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Frank Weikai LI
Singapore Management University, wkli@smu.edu.sg

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Macro Disagreement and the Cross-Section of Stock Returns*

Frank Weikai Li†

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Abstract

This paper examines the effects of macro-level disagreement on the cross-section of stock returns. Using forecast dispersion measures from the Survey of Professional Forecasters database as proxy for macro disagreement, I find that when disagreement about a macroeconomic factor is high, stocks that have high loadings on that macro-factor earn lower future returns relative to stocks with low loadings and vice versa. This negative relation between returns for macro-factors and macro-level disagreement is robust and exists for a large set of macroeconomic risk factors. These findings are consistent with the model of Hong and Sraer (2012), in which high beta stocks are more prone to speculative mispricing than low beta stocks due to their greater sensitivity to aggregate disagreement, resulting in lower subsequent returns for high beta stocks during high aggregate disagreement states.

JEL classification: D03, G12

Keywords: Macro Disagreement, Macroeconomic risk factors, Mispricing, Behavioral Finance

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†PhD student. Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong. Email:wliaj@ust.hk Tel:(852)65779764

1 Introduction

This paper studies how investors' dispersion of beliefs on certain important macroeconomic variables affects prices in the cross-section of stocks. Asset pricing theories posit that pervasive macroeconomic factors should be systematic risk factors that get priced in equilibrium. For example, in the Merton (1973) Intertemporal Capital Asset Pricing Model (ICAPM), expected stock return is determined by its return covariance with innovation in state variables that reflect time-varying investment opportunities. Macroeconomic factors (such as industrial production growth and expected inflation) naturally serve as a proxy for such state variables. The consumption-based asset pricing model predicts that an asset's return covariance with consumption growth rate determines its riskiness and, hence, expected return (Breeden, 1979). Even the Sharpe-Lintner Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965) can be viewed in some way as a macro factor-based asset pricing model in which the only state variable is the return on the market portfolio.

Despite the theoretical importance of macroeconomic risk factors in explaining the cross-section of expected asset returns, empirical evidence on the existence of risk premia on macro-factors is mixed and not robust to the different econometric methodologies used. One of the most influential papers is by Chen, Roll, and Ross (1986), who find exposures to five macroeconomic factors including industrial production growth, the change in expected inflation, unexpected inflation, the yield spread between a long-term and a short-term government bond, and the yield spread between low credit rating and high credit rating bonds, are priced in the cross-section of stock returns. Shanken and Weinstein (2006), however, find that the results of Chen, Roll, and Ross (1986) are not robust to alternative test assets and the way the betas are estimated. Macro factor-based asset pricing models also fail to explain certain cross-sectional stock return anomalies such as momentum (Griffin, Ji and Martin, 2003) and the profitability premium (Wang and Yu, 2013). Most studies commonly attribute the empirical failure of the macro factor-based asset pricing model to the large measurement errors in macroeconomic factors, the differences between a theoretical definition and its empirical counterpart, or the low frequency in reporting macroeconomic variables.

This paper offers a novel way to look at the price of macroeconomic risk factors in cross-section of stocks, motivated by Hong and Sraer (2012). They argue that the speculative nature of high beta stocks offsets the risk-sharing effect, leading to the high beta-low return puzzle. In their model, investors disagree on the mean value of a common market factor. Because high beta stocks have high loadings on this market factor, investors naturally disagree more on the cash flows of high beta stocks when disagreement about the market factor is high.[1] As a result, the value of high beta stocks more likely is determined by optimists who have a positive view of the market factor. Arbitragers are not able to fully correct the mispricing due to short-selling constraints and other market frictions, resulting in lower subsequent returns for high beta stocks relative to low beta stocks. Extending Hong and Sraer (2012)'s argument regarding general macroeconomic factors, I hypothesize that high macro beta stocks will experience lower future returns relative to low macro beta stocks when disagreement on this macro factor is high. Furthermore, high macro beta stocks should earn higher average returns during normal times when risk-return trade-off works. Depending on the magnitude of macro-level disagreement and how sensitive these high macro beta stocks are to the macro-factors, the overpricing effect can even dominate the risk-return trade-off mechanism. The unconditionally insignificant price of risk found on these macro-factors could be due to the offsetting effects on high macro beta stocks coming from two forces: risk compensation and speculative mispricing.

Empirical evidence strongly supports my hypothesis. While the unconditional return differences between the low and high macro beta stocks are all close to zero, I find that, for positively priced macroeconomic factors, high macro beta stocks earn higher (lower) future returns during low (high) disagreement months relative to low macro beta stocks. I use the cross-sectional forecast dispersion measure from the Survey of Professional Forecasters (SPF) database to proxy for investors' disagreement on macro-factors. A zero-investment portfolio that longs stocks in the highest macro beta decile and shorts those in the lowest beta decile generates positive excess returns following low macro disagreement months, while the excess return on this long-short portfolio is significantly lower or even negative following

[1] The model of Hong and Sraer (2012) predicts that an individual stock's sensitivity to aggregate disagreement should be positively related to its absolute value of beta, not beta itself. For the market factor and most positively priced macro-factors, because stock returns are positively correlated with that factor, high (low) absolute beta stocks correspond to high (low) beta stocks.

high disagreement months. The negative relation between risk premium for macro-factors and macro disagreement is robust and exists for a large set of macroeconomic risk factors, including industrial production growth, labor income growth, short-term interest rate, real GDP growth, real nonresidential fixed investment growth and change of expected inflation. Industrial production growth, for example, has a high-minus-low monthly excess return of 0.57% following the lowest quartile of disagreement months. It has a negative monthly return of -1.01% following the highest quartile of disagreement months. The excess return difference in these two disagreement states is -1.58% and statistically significant at the 5% level. Results on other macro-factors show similar or even stronger patterns.

I conduct further time-series regression analyses to systematically examine the relation between macro-factor risk premia and disagreement, controlling for other well-known return predictability effects. My results show a reliable negative relation between the high-minus-low portfolio excess return and the lagged macro disagreement measure for positively priced macro-factors. Of the six macroeconomic factors examined in this paper, five have significant regression coefficients on the lagged macro disagreement measure. For example, the coefficient on dispersion for industrial production growth is -0.007 (t=-2.59) in the univariate predictive regression. A one standard deviation increase of dispersion on industrial production growth leads to a 0.66% reduction of the monthly excess return on the high-minus-low portfolio. The results barely change or even become stronger when I control for Fama-French (1993) three factors or Carhart (1997) four factors in the predictive regression, indicating that my findings are not driven by some well-known cross-sectional stock return predictability patterns in the data.

The effect of macro disagreement on the cross-section of stock returns I document in this paper could simply reflect time-varying risk premium, instead of the mispricing story advocated by Hong and Sraer (2012) and my paper. My macro disagreement measures could also be interpreted as economic uncertainty measures.[2] They are highly correlated with several business cycle indicators, such as the National Bureau of Economic Research (NBER) recession dummy, the dividend/price ratio (D/P), and the default premium. However, the time-varying risk premium explanation cannot fully account for the return predictability

[2]See Bali et al. (2014) for such an interpretation.

I identify in this paper. First, macro disagreement tend to be high during recessions and market downturns when underlying economic uncertainty also increases. The time-varying risk premium story predicts that the return spread between high and low macro beta stocks should be higher following high disagreement than following low disagreement periods. My empirical results are contrary to this prediction. Furthermore, I control for an extensive list of lagged macroeconomic state variables that have been found to predict time-varying equity risk premia in the predictive regressions, including the dividend/price ratio, the term spread, the default premium, the detrended one-month Treasury-bill rate, the consumption-to-wealth ratio, the Chicago Board Options Exchange (CBOE) Market Volatility Index (VIX), and the TED spread. The main results survive even after I control for all these lagged return predictors.

My results show that despite an insignificant average price of risk for macroeconomic factors, some of these factors are priced during low disagreement periods when the risk-sharing incentive dominates, lending support to the traditional asset pricing theories. When macro disagreement is high, however, high macro beta stocks become increasingly speculative and overpriced due to their larger sensitivity to macro-factors, resulting in lower future returns. To pin down the underlying mechanism of the negative relationship between macro disagreement and macro factor risk premium, I look at how stock-level disagreement relates to macro-level disagreement, using the standard deviation of analysts' forecast of long-term growth (LTG) rate of earnings per share (EPS) from the Institutional Brokers' Estimate System (I/B/E/S) as a proxy for stock-level disagreement. Stocks with high absolute macro betas have higher stock-level disagreement, and the difference of stock-level disagreement between high and low macro beta stocks becomes larger as macro disagreement increases. Previous studies (Diether, Malloy and Scherbina 2002) document that stocks with high analyst forecast dispersion have lower subsequent returns in the cross-section. This test further supports my hypothesis that high macro beta stocks earn lower future returns precisely because these stocks are subject to higher stock-level disagreement arising from their high exposure to macro disagreement.

This paper contributes to several strands of the literature. My work builds on the model of Hong and Sraer (2012) and shows that the central prediction of their model holds well for a large set of macroeconomic factors in addition to the aggregate market factor. My paper differs from their paper in several important ways, however. My interest is in the price of risk for fundamental macroeconomic factors, not just an aggregate market factor. To the extent that stocks have exposure to multiple systematic risk factors, my paper provides independent evidence that disagreement on these important macro-factors could also have a pervasive effect on asset prices and cross-sectional risk-return trade-off. Also, while Hong and Sraer (2012) construct an aggregate disagreement measure by weighting individual stocks' forecast dispersion using their market betas, my measures of macro disagreement are taken directly from survey data. My macro disagreement measures are more likely exogenous to the financial market, thus suggesting causality from macro-level disagreement to stock-level disagreement. Causality is less clear for a macro disagreement measure constructed using individual stocks' disagreement measures. While several previous studies have examined stock-level disagreement and its impact on stock prices (e.g., Diether, Malloy and Scherbina, 2002; Chen, Hong and Stein, 2002; Goetzmann and Massa, 2005), few studies look at the effect of disagreement over macroeconomic states on asset prices. My study is also related to the investor sentiment literature showing that time-varying aggregate sentiment combined with limits to arbitrage could affect the cross-sectional as well as time-series risk-return trade-off. Baker and Wurgler (2006, 2007) find stocks that are difficult-to-value and hard-to-arbitrage are more subject to changes in investor sentiment and, hence, mispricing. Yu and Yuan (2011) and Stambaugh, Yu and Yuan (2012) document that the risk-return tradeoff in aggregate stock market and the profitability of certain cross-sectional stock return anomalies depend on sentiment. The predictive power of macro disagreement is unaffected when I control for the sentiment index, however.

The rest of the paper proceeds as follows. Section 2 reviews the relevant literature and develops the main hypotheses to be tested in this paper. Section 3 describes the data, how I choose macroeconomic factors, and how I construct macro beta-sorted portfolios as test assets. In Section 4, I show that high macro beta stocks earn lower future returns than low macro beta stocks following high disagreement states, using portfolio sorts, predictive regressions, and the Fama-Macbeth (1973) two-stage regression approach. In this section, I also examine the role played by macro disagreement on the relation between stock-level disagreement and macro beta. In Section 5, I conduct robustness tests and rule out alternative explanations. The last section concludes.

2 Hypothesis Development

2.1 Disagreement, Short-Sales Constraints and Asset Prices

A large and growing literature explores the effect of investor disagreement, or heterogeneous beliefs on asset prices. Miller (1977) argues that when investors have divergences of opinion and short-selling is not allowed, stock prices in equilibrium will reflect only the optimists' view and, hence, will more likely be overvalued. The central prediction from the Miller (1977) model is that the higher the differences of opinion, the more overvalued the stock will be contemporaneously, and the lower its future returns. Subsequent empirical studies generally find evidence supporting Miller's prediction that stocks with higher analyst forecast dispersion or lower breadth of ownership earn lower risk-adjusted return (Chen, Hong, and Stein, 2002; Diether, Malloy, and Scherbina, 2002). Recently, Yu (2011) finds that Miller's prediction also holds for the market portfolio, in which high aggregate disagreement predicts lower subsequent aggregate equity returns. In a dynamic setting, Harrison and Kreps (1978) show that stock price could even exceed the most optimistic investors' valuation as these investors anticipate selling the stock to a more optimistic trader in the future. The key insight in the Harrison and Kreps model is that the combination of short-sales constraints and fluctuating heterogeneous beliefs create a valuable "resale option" embedded in stock prices, which can push the price above the most optimistic investors' valuation of fundamentals. Recent contributions to this line of research include Morris (1996), Scheinkman and Xiong (2003) and Hong, Scheinkman, and Xiong (2006).[3]

A necessary condition for investors' difference of opinion to have an asymmetry effect on asset prices is short-selling constraints. Otherwise, pessimists could simply short sell

[3] Empirical evidence supporting the heterogeneous beliefs-based bubble theory include Lamont and Thaler (2003), Ofek and Richardson (2003) and Xiong and Yu (2011).

overvalued stocks aggressively and drive price to consensus view. Numerous studies have argued pervasive short selling costs exist in the stock market, due to institutional constraints, trading costs, or arbitrage risks. Many institutional investors such as mutual funds are prohibited by charters from taking short positions in stocks. Almazan et al. (2004) find that 69% of mutual funds are not permitted to short sell. Even for the 21% of mutual funds that are allowed to short sell, only 9.6% of them ever shorted. Furthermore, short selling can be too costly to implement for certain kinds of stocks. D'Avolio (2002) finds that the rebate rate for short selling can become economically significant when the short-selling demand increases relative to the supply of lendable shares. Short sellers also face the "uptick rule" and recall risk.[4] Arbitrage risk can deter short-selling behavior even in the absence of explicit short-selling costs. One type of arbitrage risk is "noise trader risk", which is the temporary worsening of the initial mispricing caused by sentiment-driven investors, as emphasized in De Long et al. (1990). As long as arbitrageurs have finite horizons, they always worry th the mispricing they are trying to arbitrage away will get worse in the short run, forcing them to liquidate their positions prematurely and suffer losses. In practice, most of the sophisticated arbitrageurs are professional investors who manage clients' money. This means that investors might withdraw money from their funds precisely when mispricing widens and the arbitrageurs suffer losses temporarily (Shleifer and Vishny, 1997). Fear of premature liquidation and temporary losses limits the size of arbitrageurs' initial positions, rendering the arbitrage effect less powerful in reestablishing equilibrium prices.[5]

2.2 Macro Disagreement and the Cross-Section of Stock Returns

While the aforementioned studies mainly look at stock-level disagreement and its impact on asset prices, my study focuses on disagreement about macroeconomic state variables.

