-1.84
		(-0.66)					(-0.79)
P/D			-2.69				-0.16
			(-1.19)				(-0.05)
DYS				2.44			-3.11
				(1.36)			(-0.72)
VIX					4.40		2.72
					(2.00)		(0.80)
R_{past}						-1.21	1.64
						(-0.61)	(0.44)
Adj. R^2	0.14	0.08	0.09	0.09	0.11	0.08	0.15
n	216	216	216	216	216	216	216

Panel B reports results from multivariate regressions where we regress future market returns on RP and control for each state variable individually as well as for all state variables at once. RP substantially reduces the magnitude and statistical significance of the state variables compared to the univariate regressions. The coefficients of CAPE, P/D, DYS, and R_{past} are especially reduced in these multivariate regressions to levels that are statistically insignificant. In a regression with RP and all state variables as independent variables, RP is the only significant predictor of future returns. These findings suggest that market returns are predictable, to a substantial extent because of time variation in risk premia.

Nonetheless, risk premia as presumed by financial analysts are unlikely the only reason why state variables predict subsequent returns. Pointing in this direction, the state variable coefficients are reduced, but not zero in Panel B of Table 2. Moreover, comparing Tables 1 and 2, a one standard deviation change in the state variables has a stronger effect on future returns than on RP (see similar approach in Nagel and Xu, 2022b). Hence, procyclical optimism and extrapolative beliefs might still cause the return predictability of state variables to a substantial extent, too (see corresponding arguments in Barberis et al., 2015; Adam et al., 2017; and Jin and Sui, 2022). Reconciling these arguments, a combination of behavioral and rational forces seems most promising to explain the empirical evidence: while the extrapolative beliefs of some investors might cause market prices in down-markets to decrease even further, these price effects are not compensated or corrected by rational investors if the low prices comply with the high risk premia they apply.

4.3. Comparison to Subjective Return Expectations

Portfolio optimization arguments imply that an investor's subjective return expectation should equal her subjective risk premium. For this reason, we examine the relationship between analysts' presumed risk premia and subjective return expectations. Many surveys imply that investor expectations are procyclical and extrapolative. Nonetheless, this observation seems to strongly depend on the surveyed investor group. While individual investors and pension funds tend to have extrapolative return expectations (Greenwood and Shleifer, 2014; Amromin and Sharpe, 2014; Da et al., 2021; Andonov and Rauh, 2022), the return expectations of CFOs seem to be acyclical (Graham and Harvey, 2018), whereas economists', financial analysts', and asset managers' expectations tend to be countercyclical (Møller et al., 2022; Wang, 2021; Dahlquist and Ibert, 2022).

Figure 2. Analysts' Presumed Risk Premia and Subjective Return Expectations
This figure depicts analysts' presumed risk premia RP_t and several time-series of subjective return expectations. RP_t is the monthly average of RP_{kt} among all analysts. RP_{kt} is the risk premium that analyst k deems reasonable for a representative investor in month t and is estimated based on Equation (3). NX are subjective excess return expectations of individual investors from Nagel and Xu (2022a), covering several surveys. CFO and Livingston are subjective excess return expectations from the Graham-Harvey CFO survey and the Livingston survey, respectively. The grey bars indicate NBER recessions. The sample period is from January 2003 to December 2020.

