Dispersion of Beliefs, Ambiguity, and the Cross-Section of Stock Returns

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Abstract

We examine whether ambiguity is priced in the cross-section of expected stock returns. Using the cross-sectional dispersion in real-time forecasts of real GDP growth as a measure for ambiguity, we find that high ambiguity beta stocks earn lower future returns relative to low ambiguity beta stocks. This negative predictive relation between the ambiguity beta and future returns is consistent with theory that predicts the marginal utility of consumption rises when ambiguity is high. A long-short portfolio formed on the ex-ante measure of the ambiguity beta generates an ambiguity premium that is statistically and economically significant. We also find that time variation of the ambiguity premium is systematically related to changing economic conditions, but is not related to the investor sentiment index. Our results are robust to controlling for stock characteristics that are known to predict cross-section returns.

JEL classification: G12, G14

Keywords: Ambiguity; Dispersion of beliefs; Stock returns

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1 Introduction

Asset pricing models based on rational expectations perform poorly in explaining asset markets data.[1] The rational expectation hypothesis assumes that decision makers know the probabilities of future returns, but Knight (1921) and Keynes (1937) point out that decision makers are uncertain about these probabilities due to cognitive or informational constraints. The Ellsberg paradox (Ellsberg, 1961) and related experimental evidence demonstrate that decision makers are averse to not only uncertainty regarding future outcome with known probabilities (risk), but also uncertainty regarding future outcome with unknown probabilities (ambiguity or Knightian uncertainty). The literature on ambiguity and asset markets show that ambiguity has important implications for the pricing of financial assets.[2] Most of the literature has focused on theoretical aspects, however, presumably because ambiguity is harder to be quantified empirically than risk. In particular, the question of how ambiguity affects the cross-section of expected returns has received less attention.

The main objective of this paper is therefore to investigate whether ambiguity is priced in the cross-section of expected stock returns. We evaluate the economic significance of the premium for bearing ambiguity using a portfolio sorting approach where portfolios are formed on fully *ex-ante* information. We examine the out-of-sample performance of the ex-ante measure of the ambiguity beta in predicting the cross-section of future stock returns. Therefore, there is no look-ahead bias in our analyses. We also estimate the ambiguity premium by running Fama-MacBeth (1973) cross-sectional regressions.

The theoretical motivation for our study comes from recent asset pricing models which predict that ambiguity averse investors command a premium for bearing ambiguity (Epstein and Schneider,

[1] See Cochrane (2007) for a review on the limitations of extant asset pricing models in explaining asset market data.
[2] Epstein and Schneider (2010) and Guidolin and Rinaldi (2013) make an excellent review on the implications of ambiguity for asset pricing.

2010; Ui, 2011; Ju and Miao, 2012; Brenner and Izhakian, 2015). In these models, the total equity premium constitutes a risk premium and an ambiguity premium. In particular, Ju and Miao (2012) develop a consumption-based asset pricing model that accounts for ambiguity and show that it can explain a variety of asset pricing puzzles.[3] In their model, the marginal utility of consumption rises when the economic model is unfavorable (i.e., when ambiguity is high). Investors must therefore be rewarded with high expected returns to hold stocks that deliver low returns during bad times when marginal utility rises. In other words, low ambiguity beta stocks, which deliver low return when ambiguity is high, must have high expected returns to reward the investor for bearing ambiguity. On the other hand, stocks that deliver high return when ambiguity is high (i.e., high ambiguity beta stocks) provide a good hedge and therefore must have low expected returns.

Following Drechsler (2013) and Ulrich (2013), we measure the level of ambiguity by the cross-sectional dispersion in real-time forecasts of next quarter's real GDP growth, from the Survey of Professional Forecasters (SPF). The dispersion is computed simply as the standard deviation in the growth forecasts, which are reported around the beginning of every quarter. Our measure of ambiguity is unlikely to reflect information asymmetry, since the relevant information for forecasting an aggregate quantity such as GDP is publicly accessible and actively circulated in the media. In fact, Patton and Timmermann (2010) show that dispersion in economic forecasts cannot be attributed to differences in information sets, but instead arises from heterogeneity in models (i.e., model uncertainty).