[4]The "uptick rule" refers to short selling not being allowed except on an uptick. Regarding recall risk, the lender has the right to recall his shares at any time. In the case of recall, the short seller must either locate another lender who is willing to provide the same security or cover its position by directly purchasing from the market. The short seller thus faces the risks of having to close out his positions at a loss when lenders recall shares in a rising market.

[5]Consistent with the argument that short-selling constraints deter arbitrage activities, Nagel (2005) finds the under-performance of stocks in the short-leg of several cross-sectional anomaly strategies is most pronounced among stocks with low institutional ownership. Recently, Drechsler and Song (2014) document that many anomalies exist only among stocks with high short fees.

Substantial evidence, from both anecdotal stories and survey data, suggests that economists and investors alike tend to disagree on certain important macroeconomic state variables. Macro-level disagreement can come from various sources, such as overconfidence, infrequent updating of information, or differential interpretation of public signals (Kandel and Pearson, 1995).[6] In this paper, I do not model the source of macro-level disagreement, but take it as given and study its effect on the cross-section of stock prices.

Hong and Sraer (2012) assumes the dividend process of individual firms follow one factor structure, with differential exposures to the common market factor. Investors disagree only on the common market factor and stocks with high exposure to the market factor naturally subject to more stock-level disagreement. I extend their argument further, assuming that the dividend process of individual firms have exposures to not only the market factor, but also other pervasive economy-wide factors such as GDP growth and inflation rate:

$$d_i = d + b_i * Z + c_i * X + \epsilon_i \tag{1}$$

Here d_i is stock i's dividend, Z is the market factor and X is the macro factor. The idiosyncratic component in stock i's dividend is ϵ_i. b_i and c_i are individual stocks' cash flow exposure to the common market and macro factor, respectively. When investor disagreement on macro factor X is high, other things being equal, stocks that have high exposures to the macro factor will also subject to more stock-level disagreement. In other words, stock-level disagreement can be decomposed into a systematic component and an idiosyncratic component, with the former being a product of macro-level disagreement and the stock's loading on that macro-factor. My first hypothesis follows directly from this decomposition.

Hypothesis 1: Other things equal, high absolute macro beta stocks have higher stock-level disagreement when macro disagreement is high.

My second hypothesis combines the insight from the disagreement and short-sales constraints literature. Because high macro beta stocks are subject to a greater divergence of

[6] In the Mankiw and Reis (2002) model, only a subset of agents updates information at a given time due to the costs in collecting and processing macroeconomic information. When the macroeconomic environment changes, disagreement arises naturally between the agents who have updated information and those who have not done so.

opinion on macro-factors, their valuations more likely tend to be set by optimists than low macro beta stocks. This effect is stronger when macro disagreement is high. Consequently, the future returns of high macro-beta stocks are lower following high macro disagreement periods than following low disagreement periods. When macro disagreement is low, however, risk-return trade-off should work and high macro beta stocks should earn higher average returns than low macro beta stocks to compensate for the larger systematic risks embedded in these stocks.

Hypothesis 2: For positively priced macro-factors, the return differential between the high and low macro beta portfolios will be lower following high macro disagreement states than following low macro disagreement states.

In the subsequent sections, I take the two hypotheses to the data and examine the conditioning role played by macro disagreement on the cross-sectional risk-return trade-off, and I consider whether this could shed light on the puzzle with respect to the pricing of macro-factors. That is, high macro beta stocks do not earn higher average returns than low macro beta stocks unconditionally.

3 Data Description and Empirical Approach

In this section, I describe the measures of macro-level disagreement, and my choice of macroeconomic factors, and I outline how I construct macro-beta sorted portfolios as test assets.

3.1 Measuring Macro Disagreement

My measures of macro disagreement are taken from the Survey of Professional Forecasters (SPF) database, currently maintained by Federal Reserve Bank of Philadelphia. The Survey of Professional Forecasters is the oldest quarterly survey of macroeconomic forecasts in the United States.[7] In addition to the mean and median forecasts of individual responses from

[7]Market economists from Wall Street financial firms, banks, economic consulting firms, independent research institutes and Fortune 500 companies provide the forecasts as part of their daily jobs. The survey began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research at that time. The Federal Reserve Bank of Philadelphia took over the survey in 1990.

each economist, this dataset contains the cross-sectional measures of forecast dispersion for several important macroeconomic variables. The cross-sectional forecast dispersion measure is defined as the difference between the $75th$ Percentile and $25th$ percentile of the forecasts. This measure directly captures market participants' belief dispersions on various aspects of the macro-economy and is ideal for the purpose of my study. Detailed discussions on this dataset can be found in Croushore (1993). The SPF dataset contains forecasts on both the level and the growth rate of macroeconomic variables. For industrial production, GDP, and nonresidential fixed investment, I use the disagreement measures for the quarterly growth rates of these variables. For Treasury bill rate and inflation rate, I use the disagreement measures for the levels of the rates. The SPF data doesn't contain disagreement measure for labor income growth, so I use forecast dispersion on unemployment rate as a proxy for disagreement for labor market conditions. At each survey date, the quarterly forecast horizons are one to four quarters ahead. I take the mean value of the cross-sectional forecast dispersion available at all forecast horizons as the measure of macro disagreement. The time series of these forecast dispersion measures starts from the third quarter of 1981 and ends in the last quarter of 2011.[8]

I construct several important macroeconomic state variables in addition to the macro disagreement measure. The consumption growth rate (Con_g) is the monthly per capita growth of nondurable consumption and service, seasonally adjusted. The expected market volatility (Mkt vol.) is the fitted value from modeling the variance of the value-weighted CRSP index return as GARCH (1,1) process. The Dividend/Price ratio (D/P) is the difference between the log of dividends and the log of prices, where dividends are 12-month moving sums of dividends paid on the S&P 500 index. The dividend/price ratio is available on Amit Goyal's website. Following Yu (2011), I construct the aggregate disagreement measure (Agg Disp.) by value-weighting analysts' forecast dispersion on individual stock's EPS long-term growth rate (LTG) in each month. The investor sentiment index (Sentiment) is

[8]During my sample period from 1981Q3 to 2011Q4, the average number of macro forecasters is 35, with a minimum of 9 and a maximum of 53 forecasters. Most of the time the number of forecasters is greater than 30, but during the transition period from 1987Q4 to 1990Q3 (when the Philadelphia Fed took over the survey), the number is significantly lower. This could mechanically reduces the forecast dispersion on macro variables, but my results still hold if this transition period is excluded.

the market-based sentiment measure constructed by Baker and Wurgler (2006, 2007). I use the monthly sentiment index which has been orthogonalized with respect to a set of macroeconomic conditions.[9] Term spread is the yield spread between the ten-year Treasury bond and the one-year Treasury bond. The default premium is the yield spread between Moody's Baa and Aaa corporate bonds. The TED spread is defined as the difference between the three-month London Interband Offered Rate (LIBOR) and the three month T-bill rate. The VIX index is constructed so that it measures the market's expectation of 30-day volatility implied by at-the-money S&P 500 index option prices.[10] The sample period is from the third quarter of 1981 to the last quarter of 2011.[11]

Table 1 presents the summary statistics of the six macro disagreement measures and other macro variables. As can be seen in Panel A, the minimum and maximum value and the standard deviation of disagreement measures are large relative to their mean value, indicating large time variation in macro disagreement. Panel B reports the pairwise correlation of these variables. The disagreement measures for different macro-factors are correlated, but they also contain independent information. The correlation between my macro disagreement measure extracted from survey data and the bottom-up aggregate stock market disagreement measure is moderate. The aggregate disagreement measure captures investors' differences of opinions on the earnings growth potential of the whole economy, which may not necessarily coincide with forecast dispersion on other aspects of the macro-economy such as inflation or unemployment rate. The correlation with the Baker-Wurgler sentiment index is high, which is consistent with a disagreement-based explanation of investor sentiment shifts. The correlation of macro disagreement with expected market volatility and VIX index is also very high. This is to be expected, as disagreement among agents naturally increases as economic uncertainty increases. My macro disagreement measures are highly correlated with the D/P ratio and the default premium, indicating that macro disagreement tends to increase during

[9]For more details on the construction of the index, see Baker and Wurgler (2006). We thank Malcolm Baker and Jeffrey Wurgler for making the Sentiment Index publicly available.

[10]The VIX index is backfilled only to 1990. Prior to 1990, I use the volatility index based on the S&P 100 index, which is available at the CBOE's website, starting from January 1986.

[11]The monthly sentiment index is available from July 1965 to December 2010. The aggregate disagreement measure is available from December 1981, and the time series of VIX index and TED spread starts from January 1986.

recessions when the risk premium is also high. Only moderate correlation exists between macro disagreement and the consumption growth rate.

[Insert Table 1 near here]

Figure 1 plots the time series of six macro disagreement measures, with NBER-dated recession periods in the shaded area. The figure clearly shows large inter-temporal shifts in disagreement level for all six macro factors across time. As expected, macro disagreement is usually high during recession periods such as the recent financial crisis.[12] However, for real GDP growth and investment growth factors, disagreement is also high during the boom times, such as the dot-come bubble period in the late 1990s.

[Insert Figure 1 near here]

Panel C of Table 1 report the autocorrelations of these macro disagreement measures, up to 12 lags (three years). The first order autocorrelation is around 0.5 for almost all the disagreement measures, indicating a half-life of one quarter. The persistence of the macro disagreement measure from the SPF dataset is strikingly lower than that of the aggregate disagreement measure in Yu (2011). This further supports the notion that my macro disagreement measures capture different aspects of the macro-economy from the disagreement measure for the aggregate stock market.

Other data used in this paper come from various sources. U.S. stock monthly return data are from CRSP and include all the common stocks listed on the NYSE, AMEX, and NASDAQ exchanges from January 1976 to December 2011. Excluded are closed-end funds, real estate investment trust, American depository receipts, and foreign stocks. The data on macroeconomic variables are from the Federal Reserve Bank of St. Louis, Bureau of Economic Analysis, and Bureau of Labor Statistics. I use the standard deviations of analysts forecast of EPS long-term growth rate (LTG) as the proxy for stock-level disagreement. These data are provided in the I/B/E/S database. I use analyst forecasts data from December 1981 through December 2011.

[12] Regressions of macro disagreement measures on a dummy variable indicating NBER-dated recession periods all yield significant positive coefficients.

3.2 Macroeconomic Factors and Factor Mimicking Portfolios

The macroeconomic factors considered in this paper are industrial production growth (IPG), labor income growth (LaIncome), short-term interest rate (Tbill), real GDP growth (GDP), real nonresidential fixed investment growth (Investment) and change in expected inflation (DEI).

The choice of macroeconomic factors is governed by both asset pricing theories and data availability for the disagreement measures. Among the six macro-factors, industrial production growth and change in expected inflation are also studied by Chen, Roll and Ross (1986) in their seminal study.[13] Following Chen, Roll, and Ross (1986), I define industrial production growth as $IPG_t = logIP_t - logIP_{t-1}$, where IP_t is the index of industrial production at month t. I lead industrial production growth by one month since IP_t actually is the flow of industrial production during month t.

I measure inflation rate from month t-1 to month t as $I_t = logCPISA_t - logCPISA_{t-1}$, where $CPISA_t$ is the seasonally adjusted consumer price index at time t. Change in expected inflation is defined as $DEI_t = E[I_{t+1}|t] - E[I_t|t-1]$. The expected inflation $E[I_t|t-1]$ is the one month Treasury bill rate minus ex-ante real rate. I use the Fama and Gibbons (1984) method to measure the ex-ante real rate. I use the change in expected inflation instead of unexpected inflation because it is more closely aligned with the disagreement measure on inflation expectation.

Mayers (1972), Campbell (1996), Jagannathan and Wang (1996) and Santos and Veronesi (2006) argue that human capital should be part of the market portfolio, and that stocks' covariance with the return on human capital should be priced in the equilibrium. Labor income growth is used as a proxy for return on human capital in these studies and is found to be positively priced in cross-sectional tests. I follow Jagannathan and Wang (1996) and measure labor income growth as $LaIncome_t = [L_{t-1} + L_{t-2}]/[L_{t-2} + L_{t-3}]$, where L_{t-1} is the monthly per capita labor income at month t-1.