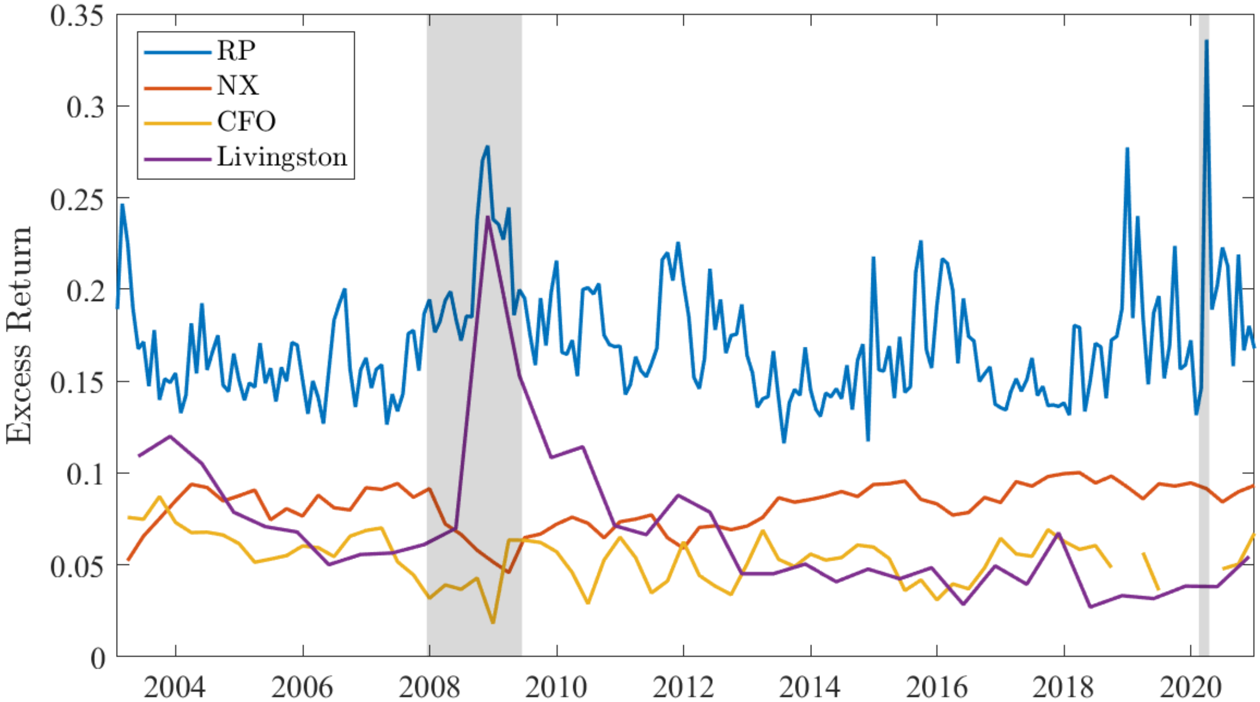


Figure 2 compares RP with the return expectations of individual investors (NX), CFOs (CFO), and economists (Livingston). As these surveys elicit subjective return expectations, we subtract the annual risk-free rate from each measure to obtain excess return expectations that are comparable to RP. Note that NX and CFO are based on quarterly data and that the Livingston survey is conducted semiannually, while we estimate RP on a monthly basis. Figure 2 shows that Livingston and RP both follow a similar pattern over time. They are high during the financial crisis and exhibit countercyclical behavior. On the contrary, CFO and NX are comparably low during the global financial crisis, the longest recession in our sample period, which speaks in favor of a procyclical pattern. Along with the graphical evidence, we provide summary statistics and correlation coefficients of all these time-series and the VIX in Table 3. Indeed, RP is positively correlated with Livingston and negatively correlated with NX and CFO. Furthermore, RP and Livingston are positively correlated with the (countercyclical) VIX, while NX and CFO are negatively correlated with the VIX.

Table 3. Summary Statistics: Analysts' Presumed Risk Premia and Subjective Return Expectations This table reports summary statistics and correlation coefficients for RP, several surveys of subjective return expectations, and the VIX. RP_t is the monthly average of RP_{kt} among all analysts. RP_{kt} is the risk premium that analyst k deems reasonable for a representative investor in month t and is estimated based on Equation (3). NX are subjective excess return expectations of individual investors from Nagel and Xu (2022a), covering several surveys. CFO and Livingston are subjective excess return expectations from the Graham-Harvey CFO survey and the Livingston survey, respectively. SD is the standard deviation and q_x is the x-quantile. The sample period is from January 2003 to December 2020.

	RP	NX	CFO	Livingston	VIX
mean	0.1708	0.0816	0.0537	0.0693	19.1502
SD	0.0320	0.0124	0.0131	0.0414	8.4374
$q_{0.1}$	0.1381	0.0648	0.0361	0.0338	11.9810
$q_{0.5}$	0.1655	0.0848	0.0543	0.0561	16.4800
$q_{0.9}$	0.2154	0.0946	0.0688	0.1137	29.1270

Correlation Coefficients

	RP	NX	CFO	Livingston	VIX
RP	1.0000				
NX	-0.2813	1.0000			
CFO	-0.3225	0.1254	1.0000		
Livingston	0.5918	-0.6678	-0.1038	1.0000	
VIX	0.7212	-0.5145	-0.2599	0.7731	1.0000