Our main finding is that ambiguity regarding economic conditions is significantly priced in the cross-section of returns. We find that high ambiguity beta stocks earn lower future returns relative to

[3] Ju and Miao (2012) show that their calibrated model can explain a number of asset pricing puzzles, including the equity premium puzzle, the risk-free rate puzzle, the volatility puzzle, the procyclical variation of price-dividend ratios, the countercyclical variation of equity premium and equity volatility, the leverage effect, and the mean reversion of excess returns.

low ambiguity beta stocks, that is, ambiguity carries a negative market price, consistent with Ju and Miao (2012). This predictive relation between the ambiguity beta and future returns suggests that realized returns on the ambiguity beta sorted portfolios are likely to reflect expected returns. Ambiguity premium is also important economically. A zero-investment portfolio that longs stocks in the lowest ambiguity beta quintile and shorts those in the highest ambiguity beta quintile has an annual return of 4.56%. It is worthwhile to note that this ambiguity premium is a return on a fully tradable, ex-ante portfolio formed on publicly available information at each point in time. Similarly, using Fama-MacBeth (1973) regressions we find that a two-standard deviation increase across stocks in ambiguity betas is associated with a -5.09% drop in expected annual returns.

We also find that the predictive power of the ambiguity beta for the cross-section of stock returns is not subsumed by stock characteristics that are known to predict cross-section returns. When we perform double portfolio sorts to control for the size, book-to-market, and past returns, the negative relation between the ambiguity beta and future returns remains significant. In Fama-MacBeth regressions that control for various stock characteristics, the reward for bearing ambiguity is always negative, stable, and both economically and statistically significant in most specifications. The results suggest that our findings are not driven by some well-known cross-sectional stock return predictability patterns in the data.

Related to our study, Goetzmann, Watanabe, and Watanabe (2012) use the expected real GDP growth as a proxy for business cycles, and find that high business cycle beta stocks earn higher returns relative to low business cycle betas. Since the expected real GDP growth and our measure of ambiguity are constructed as the first and second moment of forecasts, respectively, it is of great interest to compare them. The results from both a double-sorting portfolio approach and Fama-MacBeth regressions that control for the expected real GDP growth show that the predictive power of the ambiguity beta for stock returns remains highly significant. The results, therefore, suggest that the ambiguity premium is distinct from the procyclicality premium.

To understand better what drives the ambiguity premium, we explore *time variation* of the ambiguity premium. In particular, we are interested in whether the ambiguity premium systematically varies across different economic states and/or investor sentiment. We define economic expansions and recessions, based on either the NBER business cycle classification (ex-post measure) or the Chicago Fed National Activity index (ex-ante measure). We then examine the ambiguity premium, which is the return spread between the stocks with lowest ambiguity betas and those with the highest ambiguity betas, conditional on these measures of economic states. We find that the ambiguity premium is significantly higher during bad states of the economy. This counter-cyclical ambiguity premium reinforces our interpretation that the return spread between low and high ambiguity beta stocks reflects a compensation that ambiguity averse investors command for bearing ambiguity. In a sharp contrast, the ambiguity premium is not affected by the investor sentiment index of Baker and Wurgler (2006), which suggests that the ambiguity premium is unlikely to be related to mispricing or behavioral biases.

We perform a battery of robustness checks. We examine whether the ambiguity beta on each stock is predicted by stock characteristics, and find that the ambiguity beta is not correlated with them. We also examine the long-term predictive power of the ambiguity beta. We find that the predictive power of the ambiguity beta for stock returns holds up to the following three quarters. Next, we combine the nominal GDP forecasts with the inflation forecasts, and construct the implied real GDP forecasts. We alternatively measure ambiguity using this implied real GDP forecasts, and re-do our analyses. We obtain the similar results. Lastly, we measure ambiguity regarding longer-term (up to four quarters ahead) economic conditions. We find that the ambiguity regarding longer-horizon economic conditions has similar predictability for cross-section returns.

We build on the model of Ju and Miao (2012) but differ by focusing on the role of ambiguity in explaining the cross-section of expected returns. We also do estimate the ambiguity premium with real data, while Ju and Miao evaluate their model by doing calibration (i.e., a combination of simulation and momentum-matching).