The short-term interest rate factor is included because it can predict future stock returns

[13] The forecast dispersion measures for the term spread and default spread start from the first quarter of 1992 and the first quarter of 2010, respectively. Due to the limited sample period, in this paper I do not include these two factors, which are also studied by Chen, Roll, and Ross (1986).

(Fama and Schwert, 1977; Campbell, 1987) and may serve as a state variable capturing time-varying investment opportunities (Ferson, 1989). Recently, Lioui and Maio (2012) build a general equilibrium asset pricing model including an interest rate as a priced factor and find that stocks' loadings on this factor can explain the cross-section of stock returns well. I take the first difference of a three-month Treasury bill rate as a proxy for short-term interest risk factor.[14]

Real GDP growth is a pervasive systematic risk factor that should be positively priced. Liew and Vassalou (2000) and Vassalou (2003) find that returns on Fama-French factors such as SMB and HML can predict future GDP growth rate and interpret the evidence as supporting a GDP risk-based explanation of the size effect and value premium. I include real GDP growth rate as an additional macroeconomic risk factor.

Finally, I consider real nonresidential fixed investment growth as motivated by a production-based asset pricing model.[15] Both GDP growth and investment growth rate at quarter t are defined as the log difference of the level between quarter t and t-1.

Most macroeconomic variables are subject to large measurement errors, infrequent reporting, and summation bias (Breeden et al. 1989), so I do not use them directly in the empirical tests. Following Breeden et al. (1989) and Lamont (2001), I create mimicking portfolios to track the underlying macro-factors by estimating the coefficient w in the regression:

$$y_t = a + wX_t + u_t \tag{2}$$

where y_t is the underlying macro-factor and X_t is the excess returns on a set of base assets. The corresponding portfolio return wX_t is the portfolio that has the maximum in-sample correlation with the underlying macroeconomic factor. I use the Fama-French ten industry portfolios, a value-weighted market portfolio, Fama-French 25 size and book-to-market

[14] I do not use sophisticated time series methods to extract the residual part but instead use the monthly first difference or growth rate as a measure of unanticipated movements of macro variables. The reason is because the first order autocorrelation of the level of these macro variables are high. Also, as argued by Chen, Roll, and Ross (1986), using sophisticated time series model to filter out the expected movement in an independent variable may lead to errors due to mis-specification of the estimated equation for determining the expected movement.

[15] Cochrane (1996) finds that the growth rate of aggregate investment can help explain the cross-section of stock returns.

sorted portfolios, and five bond portfolios as the base assets. The Fama-French portfolio returns are available on Kenneth French's website. The five bond portfolios are from the Lehman Brothers Corporate Bond indexes database, including four investment-grade tiers (AAA, AA, A, BBB) and one non-investment-grade credit tier. I run the regression (2) using the full sample data to get the estimated coefficient w.[16] This factor mimicking portfolio approach has been widely used by previous studies on the pricing of non-return risk factors, including Vassalou (2003) and Ang et al. (2006). Another advantage of using factor mimicking portfolios is that quarterly observations of real GDP growth and investment growth rate can be transformed into monthly frequency by simply multiplying the estimated portfolio weights w with monthly excess returns on the base assets.

Table 2 reports the correlations among the six macro-factors. Panel A shows the correlations among the original macroeconomic factors, Panel B, the factor mimicking portfolio returns. As expected, the correlations among industrial production growth, real GDP growth and investment growth are high, and change in expected inflation and T-bill rate have only moderate correlation with other macro-factors. Correlations among mimicking portfolios track closely those among original factors.

[Insert Table 2 near here]

3.3 Constructing Macro Beta-Sorted Portfolios

Chen, Roll, and Ross (1986) use 20 equal-weighted size sorted portfolios in examining the price of risk of macroeconomic factors. The idea is that the test assets should have a large spread in average returns to detect the pricing effects of macro-factors. In this paper, however, I want the test assets to have large spreads in their exposures to macroeconomic factors, because my story is that high macro beta stocks will amplify macro-level disagreement and, hence, be overvalued during high macro disagreement months. I sort stocks based on their past sensitivities to macro-factors and use these macro beta-sorted portfolios as test assets.

[16] The correlations between the original macro-factors and the mimicking portfolios are high, ranging from 0.33 to 0.60. The weights on the base assets for each macro-factor are reasonable and are reported in the Internet Appendix.

For each macroeconomic factor studied in this paper, I use the past 60 months of monthly return to estimate the macro beta for each stock in the cross-section at the beginning of every year. This is done by regressing each stock's excess return on the contemporaneous corresponding factor-mimicking portfolio return.[17] I require at least 24 months of stock return data to reliably estimate a stock's macro beta. I then sort all the stocks into ten deciles based on these pre-ranking macro betas and hold the stocks for one year. I compute the monthly value-weighted returns for each portfolio and then estimate the portfolio's post-ranking macro beta by regressing each portfolio's monthly returns on the mimicking factors using the whole sample data (Fama and French, 1992). If the pre-ranking macro betas truly captures portfolios' different exposures to macro-factors, I expect the post-ranking macro betas to preserve the order of pre-ranking macro betas for the decile portfolio. As can be seen from Table 3, the pre-ranking betas and post-ranking betas are aligned very well for each macro-factor, indicating that the sorting procedure captures stocks' true sensitivities to macroeconomic factors instead of just sorting on measurement error in macro betas.

4 Empirical Tests

4.1 Portfolio Sorts

I first use portfolio sorts to examine the effect of macro disagreement on the cross-section of stock returns. Table 3 reports the monthly average excess returns as well as portfolio alphas adjusted using the Fama-French three factor model for decile portfolios sorted on macro betas. As is evident in Table 3, sorting stocks into portfolios with large spreads in macro betas generates little variation in average returns unconditionally. The high-minus-low monthly portfolio excess return is close to zero for all the macroeconomic factors and is statistically insignificant. The results are qualitatively similar for the Fama-French three factor adjusted alphas, in which the alpha of the high-minus-low portfolio is close to zero

[17] In the baseline regression, I include only one macro factor at a time when calculating pre-ranking macro betas for individual stocks. My results are robust if I also include the market return factor plus the macro factor. Results are available in the Internet Appendix. I do not try to include all the macro factors at once because the pre-ranking macro betas will be estimated with considerable noise this way. My results depend crucially on using portfolios with different sensitivities to a specific macro factor, and using portfolios sorted on poorly estimated pre-ranking macro betas reduces the power of my empirical design.

for most of the macro-factors. The results are consistent with recent studies (Shanken and Weinstein, 2006) showing that macroeconomic factors are only weakly priced in the cross-section of average stock returns.

[Insert Table 3 near here]

My hypothesis predicts that during normal times (low disagreement periods), the risk-return trade-off should work and stocks with high macro beta should earn high average return if the macro factor is positively priced. During high disagreement periods, however, high macro beta stocks are also subject more to the macro-level disagreement, and tend to be overvalued by optimists due to short selling constraints. The overpricing of high macro beta stocks decreases their subsequent returns, which partially offset the higher expected return resulting from compensation for bearing higher macroeconomic risks. Thus, if the sample period is divided based on the macro disagreement level, high macro beta stocks should be seen to earn higher average returns than low macro beta stocks following low disagreement months, while the positive relation between macro beta and average excess return should be attenuated following high disagreement months.

The results from Table 4 confirm my hypothesis. The table reports the mean excess portfolio returns following low and high disagreement periods. For each of the ten portfolios in the sample, I compute the average excess portfolio return following high and low disagreement months separately (defined as the top and bottom quartile of the whole sample macro disagreement level). Consistent with my hypothesis, risky stocks earn higher average returns than less risky stocks following low disagreement periods, and they under-perform significantly following high disagreement periods. The differences of the high-minus-low portfolio returns across high and low disagreement months are significant for five out of six macro-factors and the magnitudes are large, ranging from 0.43% to 2.01%. Take industrial production growth as an example. The high-minus-low excess portfolio return is a monthly 0.57% following low disagreement periods and becomes -1.01% following high disagreement periods. The difference of high-minus-low excess return between the two regimes is -1.58% (t=2.23) and is statistically significant at the 5% level. Results on other macroeconomic factors follow a similar two-regime pattern.

[Insert Table 4 near here]

The sign of the risk premium on the macro factors following low disagreement periods is consistent with the prediction of asset pricing theory.[18] Industrial production growth, labor income growth, real GDP growth, investment growth and change in expected inflation are positively priced macroeconomic risk factors. I find that, for these factors, high beta stocks earn higher average return than low beta stocks following low disagreement states, although the return spread is significant only for GDP growth factor.[19] For Treasury bill rate, because it is a negatively priced risk factor, I expect that the high T-bill beta stocks (less risky stocks) earn lower return than low T-bill beta stocks (risky stocks) during normal times. This is indeed what I find, as the high-minus-low excess portfolio return is -1.55% (t=2.39) during low disagreement months. In high disagreement periods, however, the low T-bill beta stocks under-perform high T-bill beta stocks by 0.46%. This is consistent with my hypothesis. The model of Hong and Sraer (2012) predicts that it is the stocks with high absolute value of macro beta that should be more sensitive to macro disagreement. Because most stocks are negatively correlated with change in T-bill rate, the low T-bill beta stocks are those with high absolute value of beta and, hence, have larger exposure to forecast dispersion on the T-bill rate. These stocks are thus more likely to be overvalued when disagreement about short-term interest rates is high, resulting in lower subsequent returns.

Another fact evident from Table 4 is that, the large difference in high-minus-low portfolio excess return during the two disagreement regimes is mainly driven by the under-performance of high macro beta stocks relatively to low macro beta stocks following high disagreement

[18] Asset pricing theory such as consumption-based CAPM strongly predicts that industrial production growth, labor income growth, real GDP and investment growth are positively priced macroeconomic risk factors as these variables are positively correlated with consumption growth. Periods of high interest rates are usually periods of tight monetary conditions in which inflation expectations are high and liquidities are in limited supply, so the risk price associated with the change in T-bill rate should be negative. As argued by Chen, Roll, and Ross (1986), there is no strong a priori preassumption that would sign the risk premia for DEI. Given that positive inflation innovation tends to occur during economic booms, I conjecture that the price of risk for inflation has a positive sign.

[19] Two out of six macro factors have significant high-minus-low portfolio return spread during low disagreement states. However, even when disagreement is in the lowest quartile of the sample period (but not zero), the high macro beta stocks could still be overvalued by optimists as long as the high macro beta stocks have very large exposure to the macro factor. In the univariate predictive regression and the risk premium regression, three and four out of six macro factors, respectively, have significant constant terms, which could be interpreted as the existence of risk premium in the zero disagreement world. For other factors, the constant terms are positive and have similar magnitude, though they are not significant.

months. For example, the highest macro beta portfolio sorted on industrial production growth factor earns 1.41% lower return over the highest macro disagreement months than over the lowest macro disagreement months. In contrast, average returns on the lowest macro beta portfolio are similar with only 0.18% differences across two disagreement regimes. This is consistent with my hypothesis. When macro disagreement is high, stocks that are most sensitive to macro factors will be subject to more stock-level disagreement. Due to short-selling constraints, arbitrage activities are not sufficient to correct the over-pricing of high macro beta stocks, leading to lower subsequent returns. Low macro beta stocks are not very sensitive to forecast of macroeconomic factors, so their returns should be similar across different disagreement states.

4.2 Predictive Regression

In Subsection 4.1, I show that the return spread between risky and less risky stocks depends on the macro-level disagreement. Another way to look for conditional effects of macro disagreement is to use the macro disagreement measure to predict long-short portfolio excess returns, long in stocks with the highest macro betas and short in stocks with the lowest macro betas, similar to Baker and Wurgler (2006). A regression approach allows me to conduct formal statistical tests, incorporate the continuous nature of the macro disagreement measure, and control for other well-known stock return predictability effects.

Specifically, I run the following predictive regression:

$$R_{high_t - low_t} = a + bDisp_{t-1} + \epsilon_t \tag{3}$$

The dependent variable is the monthly return on a long-short portfolio strategy in which I long stocks in the highest decile and short stocks in the lowest decile portfolio sorted on pre-ranking macro betas. The independent variable $Disp_{t-1}$ is the cross-sectional forecast dispersion measure on the corresponding macroeconomic factor prevailing in the previous quarter. Standard errors are Newey-West (1987) adjusted to account for heteroskedasticity and autocorrelation.

Column (1) of Table 5 shows the results from this univariate predictive regression. The results are consistent with the findings regarding portfolio sorts and provide formal support to my hypothesis. The coefficients on the lagged macro disagreement measure are statistically significant for five out of six macro-factors. For change in expected inflation, the coefficient on the disagreement measure is negative but not significant. The negative coefficient on the lagged macro disagreement means that high macro beta stocks are relatively overvalued contemporaneously. Hence, returns are lower over the coming quarter when disagreement on this macro factor is high compared with when disagreement is low. The economic magnitude is also large. The coefficient on the disagreement measure of industrial production growth, for example, is -0.007 (t=-2.59). A one standard deviation increase of the disagreement measure on industrial production growth leads to a 0.66% lower monthly return on the high-minus-low portfolio. The effect is large relative to the unconditional monthly return spread of 0.20% between the two extreme decile portfolios.