To the extent that subjective return expectations equal subjective risk premia (see discussion in footnote 2), the subjective risk premia of economists follow similar patterns as RP while those of individual investors and CFOs strongly differ from RP. Hence, in line with substantial investor heterogeneity, the subjective risk premia of different investors and those deemed reasonable by analysts are very different. Further, the procyclical beliefs of individual investors and CFOs might be the consequence of return extrapolation and resulting excessive optimism such that their lower return expectations during recessions might not reflect a lower risk premium of a representative investor. These investors' subjective risk premia might simply be low because they have decreased their market risk exposure substantially to obtain a subjective optimal portfolio. On the contrary, analysts' comparably high presumed risk premia during recessions cannot be explained by more favorable recommendations: in the Online Appendix, we show that the proportion of favorable recommendations is slightly procyclical. Consequently, as intended by our methodology, RP is not systematically affected by analysts' beliefs in over- versus undervaluation. Thus, RP should reflect fluctuations in a representative investor's risk premium better than belief-based subjective risk premia of specific investor groups. In particular, the positive correlation between RP and subsequent returns lends support to this hypothesis.

5. The Cross-Section of Presumed Risk Premia

We do not only want to know how the risk premia presumed by analysts vary over time, but also which stocks analysts deem particularly risky and how they price common risk characteristics. As risk characteristics in our main analyses, we use market beta ($BETA$), a stock's market capitalization ($SIZE$), and the book-to-market ratio (BM) in accordance with the Fama-French three-factor model. Table 4 provides summary statistics and correlation coefficients for the recommendations (rec), the target price implied expected excess returns (ER), and the three characteristics. Referring to rec, 56% of all recommendations are favorable (i.e., "buy" or "strong buy"). The mean ER of 20% reflects the typical upward-bias in target prices that is frequently documented in the literature (e.g., Brav and Lehavy, 2003; Asquith et al., 2005; Bradshaw et al., 2013; Gleason et al., 2013). rec and ER are positively correlated as an analyst's propensity to issue a favorable recommendation naturally increases in her subjective return expectation. Notably, analysts' subjective return expectations are considerably higher for small compared to big firms. However, this does not directly imply that analysts consider small firms riskier and require a corresponding risk premium as compensation. Since analysts also tend to issue more favorable recommendations with respect to small firms, as alternative explanation, the ER-$SIZE$-correlation might reflect analysts' belief that small firms are undervalued on average. This simple example underlines that the recommendations and target prices need to be examined jointly in order to disentangle beliefs in mispricing from presumed risk premia. Referring to $BETA$ and BM, the correlations with ER and rec indicate that analysts consider high-beta and value stocks riskier because these stocks have higher subjective return expectations that seemingly do not result in more favorable recommendations.

Table 4. Summary Statistics: Cross-Sectional Variables
This table reports summary statistics and correlation coefficients for analyst recommendations (*rec*), target price implied excess returns (ER), $BETA$, $SIZE$, and BM. $BETA$ is a stock's market beta following Frazzini and Pedersen (2014), $SIZE$ is the stock's log market capitalization, and BM is the stock's book-to-market ratio following Fama and French (1993). SD is the standard deviation and q_x is the x-quantile. The sample period is from January 2003 to December 2020.

	rec	*ER*	*BETA*	*SIZE*	*BM*
mean	0.56	0.20	1.12	21.78	0.55
SD	0.50	0.24	0.33	1.81	0.93
$q_{0.1}$	0.00	-0.04	0.75	19.47	0.09
$q_{0.5}$	1.00	0.17	1.08	21.73	0.39
$q_{0.9}$	1.00	0.44	1.54	24.13	1.07
Correlation Coefficients					
	rec	*ER*	*BETA*	*SIZE*	*BM*
rec	1.00				
ER	0.55	1.00			
BETA	-0.01	0.07	1.00		
SIZE	-0.05	-0.25	-0.10	1.00	
BM	-0.07	0.05	0.12	-0.15	1.00

5.1. Prices of Risk

As described in Subsection 2.2.2, for each month t, we estimate the prices of risk for a representative analyst by minimizing the sum of squared error terms in Equation (5). As β_{it}, we either use each of the three risk characteristics individually or all three characteristics at the same time. Recall that the optimization approach relies on several inequality conditions, such that we usually do not obtain a single optimal price of risk γ_t, but a range of optimal values for each month.