Our work is related to recent studies that empirically measure ambiguity and examine its relation to stock returns. Brenner and Izhakian (2015) and Andreou et al (2014) measure stock market ambiguity using financial market data, and both study the intertemporal relation between ambiguity and the equity premium. Anderson, Ghysels, and Juergens (2009) measure ambiguity using the dispersion of forecasts for aggregate corporate profits, and propose an uncertainty factor that helps explain the cross-section of stock returns. Viale, Garcia-Feijoo, and Giannetti (2014) construct an ambiguity measure by estimating a regime-switching model for a market return, and study its implication for the cross-section of asset returns. While these studies examine stock market ambiguity or measure ambiguity using financial market data, we measure ambiguity regarding the state of the economy, which is more likely exogenous to the financial market. More importantly, unlike these studies, in our analyses portfolios are formed on fully ex-ante information.[4] This difference is particularly critical to investors looking to develop a real-time implementable trading strategy exploiting the ambiguity beta.

The remainder of the paper is organized as follows. Section 2 describes the data and our empirical proxy for the degree of ambiguity. Section 3 presents our main results obtained from sorting stocks into quintiles based on the ambiguity beta, as well as Fama-MacBeth cross-sectional regressions. Section 4 examines the robustness of our results. Section 5 concludes.

[4] Although Anderson, Ghysels, and Juergens (2009) use the survey data to measure ambiguity as ours, they have to rely on the full sample to estimate some parameters, which are necessary to construct their ambiguity measure.

2 Data and Ambiguity Measure

2.1 Data

Our initial sample consists of all common stocks on the Center for Research and Security Prices (CRSP) that are traded on the NYSE, AMEX, and NASDAQ. We merge quarterly stock files with COMPUSTAT fundamental annual data to calculate the book-to-market ratio. Following Fama and French (1993), we match the book-to-market ratio with the returns for July of year t to June of $t + 1$. Also, we use the firm size at the end of year $t - 1$ to returns for July of year t to June of $t + 1$. To control for the momentum effect, stocks in our sample should have 12-month past returns. We exclude stocks with a price of \$5 or less at the beginning of each holding period to minimize microstructure issues such as illiquidity.

The Fama and French three factors are obtained from Kenneth French's online library. We compound the monthly return into a quarterly frequency, and calculate the quarterly excess return as the quarterly return minus quarterly risk free rate. We use the market-wide investor sentiment index constructed by Baker and Wurgler (2006), which is obtained from the Jeffrey Wurgler's website. Our empirical analysis begins in the fourth quarter of 1968 and ends in the fourth quarter of 2013. Since the sentiment index ends in 2010, the sample ends in the 2010 when our analysis uses the sentiment index.

2.2 Measuring Ambiguity

The ambiguity regarding economic conditions, which is our primary variable in interest, is measured by the dispersion in beliefs among economists about future real GDP growth. Fundamentally, disagreement among economic agents can emerge from two sources: difference in information and/or in prior models. The dispersion in beliefs among economists should not reflect informational asymmetry since information related to forecasting the future economy is widely accessible and actively released in public. This intuition is supported by Patton and Timmermann (2010), who argue that disagreement among economists reflects heterogeneity in their models, rather than heterogeneity in information signals. Patton and Timmermann show that there is greater degree of disagreement at long-horizon forecasts than at short-horizon forecasts. Given that the contribution of the difference in information signals is stronger at short-horizon forecasts, this suggests that heterogeneity in priors or models matters more. Using a structural model, Patton and Timmermann further show that heterogeneity in priors or models explains well the term structure of cross-sectional dispersion, but heterogeneity in information signals does not.

In line with this intuition, several studies use the disagreement among economists as the ambiguity regarding economic conditions. For example, Bansal and Shaliastovich (2010) use cross-sectional dispersion in beliefs as a confidence measure. Ulrich (2013) serves the dispersion in forecasts for the inflation as a proxy for the degree of inflation ambiguity. Drechsler (2013) argues that the dispersion in forecasts of economist can be a proxy for the degree of ambiguity. Anderson, Ghysels, and Juergens (2009) measure the ambiguity level based on the dispersion on the corporate profits via their theoretical model.