[Insert Table 5 near here]

The constant term from regression (3) can be interpreted as the return spread between extreme decile portfolios when there is no disagreement on this macro factor. Unlike the unconditional sorting results, the return spread is significantly positive for portfolios sorted on industrial production growth and investment growth and significantly negative for Treasury bill rate. For labor income growth, GDP growth and change of expected inflation, the constant terms are still positive and have similar magnitude, though not significant. For example, the return difference between portfolios with the highest and lowest IPG beta is a hypothetical 1.60% (t=2.44) under zero disagreement states. In other words, the prediction of asset pricing theory that macroeconomic factors should be systematic risk factors that get priced in the cross-section of stock returns holds relatively well when investors agree over these macro-factors. However, when macro disagreement is high, high macro beta stocks become increasingly speculative and overvalued, thus offsetting the risk-return trade-off.

In the Hong and Sraer (2012) model, an individual stock's sensitivity to macro disagreement should be positively related to its absolute value of macro beta. I use the return spread between the highest and lowest macro beta portfolio as the dependent variable mainly following the literature and facilitating the discussion. From a theoretical point of view, the return spread between the highest and lowest absolute macro beta portfolio should be used as the dependent variable in the predictive regression.[20] As can be seen in Table 3, the absolute value of the highest macro beta portfolio is larger than the absolute value of the lowest macro beta portfolio for four out of six macro factors. Therefore, the high-minus-low excess portfolio return should still be negatively related to macro disagreement for these factors. My results (untabulated) show that the coefficients on lagged macro disagreement are still significantly negative for most of the macro factors if the dependent variable is changed to the return spread between the highest and lowest absolute macro beta portfolios. In a univariate (multivariate) predictive regression, five (four) out of six macro factors have significant coefficients. Even the previous insignificant DEI now becomes significant. The only factor that does not work is investment growth, which has a negative but insignificant coefficient.

Previously I show that my macro disagreement measure is correlated with the investor sentiment index constructed by Baker and Wurgler (2006). They find that sentiment has stronger effects on stocks that are hard-to-value and costly-to-arbitrage, such as small stocks, young stocks, unprofitable stocks and financially distressed stocks. When sentiment is high, the future returns on these hard-to-value and difficult-to-arbitrage stocks are relatively low. It is thus conceivable that my high macro beta stocks may pick up these hard-to-value stocks and my macro disagreement measure is just a proxy for investor sentiment.[21] To differentiate my disagreement story from their sentiment story, I control for the monthly sentiment index directly in the predictive regression framework.

The effect of macro disagreement on the cross-section of stock returns that I document here could simply reflect the time-varying nature of risk premium. It is widely known that equity risk premium is time varying and counter-cyclical (Keim and Stambaugh, 1986; Fama

[20] I thank the editor for pointing this out to me.

[21] While the sentiment and disagreement stories are not necessarily inconsistent with each other, the channels through which each affects the stock market is different. In Baker and Wurgler (2006), sentiment-driven investors overvalue those stocks that are more opaque and hard to value and they classify stocks based on observable characteristics such as firm size and age. In Hong and Sraer (2012), optimists overvalue high beta stocks because they are overly optimistic about aggregate economy. Recently, Shen and Yu (2013) document a two-regime pattern similar with my paper that sentiment can affect the pricing of a set of macro-related risk factors. Antoniou et al. (2013) find the pricing of market beta varies negatively with investor sentiment.

and French, 1989). The predictability of the macro disagreement measure may come from its correlation with business cycle indicators. The time-varying risk premium explanation cannot fully account for the return predictability pattern documented in this paper for three reasons. First, because macro disagreement is usually higher during recessions and market downturns, the risk-based story predicts that risky (high macro beta) stocks should have higher expected returns than less risky stocks following high disagreement months. The empirical results are contrary to this prediction. When the proxy for macroeconomic volatility[22] is added to the predictive regression that is proposed by the long-run risk literature, the coefficient on the volatility of industrial production growth is positive, but the coefficients on macro disagreement are still negative and significant. Second, time-varying risk premium cannot explain why risky stocks earn lower return than less risky stocks when macro disagreement is high. Time-varying risk premiums can explain the changing magnitude but not the changing sign of the return difference between high and low macro beta stocks. Third, I add the term spread, the default premium, the D/P ratio, and the detrended one-month T-bill rate into the predictive regression.[23] These variables are chosen as additional controls because of their strong predictability for expected equity risk premium documented in the literature (Fama and Schwert, 1977; Fama and French, 1988; Campbell and Shiller, 1986).

Column (2) of Table 5 reports the regression results when I control for the lagged sentiment index and a set of predictors. Even after controlling for all these additional macroeconomic state variables, the coefficients on macro disagreement barely change and remain significant for five out of six macro factors.[24] In contrast, the coefficient on sentiment index is significantly negative only for two out of six macro factors. Among other controls, only lagged D/P ratio has some predictive power. Thus my results do not appear to merely reflect the effect of investor sentiment or time-varying risk premium.

[22]To identify the fluctuations in aggregate economic volatility, I construct a realized variance measure based on the rolling sum of squares of monthly consumption growth and industrial production growth over the past 12 months, following Bansal et al.(2013).

[23]The detrended T-bill yield is the one-month T-bill yield minus its 12-month backward moving average. This stochastic detrending method for the short rate has been used by Campbell (1991) and Hodrick (1992), among others.

[24]The reason that the coefficient on $Disp_{t-1}$ changes sign for DEI is that I add D/P ratio in predictive regression and D/P ratio has very high correlation with forecast dispersion on inflation. Moreover, the sentiment index has very high correlation with forecast dispersion on inflation, which subsumes the predictive ability of disagreement on this macro factor.

I also try to distinguish this novel return predictability pattern from other well-known effects such as size, value and momentum effects in a multivariate regression framework:

$$R_{high_t - low_t} = a + bDisp_{t-1} + cMktrf_t + dSMB_t + eHML_t + fUMD_t + \epsilon_t \tag{4}$$

The variable Mktrf is the excess return of the value-weighted stock market index over the risk-free rate. SMB is the excess return on the portfolio of small stocks over big stocks. HML is the excess return on the portfolio of stocks with high book-to-market ratio over the portfolio of stocks with low book-to-market ratio. The variable UMD is the return on high-momentum stocks minus the return on low-momentum stocks, where momentum is measured over months (-12, -2).[25] This regression thus investigates the ability of macro disagreement to predict benchmark-adjusted portfolio returns.[26] The results are reported in Table 6. As we can see, the coefficients on lagged macro disagreement are unaffected or become even stronger after I control for Fama-French (1993) three factors and the Carhart (1997) momentum factor. This illustrates that the effect of macro disagreement is essentially orthogonal from other well-known cross-sectional return predictability effects, thus adding a genuine new finding to the literature.

In summary, the predictive regressions confirm the significance of the patterns suggested in the portfolio sorts. When macro disagreement is high, future returns are relatively low for high macro beta stocks and vice-versa. In general, the results support my hypothesis that high macro beta stocks amplify macro-level disagreement and tend to be overvalued by optimists in high disagreement periods.

4.3 Macro Disagreement and Macro-factor Risk Premiums

In Subsection 4.2, the predictive regression approach is used to test the hypothesis that high macro beta stocks earn lower future returns following high macro disagreement months. This test is performed by regressing the high-minus-low excess portfolio return on the lagged macro disagreement measure. Only the returns of the highest and lowest decile portfolios

[25] These portfolios are taken from Ken French's website and are described there.

[26] Baker and Wurgler (2006), Hong and Sraer (2012) and Stambaugh, Yu and Yuan (2012) all run similar tests.

are used in the predictive regression. In this subsection, a similar analysis is presented in which I am interested in how macro disagreement affects the price of macroeconomic risk factors. This method has also been used by Hong and Sraer (2012) in their study of the relation between aggregate disagreement and the slope of the security market line.

I use a two-stage analysis procedure. I first run the monthly cross-sectional regression:

$$R^e_{it} = \alpha_t + \beta_i \lambda_t + \epsilon_{it} \tag{5}$$

where R^e_{it} is the monthly excess return for portfolio i during month t, and β_i is the post-ranking macro beta of portfolio i, computed as explained in Subsection 3.3.[27] This gives a time series of coefficient estimates $(\hat{\alpha}_t, \hat{\lambda}_t)$. I am interested in how the estimated monthly macro-factor risk premium $\hat{\lambda}_t$ correlates with the lagged macro disagreement measure. My hypothesis predicts that the risk premiums of macro-factors should be significantly lower following high disagreement months than following low disagreement months for positively priced macro factors. To formally test this, I regress the monthly time-series of estimated macro-factor risk premia on the lagged macro disagreement measure:

$$\hat{\lambda}_t = a + bDisp_{t-1} + cX_{t-1} + \epsilon_t \tag{6}$$

where X_{t-1} includes all the control variables used in the predictive regression.[28] This is a more stringent test than the predictive regression test.[29] In Table 7, Column (1) reports the second-stage regression results without controls and Column (2) reports the results with

[27] A factor model implies that a contemporaneous relation should exist between factor loadings and average returns. For example, in a standard CAPM, stocks that co-vary strongly with the market factor should, on average, earn high returns over the same period. Black, Jensen, and Scholes (1972), Fama and French (1992, 1993), Jagannathan and Wang (1996), and Ang et.al (2006), among others, all form portfolios using various pre-formation criteria, but examine post-ranking factor loadings that are computed over the full sample period. That is why I use post-ranking macro betas when estimating factor risk premium.

[28] Controlling for Cahart (1997) four factors doesn't affect our results.

[29] The high-minus-low macro beta portfolio uses the returns of only two extreme portfolios, while the estimated factor risk premium is a linear combination of returns to all ten portfolios, with the weights being a function of post-ranking macro beta. These two normally are not be the same. According to the Hong and Sraer (2012) model, macro disagreement should affect not only stocks with the highest and lowest macro betas, but also the entire slope of the curve linking macro betas with average returns. Finding a negative relation between the high-minus-low excess portfolio return and macro disagreement does not necessarily imply that the slope of the entire curve will also be negatively affected. In this sense, the test performed in this subsection is more stringent.

all the controls. The table shows that the macro-factor risk premia are significantly lower following high macro disagreement months. The coefficient estimates on the lagged macro disagreement measure are all negative (except for T-bill rate) and statistically significant in five out of six macro-factors with and without controls. The results are also in line with the coefficient estimates from the predictive regression (3). Take again industrial production growth as an example. The coefficient on the lagged macro disagreement measure is -0.001 (t=-2.85). A one standard deviation increase in disagreement about industrial production growth is associated with -0.10% lower expected return per unit of macro beta. Because the difference in post-ranking beta between the highest and lowest decile portfolio is 6.65 for industrial production growth factor, this translates into a reduction of 0.67% excess return for highest beta stocks relative to lowest beta stocks.

[Insert Table 7 near here]

The constant term reported in Column (1) of Table 7 can be interpreted as the price of macroeconomic risks when there is no disagreement. Industrial production growth (IPG), labour income growth (LaIncome) and investment growth (Investment) are significantly positively priced, and the Treasury bill rate (Tbill) is significantly negatively priced. The constant term for real GDP growth (GDP) and change of expected inflation (DEI) have the right sign, though insignificant. In other words, pervasive macroeconomic risk factors are indeed priced when investors agree over future macroeconomic states, which tends to support traditional asset pricing theory such as I-CAPM.

4.4 Macro Disagreement and Stock-level Disagreement

If high macro beta stocks earn lower expected return because they are more subject to macro-level disagreement, then they should have higher stock-level disagreement, especially during high macro disagreement months.

This hypothesis is confirmed by a panel regression, in which I estimate the following regression equation:

$$y_{it} = a + (b + cDisp_t)|\beta_i| + (d + eDisp_t)X_{it} + fDisp_t + \epsilon_{it} \tag{7}$$

The dependent variable y_{it} is the equal-weighted average of stock-level disagreement for portfolio i at month t, $|\beta_i|$ is the absolute value of post-ranking beta for portfolio i and X_{it} is the average characteristics of portfolio i at month t. I use standard deviations of analysts' forecast of long-term EPS growth rate as a proxy for stock-level disagreement.[30] X includes the natural log of market capitalization [Ln(ME)], the natural log of book-to-market ratio [ln(BM)] and the cumulative return from month t-12 to t-2 (Mom). Standard errors are clustered at the portfolio and quarter dimension. I use the absolute value of macro beta instead of macro beta itself as the explanatory variable because stocks with large negative macro beta are also highly sensitive to macro-level disagreement. Size, book-to-market, and past returns are included as control to account for the existing heterogeneity in the macro-beta sorted portfolios that could correlate with stock-level disagreement.[31] The coefficient of interest is c, which is expected to be positive if my hypothesis is correct.