We start our analysis by investigating whether the prices of risk associated with a specific characteristic are positive or negative. Hence, for each month t, we track whether the range of optimal estimates implies that the optimal γ_t is positive or negative. Referring to $BETA$, 176 of the 216 months in our sample imply a positive price of risk γ_t, while γ_t is negative for only 16 months. For the remaining 24 months, the optimal range of γ_t covers both positive and negative values. For those months that allow to clearly identify the sign of the optimal γ_t, Panel A in Table 5 reports the proportion of months with a positive price of risk. For $BETA$, this is 91.67%, i.e., only 8.33% imply a negative price of risk. The z-score reported below the proportion shows that 91.67% is significantly different from a naive proportion of 50% that we would expect if analysts did not associate $BETA$ with risk. Hence, analysts typically apply a positive price of risk for $BETA$ when issuing recommendations, implying that analysts deem stocks riskier when they have a higher market beta. This observation lends strong support to one of the central CAPM predictions, that investors should charge higher risk premia for stocks that strongly covary with the market portfolio. This also implies that the rather flat relation between market beta and subsequent returns typically documented in empirical asset pricing research (see, for example, Frazzini and Pedersen, 2014) does not seem to result from investors who all simply ignore market risk when pricing stocks. Our findings rather support theories arguing that market risk is indeed relevant to investors, but that realized stock returns do not reflect these risk premia due to offsetting mispricing effects (for example, see Bali et al., 2017 and Birru et al., 2023).

Table 5. Cross-Sectional Prices of Risk

This table shows summary statistics for the cross-sectional prices of risk γ_t that are estimated for each month t based on Equation (5). The estimation uses the stock's market beta $BETA$, the log market capitalization $SIZE$, or the book-to-market ratio BM as risk characteristic β_{it} in column (1), (2), or (3), respectively. In column (4), the three prices of risk are estimated simultaneously. Panel A reports the proportion of months in which the range of optimal γ_t-estimates is strictly positive relative to all months in which the sign of the optimal γ_t can be clearly identified. The z-scores in parentheses test the null hypothesis that the stated proportion equals 50%. In Panel B, for each month t, γ_t is set to the average value of potentially optimal γ_t-estimates. The table reports the time-series average with corresponding t-statistics in parentheses. Panel C reports time-series correlation coefficients of these monthly γ_t-estimates with the option-implied volatility index VIX. t-statistics are provided in parentheses. The sample period is from January 2003 to December 2020.

Panel A: Signs of the prices of risk	(1)	(2)	(3)	(4)
Proportion of $\gamma_{BETA,t} > 0$	0.9167			0.8942
	(11.55)			(10.84)
Proportion of $\gamma_{SIZE,t} > 0$		0.1921		0.3082
		(-8.19)		(-4.84)
Proportion of $\gamma_{BM,t} > 0$			0.8743	0.9240
			(10.13)	(11.09)
Panel B: Prices of risk	**(1)**	**(2)**	**(3)**	**(4)**
γ_{BETA}	5.32			4.58
	(13.88)			(13.80)
γ_{SIZE}		-0.39		-0.21
		(-9.57)		(-5.32)
γ_{BM}			3.11	2.66
			(13.84)	(14.81)
Panel C: Time-series correlations	**(1)**	**(2)**	**(3)**	**(4)**
$Corr(\gamma_{BETA,t}, VIX_t)$	0.4842			0.2928
	(8.10)			(4.48)
$Corr(\gamma_{SIZE,t}, VIX_t)$		-0.0809		-0.0252
		(-1.19)		(-0.37)
$Corr(\gamma_{BM,t}, VIX_t)$			0.3880	0.2560
			(6.16)	(3.87)