Following the aforementioned studies, we measure ambiguity regarding economic conditions as the cross-sectional dispersion in forecasts for real GDP growth rates among professional forecasters, which are obtained from the Survey of Professional Forecasters (SPF). SPF has been conducted quarterly by the Federal Reserve Bank of Philadelphia since 1969. SPF asks economists to forecast important economic indicators such as nominal GDP, real GDP, and inflation from the current quarter up to 4 quarters ahead. The forecasts are reported near the beginning of the quarter. Specifically, at each quarter t, we first calculate the forecasted real GDP growth rate from the quarter t to the quarter $t + k$ for each economist i as follows:

$$g^i_{t,t+k} = log\left(\frac{RGDP^i_{t,t+k}}{RGDP^i_{t,t}}\right), \quad (1)$$

where $RGDP^i_{t,t+k}$ is the forecast made at time t from the economist i for the level of real GDP at time $t + k$. The dispersion in beliefs among economists is then defined as the cross-sectional standard deviation of the forecasted economic growth above, and we denote it as $AMB_{t,t+k}$. Our main results are based on $AMB_{t,t+1}$, the ambiguity about the one-quarter-ahead real GDP growth rate. This simple measurement has an advantage in that we do not rely on specific econometric models. If the econometric models used are misspecified, the conclusion inferred from their use is incorrect as well. More importantly, the proposed measure is fully ex-ante information. This is particularly important because our empirical analyses do not incur any look-ahead bias. Hereafter, we simply denote the dispersion in forecasts of future real GDP growth as the ambiguity measure.

We additionally measure the expected real GDP growth (EGDP) as the cross-sectional median of forecasts for future real GDP growth. Goetzmann, Watanabe, and Watanabe (2012) show that the expected real GDP growth is priced in the stock market. We examine whether our results are affected by the impact of EGDP in Section 3.3.

We plot the number of forecasts per each period in Panel A of Figure 1. Since SPF begins in the fourth quarter of 1968, our sample period is from the fourth quarter of 1968 to the fourth quarter of 2013. The number had been larger than 30 until the early 1980s. Although the number of forecasters had decreased to around 10 during ten years since then, this number has been rapidly stabilized nearly to 30 since the early 1990s.

2.3 Summary Statistics

Table 1 displays the summary statistics for our ambiguity measure (AMB) and the expected real GDP growth (EGDP). The left half of the table displays the mean, standard deviation, first-order autocorrelation, and augmented Dickey-Fuller test statistics. The averages of AMB and EGDP are 0.384 and 0.646, which implies that the majority of forecasts would lie between 0.262% and 1.03% in cross-section, suggesting that forecasts for real GDP growth rate vary widely across economists. Second, time-variations of both AMB and EGDP are high in magnitude. The standard deviations of AMB and EGDP across time are 0.254 and 0.429, respectively. Third, those variables are highly persistent, but statistically stationary.

To examine how ambiguity changes over time, in the right half of the table, we report the correlations between AMB and two economic states: the NBER recession dummy and investor sentiment. The noticeable point is that the level of ambiguity fluctuates in a countercyclical manner. That is, the AMB measure is significantly positively correlated with the NBER recession dummy. It is consistent with Van Nieuwerburgh and Veldkamp (2006) suggesting that dispersion in beliefs should be greater during recessions where fewer information signals are received. In addition, provided that the expected business conditions are likely to reflect investors' rational perspective about the future economy, the significant negative correlation of the AMB measure with EGDP also supports counter-cyclicality of ambiguity. On the other hand, the correlation of the ambiguity with investor sentiment is statistically insignificant, which implies that ambiguity is not associated with investors' behavioral biases.

For further illustration, we plot AMB and EGDP in Panel B of Figure 1. We see that the AMB measure fluctuates in a countercyclical manner. Specifically, investors' ambiguity begins to rise at the onset of the NBER recessions, and spikes during those periods, especially in the late 1960s, mid-1970s, 1980s, early 2000s and 2008. It is also obvious that EGDP and AMB fluctuate in the opposite manner. Such counter-cyclicality of ambiguity is consistent with Patton and Timmermann (2010).