The results in Table 8 are consistent with my hypothesis. In Column (1), only the natural log of market capitalization [Ln(ME)] is used as the control variable. In Column (2), X also includes the natural log of book-to-market ratio [ln(BM)] and the cumulative return from month t-12 to t-2 (Mom). Note that even in low macro disagreement months, high macro beta stocks experience more stock-level disagreement than low macro beta stocks. As an extreme case, consider a month when disagreement on the IPG factor is in the lowest value of 0.92. In such a month, analysts' disagreement on a stock in the highest absolute beta decile is 0.22 ((-0.027+0.069*0.92)*5.67) larger relative to the disagreement experienced by a stock in the lowest absolute beta decile in the same month. Moreover, the relation between stock-level disagreement and macro beta becomes significantly steeper as macro disagreement increases. The coefficients on the interaction between macro disagreement and absolute macro beta are positive for five out of six macro-factors and four are significant. A one standard deviation increase in macro disagreement on the IPG factor increases the stock-level disagreement on a stock of highest IPG beta by 0.37 relative to the stock-level disagreement on a stock of

[30]Using the standard deviation of analysts' annual EPS forecast as a proxy for stock-level disagreement as in Diether, Malloy and Scherbina (2002) yields similar results.

[31]For example, small stocks tend to have high macro betas as well as more stock-level disagreement (Diether, Malloy and Scherbina, 2002). The relation between stock-level disagreement and macro beta in the time-series thus could be driven by size. This is why I control for both firm characteristics and their interaction with macro disagreement.

lowest IPG beta, which represents 7% of the in-sample standard deviation of the stock-level disagreement. The results thus support the basic premise of my analysis that high macro beta stocks are overvalued by optimists during high macro disagreement months precisely because they have more exposure to macro-level disagreement.

[Insert Table 8 near here]

While the results in Table 8 are consistent with the underlying channel that drives the overvaluation of high macro beta stocks in the first place, the relation between macro-level and stock-level disagreement could be more complex. Disagreement on macro factors could relate to disagreement about cash flow or the discount rate for individual stocks. While disagreement on an individual stock's cash flow could be directly measured by its EPS forecast dispersion, a plausible disagreement measure on a stock's discount rate is difficult to come up with. That is why regression (7) is able to capture only the relation between macro disagreement and stock-level disagreement on cash flows. Finally, while regression (7) is run at the portfolio level, the results also hold if the panel regression is run at the individual stock level. This result is not reported for brevity.

5 Robustness Checks

5.1 Controlling for Market Beta

Hong and Sraer (2012) show that high market beta stocks earn lower future return when aggregate disagreement is high. One concern is that the evidence documented in this paper may be just a refinement of their findings, especially if macro beta is also highly correlated with market beta. In this subsection, I conduct tests that can isolate the effect of macro beta from market beta.

I use two methods to control for the effect of market beta. The first is to conduct conditional double sorts based on both market beta and macro beta. Specifically, when forming testing portfolios at the beginning of every year, I sort all the stocks into ten deciles based on the pre-ranking market beta. The pre-ranking market beta is estimated by regressing the past 60 months of excess stock return on the contemporaneous excess market return.

Within each market beta-sorted portfolio, I further sort stocks into ten portfolios based on the pre-ranking macro beta, resulting in one hundred market beta-macro beta double-sorted portfolios. To form ten macro beta-sorted portfolios, the stocks with the same macro beta rank across all the 10 market beta sorted portfolios are aggregated. This approach effectively forms portfolios that have similar market beta while preserving the large spread of macro beta. Using this new set of ten macro beta-sorted portfolios (after controlling for market beta), I rerun the predictive regression as in Subsection 4.2. If my results are entirely driven by the disagreement-amplifying effect of market beta, the coefficients on the lagged macro disagreement should not be significantly negative. Table 9 reports the predictive regression results when the high-minus-low macro beta portfolio excess return is regressed on the lagged macro disagreement measure, with and without controls. The coefficients are still significant for five out of six macro factors in the univariate regression and four are significant in the multivariate regression. Thus my results provide independent evidence relative to the market beta of Hong and Sraer (2012), showing that high macro beta stocks could amplify macro-level disagreement.

[Insert Table 9 near here]

The second approach I use to control for the effect of market beta is that, when estimating pre-ranking macro beta for each stock, I also include the excess return on the market factor. I then form ten portfolios based on these pre-ranking macro betas and redo the tests. The results are qualitatively similar. For brevity, I do not report them here.

5.2 Alternative Explanations

Several competing explanations are proposed to explain the empirical failure of the CAPM. Apart from the disagreement story of Hong and Sraer (2012), the money illusion effect documented by Cohen et al. (2005), the benchmarked institutional investors story of Baker, Bradley, and Wurgler (2011), and the leverage constraints explanation of Frazzini and Pedersen (2014) all could account for the high beta-lower risk-adjusted returns puzzle. Although my results are most consistent with the disagreement-based explanation for the macro factors, other mechanisms proposed by these prior studies could drive my results.

To investigate the alternative explanations, I add additional controls in the predictive regression, including an inflation rate, an aggregate disagreement measure, the VIX index, the consumption-to-wealth ratio CAY (capturing time-varying risk premium), and the TED spread (proxy for funding constraints as in Frazzni and Petersen (2014)). The consumption-to-wealth ratio, CAY, is taken from Martin Lettau's website. The results are reported in Table 10. The coefficients on the lagged macro disagreement measure are still significant for four out of six macro factors, although the effect becomes weaker after controlling for all these variables. Among all the control variables, TED spread has the strongest predictive power. The coefficients on TED have the correct sign for all six macro factors, but only two are significant.[32]

[Insert Table 10 near here]

In addition, risk-based explanations could still work, despite my best effort in controlling for it. For example, high macro beta stocks may have large exposures to innovations in market volatility. The high correlation between macro disagreement measures and market volatility means that when macro disagreement is high, the stock market likely is volatile. If high macro beta stocks pay off at uncertain economic environments, they demand lower risk premiums in equilibrium. Bali, Brown and Tang (2014) find that economic uncertainty betas can generate cross-sectional return spread consistent with the hedging argument. They use the same SPF database to construct their economic uncertainty measure.[33] To differentiate this risk-based argument with the overpricing effect documented in this paper, I regress macro beta-sorted decile portfolio returns on innovation in the monthly VIX index. The risk-based story predicts that high macro beta stocks should have more positive exposure to innovation in volatility than low macro beta stocks. However, high macro beta stocks actually have more negative exposures to change in the VIX than low macro beta stocks (the result is not reported here but available in the Internet Appendix), so accounting for portfolios' differential exposure to market volatility only exaggerates the puzzle documented

[32]The Frazzini and Pedersen (2014) model predicts that when funding constraints tighten, expected return for high (low) beta assets should decrease (increase). Therefore, TED spread should predict the high-minus-low portfolio return spread negatively.

[33]The hedging argument, however, can explain only the unconditional return spread of different macro beta portfolios. It cannot explain the cross-sectional return pattern in different disagreement states.

in this paper.

5.3 Time-Varying Beta

The systematic risk explanation comes in two basic flavors. One is that the risk premium could vary with macro disagreement, which I have already examined by including variables such as the D/P ratio, the term spread, the default premium, the detrended one-month T-bill rate, and CAY in both predictive regressions and two-stage regression analyses. The other is that systematic risks (beta loadings) of stocks vary over the business cycle and may be correlated with the macro disagreement measures. I investigate this possibility directly in Table 11, examing whether the macro disagreement measure coincides with time-variation in market betas in a way that could at least qualitatively reconcile the earlier results with a conditional CAPM. Specifically, I predict returns on the high-minus-low portfolio with the following specification:

$$R_{high_t - low_t} = a + bDisp_{t-1} + (c + dDisp_{t-1} + fCAY_{t-1} + gTbill\_d_{t-1} + hD/P_{t-1}) * Mktrf_t + \epsilon_t \tag{8}$$

The linear model for the market beta follows Shanken (1990). The results indicate that the conditional beta model cannot explain my finding that high-minus-low portfolio excess return is negatively related to macro disagreement, as the coefficients b are still significant for five out of six macro factors.

[Insert Table 11 near here]

6 Conclusion

Macroeconomic risk factors should play an important role in explaining the cross-section of stock returns as predicted by traditional asset pricing paradigms. However, empirical evidence (as confirmed in this paper) shows that the stocks with greater risk exposure to macro-factors do not earn higher expected returns than stocks with lower exposure to macro-factors. In this paper, I argue that disagreement on macroeconomic variables, when combined with short-sales constraints, could potentially explain this puzzle. In particular, I document a striking two-regime pattern, whereas high macro beta (risky) stocks earn lower future returns relative to low macro beta (less risky) stocks following high macro disagreement periods and vice versa. I hypothesize that this is because high macro beta stocks are more sensitive to forecasts on macro-factors and are more likely to be overpriced when disagreement on the macro-factor is high. This implies that high macro beta stocks should have a larger component of stock-level disagreement coming from its exposure to macro-level disagreement, which is also confirmed in the paper.

My study shows that the underlying source of disagreement on individual stocks is partly from investors' disagreement on economic-wide macro-factors. The same macroeconomic forces should also affect other asset classes, such as Treasury bonds and commodities, the price of which are highly sensitive to forecasts about the future macroeconomic environment.[34] In future work, I hope to offer a better understanding of various sources of disagreement as well as the impact of macro disagreement on other assets.

[34] Using the same framework, Hong, Sraer and Yu (2014) find that when disagreement about future inflation rate is high, long-maturity bonds become more overvalued than short-maturity bonds and the yield curve flattens. This is consistent with the notion that high inflation beta assets (such as long-maturity bonds) have larger exposure to disagreement on future inflation rate than low inflation beta assets.

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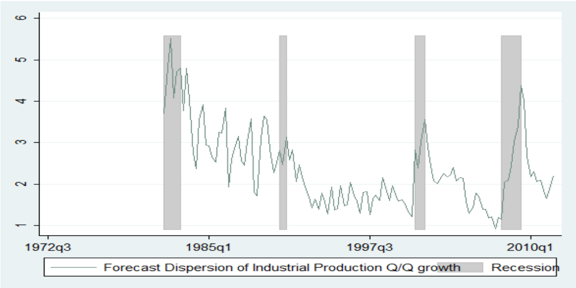
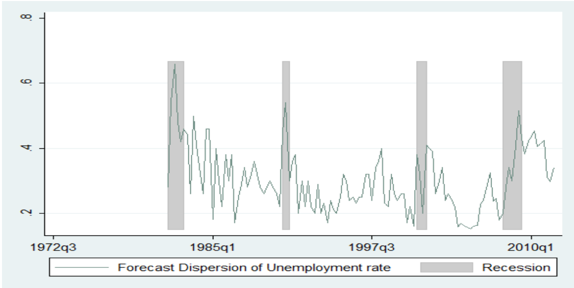
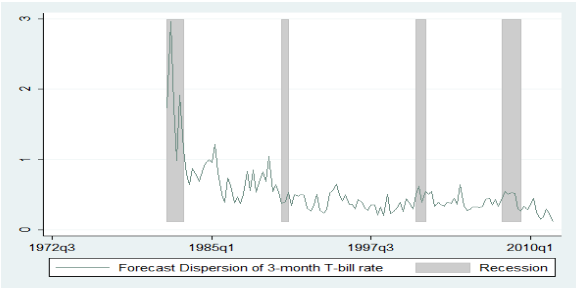


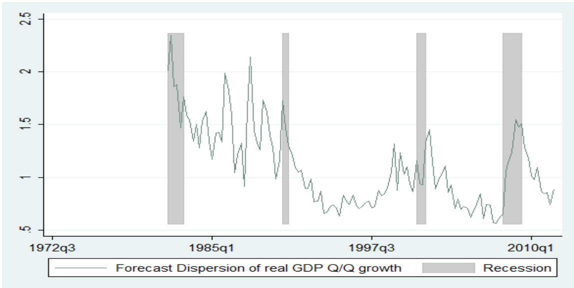
(a) Industrial Production Growth



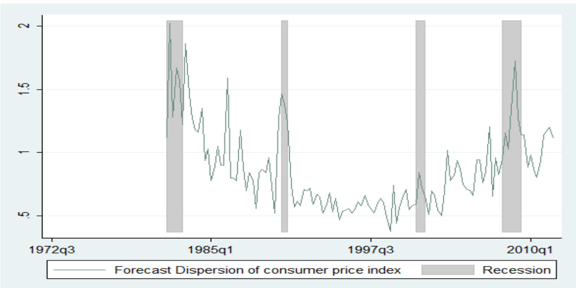
(b) Unemployment rate



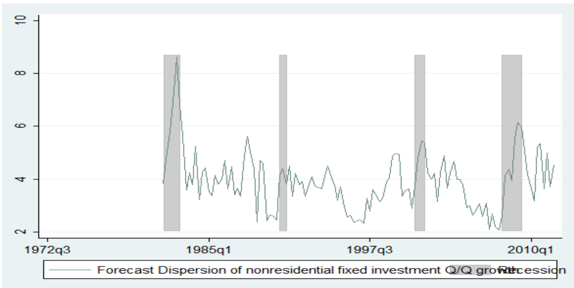
(c) 3-month T-bill rate



(d) Real GDP growth



(e) Inflation rate



(f) Real nonresidential investment

Figure 1: **Macro Disagreement, 1981Q3-2011Q4**

The figure plots the time series of cross-sectional forecast dispersion on six macroeconomic variables, including industrial production growth, the unemployment rate, the 3-month Treasury bill rate, the real GDP growth, the inflation rate and the real nonresidential fixed investment growth. The sample period runs from the third quarter of 1981 to the fourth quarter of 2011. Shaded areas are NBER dated recession periods. The data on macro disagreement is from the Survey of Professional Forecasters (SPF) database currently maintained by the Federal Reserve Bank of Philadelphia.