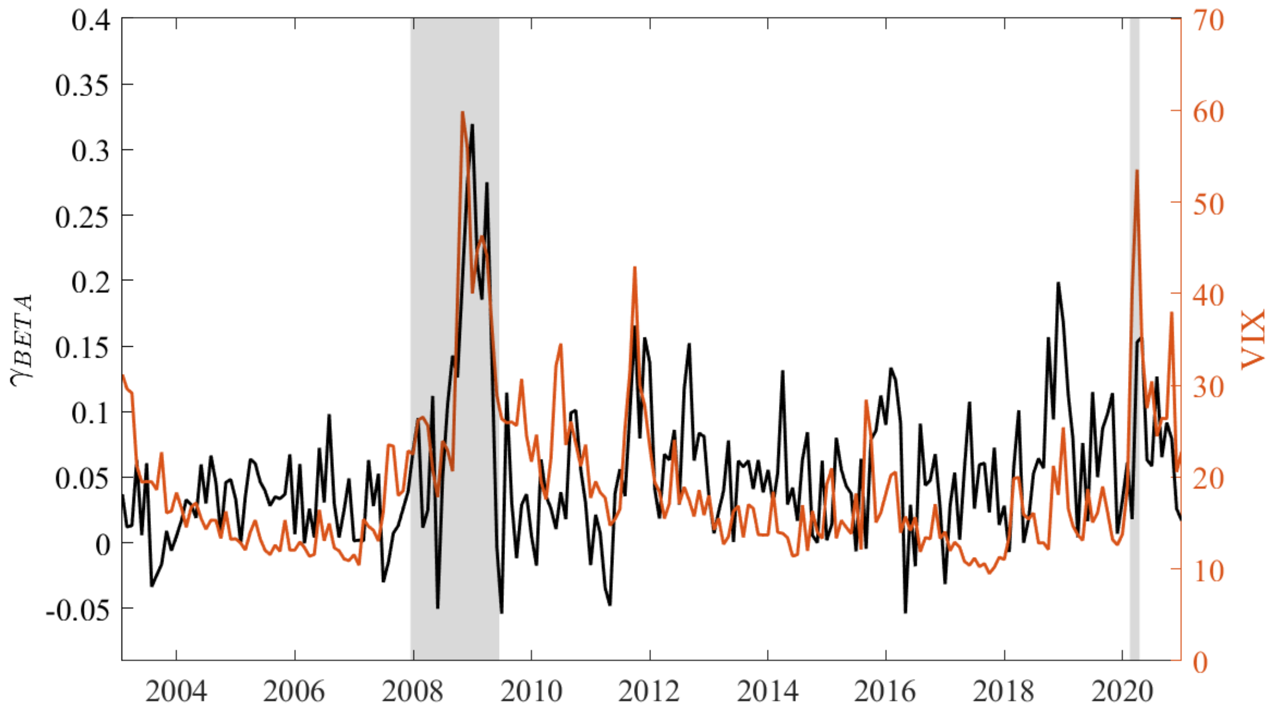
Referring to $SIZE$, we find that only 19.21% of the monthly prices of risk are strictly positive. Hence, 80.79% are strictly negative. This proportion is again significantly different from 50% ($z = -8.19$). This observation implies that analysts typically deem stocks more risky when they have a smaller market capitalization. Hence, our findings are in line with risk-based theories for the size premium (for a short review of such theories, see van Dijk, 2011) as at least the group of financial analysts seems to consider small stocks comparably risky. Finally, the book-to-market ratio goes along with a positive price of risk (87.43% of months with $z = 10.13$). Analysts therefore seem to consider value stocks riskier than growth stocks such that our findings support risk-based theories of the value premium (see, for example, Zhang, 2005; Petkova, 2006).

The evidence in columns (1) to (3) in Panel A of Table 5 is based on each risk characteristic separately. Hence, we implicitly assume that analysts consider only one stock characteristic in their risk assessment at a time. In a more realistic setting, analysts might consider multiple sources of risk and base their risk assessment on the combination of these characteristics. Therefore, column (4) reports percentages of positive prices of risk from optimizations where β_{it} is a vector constituting of $BETA$, $SIZE$, and BM. In line with the previous results, the implied signs of the prices of risk remain largely the same, i.e., high-beta, small, and value stocks are considered comparably risky by financial analysts. Again, each proportion significantly differs from the null result of 50%.