3 Empirical Results

In this section, we investigate the main hypothesis that low ambiguity beta stocks should have higher expected returns. We first run rolling quarterly time-series regressions to obtain the ambiguity betas. Next, we perform portfolio sorting approach and cross-sectional regressions to evaluate whether the ambiguity betas negatively predict stock returns. Since the ambiguity beta is estimated using publicly available information at each point in time, our analyses examines the out-of-sample predictability of the ambiguity beta.

3.1 Portfolios Sorted on the Ambiguity Beta

We employ standard portfolio sorting approach to examine our main hypothesis. To this end, for each stock we estimate the sensitivity of each stock i on the ambiguity regarding economic conditions by rolling windows regressions. In detail, for the stock i, we perform the 20 quarters rolling windows regression as follows:

$$R_{i,t} = \alpha_i + \beta_{i,t} AMB_{t-1,t} + \gamma_{i,t} MKT_t + \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t}$ is a return on the stock i, MKT_t is an excess market return at quarter t, and $AMB_{t-1,t}$ denotes the ambiguity measure based on forecasts at quarter t – 1 for real GDP growth rate for quarter t.[5] For each quarter, we estimate $\beta_{i,t}$, that is, the ambiguity beta of the stock i. We then form equal-weighted quintile portfolios at the end of each quarter t by sorting the stocks into portfolios based on the ambiguity beta. The portfolios are held until the end of the subsequent quarter. For notational convenience, we refer to the portfolio of stocks with highest (lowest) ambiguity beta as the *High* (*Low*) portfolio. We form the *LMH* portfolio as a zero-investment

[5] The results are entirely similar when MKT is excluded from the regressions, which are available upon request.

portfolio which buys the *Low* portfolio and sells the *High* portfolio. The return spread on the *LMH* portfolio represents the ambiguity premium. The first column in Table 2 reports the monthly average excess returns of the quintile portfolio formed on the ambiguity beta. The results strongly suggest that low ambiguity beta stocks earn higher returns relative to high ambiguity beta stocks. The average excess return is 1.07% for the *Low* portfolio, and monotonically drops to 0.69% for the *High* portfolio. The difference of average excess returns on the *Low* and *High* portfolios is 0.38% per month (equivalently, 4.56% per annum) with a *t*-statistic of 3.34. Our results are consistent with Ju and Miao (2012) that predicts the marginal utility of consumption rises when ambiguity is high. Specifically, stocks that deliver low returns when marginal utility rises (i.e., low ambiguity beta stocks) must have high expected returns to reward investors for bearing ambiguity. On the other hand, stocks that deliver high return when ambiguity is high (i.e., high ambiguity beta stocks) provide a good hedge and therefore must have low expected returns. Our results strongly support these predictions.

We further examine whether the ambiguity premium is significant after controlling for Carhart (1997) four factors: the excess market return (MKT), the size factor (SMB), the book-to-market factor (HML), and the momentum factor (UMD). Most importantly, the Carhart alpha of the long-short portfolio is 0.36% and highly statistically significant at the 1% level. With respect to R^2, the risk factors explain only 12.6% of the fluctuation in the return on the *LMH* portfolio. The Carhart alphas of quintile portfolios also decline with the ambiguity betas, and the loadings on the risk factors do not display any systematic pattern across the portfolios.

Next, in the last four columns of the table, we report the average characteristics of the quintile portfolios including the ambiguity betas, firm size (SIZE), book-to-market ratio (BTM), and 12-month past returns skipping 1-month (PRET). The average ambiguity beta is -0.83 for the *Low* portfolio, and increase to 0.84 for the *High* portfolio, which means that stocks in the *Low* (*High*) portfolio indeed negatively (positively) comove with our ambiguity measure (AMB). The ambiguity premium is unlikely to be driven by firm characteristics which are known to predict stock returns. If the firm size effect, initially reported by Banz (1981), explains the return on the *LMH* portfolio, the average firm size should be lowest for *Low* portfolio, but the *High* portfolio should have larger firm size than the *Low* portfolio. The portfolios with the intermediate level of ambiguity beta have higher book-to-market ratio and lower past returns. It suggests that the ambiguity beta is not systematically related to the book-to-market ratio and past returns. In the following subsection, we form double-sorted portfolios, and show that firm characteristics do not explain the ambiguity premium.