Table 1: **Descriptive Statistics**

This table reports the descriptive statistics of six macro disagreement measures for: industrial production growth (IPG), the unemployment rate (Unemploy), the consumer price index (Inflation), a three-month Treasury-bill rate (Tbill), the real GDP growth (GDP) and real nonresidential private investment growth (Investment). Panel A reports various summary statistics of these six macro disagreement measures. Also reported are summary statistics of seasonally adjusted monthly consumption growth (Con_g), an expected market volatility (Mkt vol.), the dividend/price ratio (D/P), an aggregate disagreement measure (Agg Disp.), the Baker-Wurgler sentiment index (Sentiment), the term spread, the default premium, the detrended one-month T-bill rate (Tbill_d), the monthly inflation rate, the consumption-to-wealth ratio (CAY), the TED spread and the VIX. Panel B reports the pairwise correlations among the macro disagreement measures and other macroeconomic variables. Panel C reports the regression results of macro disagreement measure on its lags. The lag ranges from one quarter to twelve quarters. The t-statistics in parentheses are adjusted for auto-correlations of 12 quarter lags using Newey and West (1987). The sample period runs from 1981Q3 to 2011Q4.

Panel A: Summary Statistics

Variable	# of obs.	Mean	Std Dev.	Min	Max
Macro Disagreement Measures					
IPG	122	2.37	0.94	0.92	5.52
Unemploy	122	0.30	0.10	0.15	0.66
Inflation	122	0.86	0.32	0.38	2.02
Tbill	122	0.53	0.37	0.11	2.96
GDP	122	1.10	0.38	0.56	2.35
Investment	122	3.93	1.08	2.06	8.63
Other Variables					
Con_g	366	0.14%	0.34%	-1.41%	1.22%
Mkt vol.	366	0.24%	0.16%	0.07%	1.09%
D/P	366	2.64%	1.15%	1.08%	6.37%
Agg Disp.	361	3.46	0.59	2.67	5.21
Sentiment	354	0.26	0.66	-0.90	2.50
Term Spread	366	1.40%	1.07%	-1.78%	3.40%
Default Premium	366	1.09%	0.48%	0.55%	3.38%
Tbill_d	366	-0.25%	0.97%	-4.22%	1.93%
Inflation rate	366	0.25%	0.27%	-1.79%	1.37%
CAY	122	0.64%	2.42%	-5.74%	4.48%
TED	312	0.65%	0.44%	0.12%	3.39%
VIX	311	20.92	7.99	10.42	61.41

Table 1 Continued

Panel B: Correlations

	IPG	Unemploy	Inflation	Tbill	GDP	Investment	Con_g	Mkt vol.	D/P	Agg Disp.	Sentiment	Term Spread	Default Premium	TED	VIX
IPG	1.00														
Unemploy	0.36	1.00													
	0.00														
Inflation	0.51	0.43	1.00												
	0.00	0.00													
Tbill	0.54	0.39	0.43	1.00											
	0.00	0.00	0.00												
GDP	0.54	0.40	0.41	0.55	1.00										
	0.00	0.00	0.00	0.00											
Investment	0.44	0.30	0.33	0.31	0.43	1.00									
	0.00	0.00	0.00	0.00	0.00										
Con_g	0.09	-0.09	-0.09	0.07	0.06	0.01	1.00								
	0.33	0.30	0.35	0.46	0.53	0.96									
Mkt vol.	0.22	0.31	0.03	-0.02	0.36	0.46	-0.02	1.00							
	0.01	0.00	0.74	0.81	0.00	0.00	0.86								
D/P ratio	0.55	0.36	0.64	0.69	0.57	0.32	0.03	0.02	1.00						
	0.00	0.00	0.00	0.00	0.00	0.00	0.74	0.79							
Agg Disp.	-0.15	0.07	-0.02	-0.37	-0.07	0.17	-0.01	0.33	-0.36	1.00					
	0.10	0.45	0.83	0.00	0.45	0.06	0.87	0.00	0.00						
Sentiment	0.30	0.19	0.38	0.44	0.35	0.19	0.07	0.00	0.38	0.15	1.00				
	0.00	0.04	0.00	0.00	0.00	0.04	0.44	0.98	0.00	0.10					
Term spread	0.08	0.07	0.08	-0.20	-0.06	0.33	0.09	0.25	-0.01	0.17	-0.21	1.00			
	0.37	0.45	0.40	0.02	0.50	0.00	0.33	0.01	0.91	0.06	0.02				
Default Premium	0.51	0.48	0.55	0.41	0.58	0.48	-0.04	0.49	0.62	0.13	0.31	0.15	1.00		
	0.00	0.00	0.00	0.00	0.00	0.00	0.69	0.00	0.00	0.16	0.00	0.09			
TED	0.17	0.03	0.25	0.36	0.42	0.05	-0.06	0.33	0.42	-0.09	0.08	-0.36	0.38	1.00	
	0.09	0.77	0.01	0.00	0.00	0.60	0.58	0.00	0.00	0.38	0.40	0.00	0.00		
VIX	0.25	0.36	0.18	-0.06	0.40	0.35	-0.11	0.80	0.05	0.36	0.15	0.13	0.63	0.46	1.00
	0.01	0.00	0.07	0.58	0.00	0.00	0.27	0.00	0.61	0.00	0.15	0.19	0.00	0.00	

Table 1 Continued

Panel C: Autocorrelations

Lag in quarters	1	2	4	8	12
IPG	0.46	0.31	0.32	0.16	0.19
t-stat	(6.42)	(2.80)	(2.54)	(1.59)	(2.49)
Unemploy	0.38	0.27	0.19	-0.03	-0.07
t-stat	(3.40)	(2.71)	(2.39)	(-0.38)	(-1.03)
Tbill	0.54	0.57	0.41	0.26	0.24
t-stat	(6.85)	(10.71)	(6.31)	(2.44)	(2.72)
GDP	0.46	0.47	0.44	0.28	0.21
t-stat	(4.19)	(5.39)	(6.29)	(2.19)	(1.93)
Investment	0.41	0.28	0.14	0.02	-0.10
t-stat	(3.73)	(1.79)	(1.22)	(0.16)	(-1.01)
Inflation	0.52	0.49	0.36	0.34	0.21
t-stat	(7.29)	(4.45)	(3.61)	(3.54)	(2.56)

Table 2: **Correlations among Macroeconomic Factors and Factor Mimicking Portfolios**

This table reports the correlations among macroeconomic factors (Panel A) and among factor mimicking portfolio returns (Panel B). GDP growth and investment growth are sampled at quarterly frequency and all other macro-factors are sampled at monthly frequency. Monthly variables are time aggregated to quarterly frequency to calculate the correlations among factors. The sample period runs from January 1976 to December 2011.

Panel A: Correlations among Macro-factors

Macro Factors	IPG	LaIncome	Tbill	GDP	Investment	DEI
IPG	1.00	0.28	-0.06	0.58	0.49	0.39
LaIncome		1.00	0.56	0.40	0.50	0.20
Tbill			1.00	0.05	0.13	-0.03
GDP				1.00	0.64	0.27
Investment					1.00	0.16
DEI						1.00

Panel B: Correlations among Factor Mimicking Portfolios

Mimicking Factors	IPG	LaIncome	Tbill	GDP	Investment	DEI
IPG	1.00	0.21	-0.19	0.77	0.61	0.68
LaIncome		1.00	0.82	0.25	0.51	0.27
Tbill			1.00	-0.04	0.16	-0.12
GDP				1.00	0.72	0.41
Investment					1.00	0.40
DEI						1.00

Table 3: **Returns and CAPM Alphas of Macro Beta-Sorted Portfolio**

This table reports the monthly average excess returns and CAPM alphas (in percentage) for ten macro-beta sorted portfolios. At the beginning of each year, ten portfolios are formed based on stocks' pre-ranking macro betas. The pre-ranking macro betas are estimated by regressing the past sixty months of excess stock return on the corresponding factor mimicking portfolio returns. The portfolios are rebalanced every year and individual stock returns are value-weighted within each portfolio. I also report excess returns to a long-short portfolio strategy in the right-most column, long the highest macro beta portfolio and short the lowest macro beta portfolio. All the t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

		Decile										
Macro Factors		low beta	2	3	4	5	6	7	8	9	high beta	High-Low
IPG	Mean return	1.07	1.15	1.18	1.10	0.80	0.96	0.77	0.93	0.99	0.84	-0.23
	t-stat	(2.93)	(4.50)	(5.19)	(4.68)	(3.33)	(3.95)	(2.74)	(3.08)	(2.65)	(1.76)	(-0.65)
	CAPM alpha	0.04	0.27	0.34	0.25	-0.06	0.09	-0.17	-0.06	-0.10	-0.34	-0.38
	t-stat	(0.21)	(2.53)	(4.06)	(3.00)	(-0.75)	(0.93)	(-1.62)	(-0.46)	(-0.53)	(-1.11)	(-1.06)
	pre-formation beta	-15.05	-7.94	-5.01	-2.88	-1.02	0.77	2.72	5.29	9.06	16.99	32.04
	post-formation beta	-0.49	0.80	0.45	1.26	2.09	2.48	3.94	4.21	5.55	6.16	6.65
LaIncome	Mean return	1.09	1.15	1.11	1.04	0.99	0.87	0.69	0.78	0.71	0.33	-0.76**
	t-stat	(3.13)	(4.36)	(4.46)	(4.41)	(3.93)	(3.31)	(2.43)	(2.44)	(1.97)	(0.73)	(-2.13)
	CAPM alpha	0.06	0.24	0.23	0.16	0.10	-0.06	-0.26	-0.21	-0.30	-0.79	-0.84**
	t-stat	(0.33)	(2.15)	(2.57)	(1.93)	(1.32)	(-0.61)	(-2.03)	(-1.36)	(-1.41)	(-2.64)	(-2.27)
	pre-formation beta	-16.22	-9.04	-5.85	-3.66	-1.67	0.43	2.84	6.11	11.17	21.67	37.89
	post-formation beta	-1.55	-1.84	-1.37	-1.85	-1.57	-1.52	-0.43	1.83	3.48	4.63	6.18
Tbill	Mean return	0.95	1.04	1.00	0.96	0.91	1.02	0.92	0.94	0.97	0.78	-0.16
	t-stat	(1.99)	(2.72)	(3.62)	(3.52)	(3.55)	(4.26)	(3.83)	(3.84)	(3.85)	(2.01)	(-0.52)
	CAPM alpha	-0.23	-0.04	0.07	0.03	-0.01	0.13	0.03	0.05	0.07	-0.30	-0.07
	t-stat	(-0.84)	(-0.21)	(0.55)	(0.26)	(-0.15)	(1.47)	(0.39)	(0.70)	(0.71)	(-1.47)	(-0.21)
	pre-formation beta	-4.77	-2.67	-1.77	-1.21	-0.79	-0.40	0.02	0.50	1.19	2.74	7.52
	post-formation beta	-1.21	-0.62	-0.51	-0.49	-0.29	-0.39	-0.18	-0.16	-0.22	0.01	1.22

Table 3 Continued

		Decile										
Macro Factors		low beta	2	3	4	5	6	7	8	9	high beta	High-Low
GDP	Mean return	0.84	1.11	1.01	1.19	1.01	0.94	1.03	0.89	0.69	0.86	0.02
	t-stat	(2.23)	(3.25)	(3.57)	(4.69)	(4.22)	(3.87)	(4.04)	(2.98)	(2.13)	(2.00)	(0.05)
	CAPM alpha	-0.17	0.16	0.09	0.30	0.12	0.06	0.13	-0.09	-0.31	-0.28	-0.11
	t-stat	(-0.75)	(0.79)	(0.78)	(3.61)	(1.79)	(0.84)	(1.35)	(-0.79)	(-1.90)	(-1.23)	(-0.33)
	pre-formation beta	-18.58	-10.52	-6.89	-4.35	-2.31	-0.49	1.48	3.90	7.61	15.23	33.81
	post-formation beta	1.96	2.82	2.68	1.47	2.34	1.67	1.79	2.50	2.91	4.44	2.48
Investment	Mean return	0.94	1.00	1.07	0.95	1.06	0.97	1.09	0.99	0.73	0.68	-0.26
	t-stat	(1.99)	(3.07)	(3.87)	(3.62)	(3.94)	(4.04)	(4.51)	(3.48)	(2.24)	(1.69)	(-0.67)
	CAPM alpha	-0.16	0.03	0.14	0.04	0.14	0.08	0.21	0.04	-0.26	-0.41	-0.25
	t-stat	(-0.54)	(0.17)	(1.24)	(0.49)	(1.47)	(1.02)	(2.67)	(0.35)	(-1.55)	(-1.77)	(-0.67)
	pre-formation beta	-8.57	-5.00	-3.37	-2.27	-1.43	-0.62	0.17	1.09	2.48	5.50	14.07
	post-formation beta	0.25	-0.36	-0.15	0.06	0.15	0.22	0.07	0.18	0.17	0.51	0.27
DEI	Mean return	0.96	1.13	1.01	0.98	0.79	0.92	0.95	0.87	1.05	0.73	-0.23
	t-stat	(2.96)	(4.65)	(4.16)	(4.14)	(3.27)	(3.50)	(3.19)	(2.68)	(2.90)	(1.48)	(-0.60)
	CAPM alpha	-0.04	0.27	0.16	0.13	-0.10	0.00	-0.04	-0.15	-0.01	-0.42	-0.39
	t-stat	(-0.25)	(2.59)	(1.68)	(1.38)	(-1.66)	(-0.00)	(-0.31)	(-0.88)	(-0.03)	(-1.28)	(-1.03)
	pre-formation beta	-81.78	-46.17	-29.61	-17.26	-5.64	6.61	20.77	39.58	66.86	125.50	207.28
	post-formation beta	-16.15	-11.78	-6.02	-6.09	-3.81	2.87	16.32	14.87	29.55	42.74	58.88