Beyond the sign of γ as examined in Panel A of Table 5, Panel B examines its magnitude, that is, γ_t is calculated as the average value from the range of optimal estimates and Panel B presents the resulting time-series averages. γ_{BETA} is 5.32% on average, which is significantly different from zero ($t = 13.88$). This means that an analyst presumes an investor to be indifferent between two stocks, that only differ in $BETA$ and expected return, when one stock has both a higher $BETA$ of one unit and a higher expected return of 5.32%. As analysts' target prices refer to an annual horizon, our estimation implies that the annual market price of risk presumed by analysts equals 5.32%, i.e., their presumed security market line is considerably upward-sloping and not flat. This magnitude even fits the historical equity risk premium well: for example, Pástor and Stambaugh (2001) provide an estimate between 4% and 6%.

For $SIZE$, we find a negative price of risk. When a stock's $SIZE$ is one unit larger compared to an otherwise identical stock, the analyst's presumed risk premium is 0.39%

Figure 3. Time-Series of Analysts' Presumed Price of Risk for *BETA* and the VIX
This figure depicts $\gamma_{BETA,t}$ and the option-implied volatility index VIX. The cross-sectional prices of risk $\gamma_{BETA,t}$ are estimated for each month t based on Equation (5) using a stock's market beta $BETA$ as risk characteristic β_{it}. For each month t, $\gamma_{BETA,t}$ is set to the average value of the range of potentially optimal $\gamma_{BETA,t}$-estimates. The grey bars indicate NBER recessions. The sample period is from January 2003 to December 2020.



higher for the smaller stock. Considering that the $SIZE$ definition is based on the natural logarithm, increasing a stock's market capitalization by factor 10, decreases the required rate of return by 0.90%. For BM, the average price of risk is 3.11%. Hence, a one unit difference in book-to-market ratio between two stocks can be offset by a 3.11% difference in expected returns. Each of the estimated prices of risk significantly differs from zero. The same holds true if we conduct a joint estimation in column (4). Each γ decreases in absolute magnitude but remains on a similar level and statistically significant. Comparing the coefficients' magnitude in column (4), a one-standard deviation increase in $BETA$, $SIZE$, and BM, changes the analysts' presumed risk premium by 1.51%, -0.38%, and 2.47%, respectively. In conclusion, these findings indicate that analysts consider multiple risk characteristics when issuing stock recommendations and that $BETA$, $SIZE$, and BM are considered as risk proxies in line with the interpretation of Fama and French (1993).

While Panel B presents time-series averages of γ_t, our estimation also allows to examine time-series fluctuations in the presumed cross-sectional return premia. While theoretical predictions are not clear with respect to $SIZE$ and BM, we expect that analysts' apply a higher market price of risk when the market's overall risk is high. This idea is in line with economic intuition on risk premia and also follows from our time-series analyses in Section 4: since analysts require higher returns during high-volatility periods and recessions, these higher risk premia should disproportionately affect high-beta stocks. In line with these arguments, Panel C of Table 5 shows that the time-series correlation between γ_{BETA} and the VIX is 48.42% ($t = 8.10$). Even if we jointly estimate γ_{BETA}, γ_{SIZE}, and γ_{BM} (column (4)), the correlation amounts to significantly positive 29.28%. The time-series dynamics of the cross-sectional market price of risk are also graphically illustrated in Figure 3. It shows both γ_{BETA} and the VIX and confirms that the presumed price of risk for $BETA$ is countercyclical. In conclusion, our time-series and cross-sectional analyses paint a fairly rational and consistent picture with respect to analysts' consideration of risk: in line with rational theories on a classical risk-return tradeoff, they require higher risk premia in times of high market volatility and for high-beta stocks.

6. Conclusion

We provide evidence on the time-series and cross-sectional properties of analysts' presumed risk premia. Our new method allows us to retrieve these risk perceptions by combining recommendation and target price data. We find that analysts' presumed risk premia are strongly countercyclical. Hence, in line with rational models explaining market return predictability, the presumed risk premia are comparably high in down-markets, high-VIX periods, and in times of low price-dividend ratios. In the cross-section, analysts seem to consider high-beta, small, and value stocks riskier than their low-beta, big, and growth counterparts. In recent years, many behavioral theories have been proposed to explain the time-series predictability associated with cyclical state indicators as well as size and value effects in the cross-section of realized stock returns. Our findings on financial analysts indicate that these empirical observations partly reflect a compensation for risk as implied by corresponding rational models.

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