In summary, we provide the evidence that low ambiguity beta stocks earns higher returns than high ambiguity stocks. We form the quintile portfolios based on the ambiguity beta, and find that average excess returns on those portfolios monotonically decrease with the level of ambiguity beta. A zero-investment portfolio that longs stocks in the lowest ambiguity beta quintile and shorts those in the highest ambiguity beta quintile delivers an economically meaningful abnormal returns. We emphasize that this ambiguity premium is a return on a fully tradable, ex-ante portfolio formed on publicly available information at each point in time. The predictive power of the ambiguity betas are not driven by the Carhart four factors as well as firm characteristics which are known to predict stock returns.

3.2 Portfolios Sorts Controlling for Firm Characteristics

In this subsection, we form double-sorted portfolios to show that the cross-sectional predictive power of the ambiguity beta is not subsumed by firm characteristics. We independently sort stocks into the 3-by-3 portfolios on the ambiguity beta and the firm characteristics including the size, book-to-market ratio, and 12-month past returns (skipping 1-month). Table 3 reports the excess returns and risk-adjusted returns of the portfolios formed on the ambiguity beta and each firm characteristic. The left (right) half of the panel reports excess returns (risk-adjusted returns) on those portfolios.

Panel A displays the returns of the portfolios formed on the ambiguity beta and the book-to-market ratio. We find that the predictive power of the ambiguity beta survives after controlling for the value premium. Within each firm characteristic tercile, the returns on portfolios monotonically decrease with the ambiguity betas. For instance, the average excess return is 0.85% on the *Low* portfolio, and 0.62% on the *High* portfolio within the smallest book-to-market tercile. Moreover, the return on the *LMH* portfolio is positive and statistically different from zero for every book-to-market tercile. The four-factor alpha show similar results.

We next form the double-sorted portfolios controlling for the firm size, and report the returns on those portfolios in Panel B. The evidence clearly shows that controlling for the firm size does not hamper the predictive power of the ambiguity beta on stock returns. The portfolio returns within each size tercile decrease monotonically along with the ambiguity beta. For instance, the excess returns on portfolios are 1.17% for the Low portfolio, and 0.90% for the *High* portfolios within the lowest size tercile. Also, the returns on the *LMH* portfolios are positive and statistically significant for every size tercile. This pattern holds true with and without risk adjustment.

Finally, we construct the double-sorted portfolios based on the ambiguity beta and 12-month past returns skipping 1-month, and report the results in Panel C. The excess returns on the tercile portfolios decline along with ambiguity beta for every past returns tercile. The returns on *LMH* portfolios are again positive and statistically significant with an exception for the highest past returns tercile.

In sum, we confirm that the ambiguity premium is not driven by firm characteristics which are well-known to predict cross-section returns. The monotonicity in the average excess returns of the tercile portfolios formed on the ambiguity betas is maintained within each tercile formed on the firm characteristics. More importantly, *LMH* portfolios deliver significant positive premium in most cases.

3.3 Portfolios Sorts Controlling for the Expected Real GDP Growth

We further examine whether the impact of ambiguity on the cross-section of stock returns is robust to the expected business condition. Goetzmann, Watanabe, and Watanabe (2012) measure the expected business condition as the expected real GDP growth (i.e., the first moment of the cross-section of economists' forecasts), and document that procyclical stocks, whose returns co-move with the expected business cycle, earn higher returns than countercyclical stocks. We want to ensure the cross-sectional predictive power of ambiguity, which is inherently the second moment of the cross-section of economists' forecasts, is distinct from the expected real GDP growth.

We therefore examine whether the predictive power of the ambiguity betas for future returns remain significant after controlling for the expected real GDP growth. First, we re-estimate the ambiguity beta with *EGDP* as an additional control, and form univariate quintile portfolios based on this alternatively estimated ambiguity betas. Second, we sort stocks into the 3-by-3 portfolios formed on both the ambiguity beta and EGDP beta.