Table 4: **Excess Returns of Macro Beta Sorted Portfolios Following Low and High Disagreement States**

This table reports the monthly portfolio mean excess returns (in percentage) for ten macro beta-sorted portfolios following low and high disagreement periods. The whole sample period is divided into quartiles based on the in-sample macro disagreement level. I then report the value-weighted portfolio excess returns over months where the prior quarter is in the lowest quartile and the highest quartile of macro disagreement. I also report excess returns to a long-short portfolio strategy in the right-most column, long the highest macro beta portfolio and short the lowest macro beta portfolio. All the t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

		Decile										
Macro Factors	Macro Disagreement	low beta	2	3	4	5	6	7	8	9	high beta	High-Low
IPG	Lowest quartile	0.77	0.79	0.88	0.90	0.85	0.84	0.88	1.11	1.11	1.35	0.57
	t-stat	(1.02)	(1.58)	(2.13)	(2.48)	(2.52)	(2.62)	(2.56)	(2.65)	(2.17)	(1.77)	(1.19)
	Highest quartile	0.95	1.21	1.12	1.09	0.98	0.92	0.87	0.75	0.53	-0.06	-1.01**
	t-stat	(1.24)	(2.16)	(2.22)	(2.08)	(1.77)	(1.65)	(1.51)	(1.15)	(0.77)	(-0.06)	(-2.02)
										Difference in High-Low:		-1.58**
											t-stat	(-2.23)
LaIncome	Lowest quartile	1.79	1.56	1.44	1.44	1.67	1.70	1.83	2.09	2.10	2.51	0.72
	t-stat	(2.49)	(2.87)	(3.17)	(3.11)	(3.83)	(3.62)	(3.99)	(4.21)	(3.08)	(2.72)	(1.09)
	Highest quartile	1.96	1.60	1.72	1.79	1.70	1.58	1.56	1.38	1.25	0.89	-1.07**
	t-stat	(2.37)	(2.54)	(3.04)	(3.32)	(3.04)	(2.69)	(2.38)	(1.97)	(1.53)	(0.90)	(-2.16)
										Difference in High-Low:		-1.79**
											t-stat	(-1.98)
Tbill	Lowest quartile	2.26	2.12	1.42	1.11	1.00	0.97	0.74	0.77	0.96	0.71	-1.55**
	t-stat	(2.97)	(3.21)	(2.79)	(2.16)	(2.42)	(2.09)	(1.61)	(1.58)	(1.87)	(0.90)	(-2.39)
	Highest quartile	0.11	0.29	0.42	0.36	0.67	0.57	0.67	0.52	0.50	0.57	0.46
	t-stat	(0.15)	(0.49)	(0.83)	(0.72)	(1.54)	(1.23)	(1.53)	(1.14)	(1.07)	(0.92)	(0.99)
										Difference in High-Low:		2.01**
											t-stat	(2.60)

Table 4 Continued

Macro Factors	Macro Disagreement	Decile										
		low beta	2	3	4	5	6	7	8	9	high beta	HML
GDP	Lowest quartile	0.59	0.76	0.88	0.96	0.96	1.09	1.14	1.33	1.34	1.36	0.76*
	t-stat	(1.12)	(1.89)	(2.72)	(3.19)	(3.14)	(3.32)	(3.35)	(3.81)	(3.16)	(2.46)	(1.86)
	Highest quartile	0.62	0.73	0.75	0.98	0.95	1.11	1.14	1.23	1.09	0.96	0.34
	t-stat	(0.71)	(1.06)	(1.23)	(1.58)	(1.57)	(1.72)	(1.69)	(1.60)	(1.14)	(0.73)	(0.43)
										Difference in High-Low:		-0.43
											t-stat	(-1.09)
Investment	Lowest quartile	-0.97	-0.49	-0.16	-0.11	0.14	0.21	0.23	0.26	-0.38	-0.40	0.57
	t-stat	(-1.57)	(-0.82)	(-0.26)	(-0.19)	(0.24)	(0.40)	(0.45)	(0.48)	(-0.64)	(-0.66)	(1.32)
	Highest quartile	0.67	0.99	0.97	0.77	0.78	0.52	0.93	0.65	0.23	0.07	-0.60
	t-stat	(0.93)	(1.59)	(1.86)	(1.41)	(1.37)	(0.92)	(1.79)	(1.03)	(0.30)	(0.09)	(-0.93)
										Difference in High-Low:		-1.17*
											t-stat	(-1.82)
DEI	Lowest quartile	1.19	0.82	0.69	0.61	0.52	0.76	0.23	0.68	0.98	1.90	0.71
	t-stat	(1.71)	(1.54)	(1.61)	(1.16)	(0.86)	(1.21)	(0.29)	(0.71)	(0.93)	(1.12)	(0.60)
	Highest quartile	1.18	1.18	1.23	1.14	0.87	0.94	1.00	0.65	0.88	0.23	-0.95
	t-stat	(1.62)	(2.17)	(2.08)	(1.99)	(1.69)	(1.59)	(1.70)	(1.07)	(1.35)	(0.27)	(-1.42)
										Difference in High-Low:		-1.66**
											t-stat	(-1.99)

Table 5: **Time Series Regression of Portfolio Returns**

This table presents the regression results of the long-short portfolio excess return on the lagged macro disagreement measure (Disp) (column 1) and also regressions controlling for a set of lagged predictors (column 2), including the Baker-Wurgler sentiment index (Sentiment), the dividend/price ratio (D/P), the term spread, the default premium and a detrended one-month T-bill rate (Tbill_detrend). The long-short portfolio is formed by long the portfolio with highest macro beta and short the portfolio with the lowest macro beta. All the t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	IPG		LaIncome		Tbill		GDP		Investment		DEI	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Disp (t-1)	-0.007***	-0.006**	-0.060**	-0.074*	0.022***	0.024***	-0.015*	-0.019**	-0.005**	-0.007**	-0.018	0.005
	(-2.59)	(-2.01)	(-2.07)	(-1.88)	(3.88)	(2.90)	(-1.87)	(-1.98)	(-2.48)	(-2.08)	(-1.34)	(0.31)
Sentiment (t-1)		0.001		-0.013*		0.005		-0.005		0.013**		-0.015**
		(0.17)		(-1.91)		(0.63)		(-0.70)		(2.09)		(-2.57)
D/P (t-1)		-0.842**		-0.511		0.618		-0.173		-0.460		-1.213***
		(-2.03)		(-1.21)		(1.24)		(-0.35)		(-0.96)		(-2.87)
Term Spread (t-1)		0.024		-0.182		0.052		0.307		0.738*		-0.193
		(0.08)		(-0.49)		(0.15)		(0.92)		(1.92)		(-0.59)
Default Premium (t-1)		1.015		1.770		-2.045*		0.420		-0.045		2.024*
		(0.98)		(1.55)		(-1.90)		(0.31)		(-0.04)		(1.88)
Tbill_detrend (t-1)		-0.336		-0.315		0.623		-0.763**		0.192		-0.215
		(-0.93)		(-0.74)		(1.57)		(-2.07)		(0.53)		(-0.51)
Constant	0.016**	0.024**	0.015	0.019	-0.015**	-0.012	0.013	0.013	0.022***	0.027**	0.010	0.008
	(2.44)	(2.34)	(1.31)	(1.29)	(-2.50)	(-0.98)	(1.47)	(0.93)	(2.69)	(2.43)	(0.93)	(0.71)
N.of Obs.	366	355	366	355	366	355	366	355	366	355	366	355

Table 6: **Time Series Regression of Portfolio Returns, controlling for Cahart (1997) four factors**

This table reports the regression results of long-short portfolio excess returns on the lagged macro disagreement measure (Disp) and Cahart (1997) four factors (column 1) and also regressions controlling for a set of lagged predictors (column 2), including the Baker-Wurgler sentiment index (Sentiment), the Dividend/Price ratio (D/P), the term spread, the default premium and a detrended 1-month T-bill rate (Tbill_detrend). The long-short portfolios are formed by longing in the portfolio with highest macro beta and shorting in the portfolio with the lowest macro beta. All the t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	IPG		LaIncome		Tbill		GDP		Investment		DEI	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Disp (t-1)	-0.008***	-0.007**	-0.066**	-0.067*	0.016***	0.018**	-0.014**	-0.019*	-0.003	-0.005*	-0.014	0.011
	(-2.84)	(-2.17)	(-2.42)	(-1.83)	(3.14)	(1.99)	(-1.97)	(-1.89)	(-1.32)	(-1.66)	(-1.26)	(0.73)
Mktrf (t)	0.254**	0.242**	-0.084	-0.083	-0.502***	-0.501***	0.380***	0.360***	-0.117	-0.116	0.141	0.118
	(2.34)	(2.32)	(-0.75)	(-0.74)	(-6.01)	(-7.15)	(3.31)	(3.12)	(-1.12)	(-1.13)	(1.37)	(1.29)
SMB (t)	0.118	0.042	0.489***	0.479***	-0.788***	-0.722***	-0.424**	-0.505***	-0.691***	-0.760***	0.622***	0.581***
	(1.01)	(0.37)	(3.04)	(2.77)	(-6.25)	(-5.74)	(-2.26)	(-2.88)	(-6.12)	(-7.14)	(4.94)	(4.42)
HML (t)	0.186	0.161	-0.453**	-0.414**	-0.148	-0.182	0.395**	0.426**	0.432**	0.395**	-0.542***	-0.560***
	(1.04)	(0.99)	(-2.40)	(-2.16)	(-0.74)	(-1.01)	(2.06)	(2.40)	(2.31)	(2.25)	(-3.15)	(-3.60)
UMD (t)	0.039	0.048	-0.132	-0.120	-0.218	-0.256**	-0.192	-0.184	0.055	0.056	-0.059	-0.051
	(0.40)	(0.48)	(-1.10)	(-0.92)	(-1.50)	(-2.02)	(-1.54)	(-1.46)	(0.51)	(0.48)	(-0.65)	(-0.54)
Sentiment (t-1)		0.001		-0.007		0.004		-0.005		0.006		-0.006
		(0.22)		(-1.06)		(0.60)		(-0.80)		(1.05)		(-1.06)
DP_ratio (t-1)		-0.960**		-0.290		0.917**		-0.502		-0.681		-1.097***
		(-2.34)		(-0.67)		(2.26)		(-1.18)		(-1.61)		(-2.88)
Term Spread (t-1)		-0.042		-0.155		0.204		0.251		0.690**		-0.174
		(-0.14)		(-0.41)		(0.68)		(0.83)		(2.34)		(-0.53)
Default Premium (t-1)		1.435		0.766		-2.682**		0.752		0.631		1.065
		(1.40)		(0.69)		(-2.56)		(0.81)		(0.56)		(1.02)
Tbill_detrend (t-1)		-0.277		-0.101		0.159		-1.111***		-0.133		0.148
		(-0.78)		(-0.23)		(0.45)		(-3.07)		(-0.36)		(0.36)
Constant	0.015**	0.023**	0.020*	0.023	-0.006	-0.006	0.011	0.016	0.012	0.018*	0.008	0.011
	(2.39)	(2.03)	(1.81)	(1.64)	(-1.18)	(-0.57)	(1.32)	(1.36)	(1.57)	(1.66)	(0.90)	(1.09)
N.of Obs.	366	355	366	355	366	355	366	355	366	355	366	355

Table 7: **Macro Disagreement and Macro-Factor Risk Premiums**

This table reports the time series regression of macro-factor risk premium on the lagged macro disagreement measure. The dependent variable is the coefficient estimate of a monthly cross-sectional regression of the ten macro beta-sorted portfolio excess returns on portfolios' post-ranking macro betas. Only the lagged macro disagreement measure (Disp) is included in column (1). In column (2), I control for a set of lagged predictors, including the Baker-Wurgler sentiment index (Sentiment), the dividend/price ratio (D/P), the term spread, the default premium and a detrended one-month T-bill rate (Tbill_detrend). All the t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	IPG		LaIncome		Tbill		GDP		Investment		DEI	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Disp (t-1)	-0.001***	-0.001***	-0.002**	-0.003**	0.004***	0.004***	-0.001*	-0.001*	-0.001**	-0.001*	-0.000	0.000
	(-2.85)	(-2.73)	(-2.39)	(-2.07)	(3.52)	(2.74)	(-1.74)	(-1.72)	(-2.21)	(-1.95)	(-1.64)	(0.05)
Sentiment (t-1)		-0.000		-0.001***		0.001		-0.000		0.003**		-0.000***
		(-0.32)		(-2.71)		(1.31)		(-0.69)		(2.58)		(-2.69)
D/P (t-1)		-0.056**		-0.020		0.077		-0.014		-0.111		-0.008**
		(-2.19)		(-1.45)		(0.91)		(-0.46)		(-1.23)		(-2.37)
Term Spread (t-1)		0.012		-0.013		0.035		0.020		0.115		-0.003
		(0.58)		(-1.04)		(0.64)		(0.95)		(1.55)		(-1.00)
Default Premium (t-1)		0.115		0.080**		-0.292		0.052		0.008		0.015**
		(1.59)		(2.50)		(-1.54)		(0.53)		(0.04)		(2.10)
Tbill_detrend (t-1)		-0.015		-0.007		0.082		-0.031		0.015		0.000
		(-0.62)		(-0.44)		(1.27)		(-1.15)		(0.22)		(0.13)
Constant	0.001**	0.001*	0.001*	0.001*	-0.003***	-0.003	0.001	0.000	0.003**	0.005**	0.000	0.000
	(2.43)	(1.96)	(1.71)	(1.69)	(-2.61)	(-1.24)	(1.19)	(0.48)	(2.17)	(2.33)	(1.26)	(0.95)
N.of Obs.	366	355	366	355	366	355	366	355	366	355	366	355

Table 8: **Macro Disagreement and Stock-Level Disagreement**

This table reports the regression results of stock-level disagreement on the absolute value of macro beta, along with the interaction between macro beta and macro disagreement.

$$y_{it} = a + (b + cDisp_t)|\beta_i| + (d + eDisp_t)X_{it} + fDisp_t + \epsilon_{it} \tag{9}$$

The dependent variable y_{it} is the equal-weighted average of stock-level disagreement for portfolio i at month t, $|\beta_i|$ is the absolute value of post-ranking beta for portfolio i and X_{it} is the average characteristics of portfolio i at month t. I use the standard deviation of analysts' forecast of long-term EPS growth rate as a proxy for stock-level disagreement. In column (1), I only include log of market capitalization [Ln(ME)] as control. In column (2), X also includes the natural log of book-to-market ratio [ln(BM)] and the cumulative return from month t-12 to t-2 (Mom). Standard errors are clustered at the portfolio and quarter dimension. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	IPG		LaIncome		Tbill		GDP		Investment		DEI	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Abs(Beta)	-0.027	-0.029	0.088**	0.038	0.260***	0.256***	-0.145***	-0.133***	0.598***	0.447***	0.042***	0.044***
	(-1.20)	(-1.17)	(2.32)	(0.75)	(3.68)	(3.07)	(-4.77)	(-3.96)	(5.80)	(2.66)	(7.55)	(6.95)
Abs(Beta)*Disp(t)	0.063***	0.069***	0.196**	0.299**	0.124	0.140	0.195***	0.187***	0.059**	0.094**	-0.005	-0.007
	(5.44)	(4.82)	(1.99)	(2.45)	(1.44)	(1.21)	(6.28)	(5.57)	(2.03)	(2.22)	(-0.92)	(-1.01)
Disp (t)	-0.818**	-1.151***	-3.691	-6.028*	0.913	1.401	-1.477	-1.675	-0.561***	-0.766***	2.304	2.609
	(-2.22)	(-2.95)	(-1.33)	(-1.89)	(0.57)	(0.75)	(-1.59)	(-1.64)	(-2.73)	(-2.67)	(1.45)	(1.52)
LnME	-0.431***	-0.580***	-0.336**	-0.554***	0.015	0.084	-0.267**	-0.323**	-0.349***	-0.493***	0.373**	0.473**
	(-3.98)	(-4.52)	(-2.51)	(-2.97)	(0.11)	(0.52)	(-2.03)	(-2.02)	(-3.40)	(-3.19)	(1.99)	(2.34)
LnME*Disp(t)	0.082	0.151**	0.541	0.965**	-0.310	-0.415*	0.023	0.074	0.095***	0.132***	-0.264	-0.346
	(1.50)	(2.39)	(1.41)	(2.13)	(-1.50)	(-1.76)	(0.17)	(0.46)	(3.63)	(3.33)	(-1.19)	(-1.40)
LnBM		-1.473**		-1.849*		0.123		-0.311		-1.051		1.121**
		(-2.56)		(-1.96)		(0.27)		(-0.43)		(-1.29)		(2.27)
LnBM*Disp(t)		0.433		3.849*		-0.204		-0.204		0.255		-0.967
		(1.60)		(1.70)		(-0.36)		(-0.31)		(1.25)		(-1.52)
Mom		0.989		1.436		-0.753		0.138		1.218**		-0.653
		(1.20)		(1.45)		(-1.35)		(0.17)		(2.02)		(-1.38)
Mom*Disp(t)		-0.204		-3.079		1.519*		0.209		-0.192		0.989**
		(-0.56)		(-1.33)		(1.90)		(0.31)		(-1.55)		(2.47)
Constant	7.360***	7.833***	5.602***	6.803***	3.382***	2.987**	7.140***	7.212***	5.492***	6.199***	0.134	-0.326
	(9.14)	(9.13)	(5.63)	(5.29)	(2.68)	(2.11)	(7.36)	(6.90)	(6.74)	(5.56)	(0.10)	(-0.23)
Adj.R-sq	0.157	0.177	0.252	0.262	0.310	0.317	0.104	0.113	0.304	0.314	0.516	0.526
N.of Obs.	3600	3600	3600	3600	3600	3600	3600	3600	3600	3600	3600	3600

Table 9: **Time Series Regression of Portfolio Returns, controlling for Market Beta**

This table reports the regression results of long-short portfolio excess returns on the lagged macro disagreement measure (Disp) (column 1) and also regressions controlling for a set of lagged predictors (column 2), including the Baker-Wurgler sentiment index (Sentiment), the dividend/price ratio (D/P), the term spread, the default premium and a detrended one-month T-bill rate (Tbill_detrend). The ten macro-beta sorted portfolios are formed by first sorting all the stocks into ten portfolios based on the pre-ranking market betas and then sort into ten macro beta portfolios based on the pre-ranking macro betas within each decile of market beta-sorted portfolios. The macro beta portfolios across all ten market beta portfolios are aggregated to control for the effect of market beta. All the t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

	IPG		LaIncome		Tbill		GDP		Investment		DEI	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Disp (t-1)	-0.007***	-0.005*	-0.051**	-0.053*	0.012**	0.004	-0.013**	-0.012*	-0.005**	-0.005**	-0.011	0.004
	(-2.87)	(-1.82)	(-2.29)	(-1.74)	(2.15)	(0.34)	(-2.20)	(-1.79)	(-2.50)	(-1.98)	(-1.01)	(0.25)
Sentiment (t-1)		0.010*		-0.009		-0.007		0.011*		0.014***		-0.003
		(1.80)		(-1.35)		(-0.86)		(1.96)		(2.59)		(-0.54)
D/P (t-1)		-0.851**		-0.300		0.994**		-0.322		-0.503		-0.951**
		(-2.48)		(-0.72)		(2.07)		(-0.99)		(-1.42)		(-2.19)
Term Spread (t-1)		0.116		-0.197		-0.523		0.291		0.332		0.019
		(0.45)		(-0.63)		(-1.63)		(1.02)		(1.13)		(0.06)
Default Premium (t-1)		0.459		1.091		-0.455		-0.476		-0.320		1.263
		(0.53)		(0.87)		(-0.30)		(-0.61)		(-0.38)		(1.00)
Tbill_detrend (t-1)		-0.043		-0.005		0.389		-0.316		0.107		0.089
		(-0.13)		(-0.01)		(1.00)		(-1.00)		(0.36)		(0.19)
Constant	0.018***	0.027***	0.017*	0.019	-0.009	-0.015	0.013*	0.018**	0.022***	0.031***	0.010	0.010
	(3.00)	(3.33)	(1.85)	(1.32)	(-1.62)	(-1.13)	(1.89)	(2.31)	(2.82)	(3.44)	(1.12)	(0.84)
N.of Obs.	366	355	366	355	366	355	366	355	366	355	366	355

Table 10: **Time Series Regression of Portfolio Returns, controlling for Aggregate Disagreement, VIX, CAY and TED**

	IPG	LaIncome	Tbill	GDP	Investment	DEI
Disp(t-1)	-0.006*	-0.132***	0.029*	-0.008	-0.007**	0.012
	(-1.78)	(-2.79)	(1.82)	(-0.69)	(-2.02)	(0.61)
Sentiment (t-1)	0.014	-0.017	-0.006	0.018	0.033***	-0.015
	(1.31)	(-1.53)	(-0.48)	(1.63)	(2.80)	(-1.57)
D/P ratio (t-1)	0.990	0.565	-0.322	2.525**	1.596	-0.387
	(1.16)	(0.48)	(-0.26)	(2.08)	(1.07)	(-0.37)
Term Spread (t-1)	-0.266	-0.496	0.133	-0.299	0.494	-0.264
	(-0.56)	(-0.99)	(0.27)	(-0.63)	(1.08)	(-0.63)
Default Premium (t-1)	0.852	0.904	-2.708*	0.711	1.031	0.301
	(0.54)	(0.47)	(-1.75)	(0.45)	(0.59)	(0.16)
Tbill_detrend (t-1)	-0.109	-0.583	0.406	-0.625	-0.079	-0.158
	(-0.21)	(-0.97)	(0.72)	(-1.17)	(-0.15)	(-0.30)
Inflation (t-1)	-0.440	-2.352	0.784	0.068	0.933	-2.118
	(-0.35)	(-1.61)	(0.52)	(0.07)	(0.64)	(-1.38)
Aggregate Disagreement (t-1)	0.001	0.001	-0.003	-0.014	-0.013	-0.002
	(0.14)	(0.10)	(-0.24)	(-1.06)	(-1.00)	(-0.16)
VIX (t-1)	0.001	0.001	0.001	0.001*	-0.000	0.000
	(0.84)	(0.69)	(0.75)	(1.78)	(-0.09)	(0.58)
CAY (t-1)	-0.197	-0.242	-0.001	-0.445	-0.458	-0.265
	(-0.83)	(-0.70)	(-0.00)	(-1.30)	(-1.15)	(-0.92)
TED (t-1)	-2.833**	-2.478	0.740	-5.103***	-2.425	-0.327
	(-2.25)	(-1.62)	(0.41)	(-3.03)	(-1.35)	(-0.22)
Constant	-0.006	0.035	0.002	0.008	0.037	0.009
	(-0.18)	(0.88)	(0.06)	(0.22)	(0.99)	(0.21)
N.of obs.	299	299	299	299	299	299

This table reports the regression result of long-short portfolio excess returns on the lagged macro disagreement measure (Disp), controlling for a set of lagged predictors, including the Baker-Wurgler sentiment index (Sentiment), the dividend/price ratio (D/P), the term spread, the default premium, a detrended one-month T-bill rate (Tbill_detrend), the inflation rate, an aggregate disagreement measure, the VIX, the consumption-to-wealth ratio (CAY), and the TED spread. The long-short portfolios are formed by long the portfolio with highest macro beta and short the portfolio with the lowest macro beta. All the t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.

Table 11: **Time Series Regression of Portfolio Returns, controlling for Conditional Market Beta**

	IPG	LaIncome	Tbill	GDP	Investment	DEI
Disp (t-1)	-0.007**	-0.060**	0.017**	-0.016***	-0.004**	-0.016
	(-2.51)	(-2.14)	(2.43)	(-2.60)	(-1.97)	(-1.20)
Mktrf (t)	-0.212	0.389	-0.024	-0.855***	-0.453	0.602***
	(-0.91)	(0.95)	(-0.09)	(-3.16)	(-1.62)	(2.81)
Disp (t-1) * Mktrf (t)	-0.046	-0.123	0.010	0.391*	-0.105	-0.090
	(-0.66)	(-0.16)	(0.03)	(1.93)	(-1.58)	(-0.30)
CAY (t-1) * Mktrf (t)	-14.220***	-14.363***	17.900***	-9.635**	-13.585***	-16.315***
	(-3.86)	(-3.33)	(4.74)	(-2.50)	(-4.26)	(-4.35)
Tbill_d (t-1) * Mktrf (t)	14.097	-2.688	-38.074***	24.820***	5.492	9.204
	(1.62)	(-0.23)	(-3.80)	(3.07)	(0.54)	(0.88)
D/P (t-1) * Mktrf (t)	24.227***	-6.434	-29.178**	31.338***	22.638***	-2.006
	(2.89)	(-0.66)	(-2.18)	(3.31)	(2.84)	(-0.20)
Constant	0.015**	0.017	-0.010	0.013*	0.022***	0.008
	(2.36)	(1.49)	(-1.57)	(1.75)	(2.60)	(0.83)
N.of Obs.	366	366	366	366	366	366

This table reports the regression results of long-short portfolio excess returns on the lagged macro disagreement measure (Disp) and the excess market return, in which the conditional beta is a function of lagged macro disagreement, the consumption-to-wealth ratio (CAY), a detrended one-month T-bill rate (Tbill_detrend), and the dividend/price ratio (D/P). The long-short portfolios are formed by long the portfolio with highest macro beta and short the portfolio with the lowest macro beta. All the t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation. ***, **, and * stands for significance level of 1%, 5% and 10%, respectively.