Panel A in Table 4 reports the returns on univariate quintile portfolios formed on the alternative ambiguity betas (with *EGDP* as an additional control). The results are similar to the results in Table 2. That is, the portfolio excess returns monotonically decrease from 1.01% for the *Low* portfolio to 0.75% for the *High* portfolio. The return spread between the *Low* and *High* portfolios is 0.26% per month on average, and statistically significant at the 5% level. The Carhart alpha of the LMH portfolio is 0.24%, being similar in magnitude to the average return on the LMH portfolio without risk-adjustment, albeit its significance becomes weaker. The results suggest that the predictive power of the ambiguity beta is not subsumed by the expected real GDP growth.

Next, we form the 3-by-3 portfolios based on the ambiguity betas and the *EGDP* betas. The portfolio returns are displayed in Panel B. We find that the predictive power of the ambiguity betas survives after controlling for the *EGDP* beta. Specifically, the systematic pattern between the ambiguity beta and average returns is maintained within each *EGDP* beta tercile. For instance, within the highest *EGDP* beta tercile, the excess return decreases from 1.15% for the *Low* portfolio to 0.78% for the *High* portfolio. The return spread is 0.38% with a *t*-statistic of 3.11. Therefore, we confirm that the predictive power of ambiguity betas remains significant after controlling for the EGDP beta.

3.4 Firm-Level Cross-Sectional Regressions

Portfolio sorting approach is an intuitive and powerful tool to evaluate the economic significance of predictive relations, but it is often difficult to control for many variables and focuses on extreme portfolios. In contrast, Fama-MacBeth cross-sectional regression can take into account many control variables simultaneously and examine the average effect. We therefore perform the cross-sectional regressions to confirm our main finding that the ambiguity betas negatively predict the cross-section of stock returns.

We perform cross-sectional regressions as follows. In the first stage, we obtain the loadings on ambiguity as well as other risk factors by 20 quarters rolling time-series regression. Specifically, for each stock i, we run the time-series regression over the periods as follows:

$$R_{i,q} = \alpha_i + \beta_{i,q}^{AMB} AMB_{q-1,q} + \beta_{i,q}^{EGDP} EGDP_{q-1,q} + \boldsymbol{\beta'_{i,q} X_q} + \varepsilon_{i,q}, \tag{3}$$

where $R_{i,q}$ is a return of a stock i at quarter q, $\boldsymbol{X_q}$ is a vector of risk factors at quarter q, and $AMB_{q-1,q}$ and $EGDP_{q-1,q}$ denote the ambiguity and expected business condition based on forecasts at quarter $q-1$. The estimated $\beta_{i,q}^{AMB}$ is the ambiguity beta at each quarter. As in the previous subsection, we include EGDP into our specification to control for the impact of the expected business conditions.

Next, we cross-sectionally regress monthly excess returns on each stock on the loadings as follows:

$$R_{i,t+1} = \gamma_{i,t+1} + \gamma_{t+1}^{AMB}\beta_{i,q}^{AMB} + \gamma_{t+1}^{EGDP}\beta_{i,q}^{EGDP} + \gamma_{t+1}^{X}{}'\boldsymbol{\beta_{i,q}} + \vartheta_{i,t+1}, \qquad (4)$$

where time $t+1$ denotes the months in quarter $q+1$. We then report the time-series average of the estimated risk prices in Table 5. *T*-statistics in parentheses are adjusted by the Newey and West (1987) *HAC* estimator.

The results clearly show that the ambiguity beta is negatively priced in the stock market. In the first row, the average risk price for the ambiguity beta is negative and statistically significant with a *t*-statistic of -2.43. The predictive power of the ambiguity beta is not subsumed by other factors. The ambiguity beta still predicts future stock returns even after controlling for the Fama and French three factors. Furthermore, when EGDP is included into the regression, the predictive power of the ambiguity beta is still statistically negative.[6] The ambiguity premium is also economically significant. The results suggest that two-standard-deviation increase across stocks in ambiguity betas leads to at least 5.14% drop in the expected rate of return per annum. Therefore, we conclude that the results from firm-level cross-sectional regressions also support the main hypothesis that low ambiguity beta stocks have higher returns.

[6] The results also show that the EGDP betas has a predictive power for future stock returns. The average slope coefficient on EGDP is positive, and statistically significant in the fourth to the sixth rows. This is consistent with Goetzmann, Watanabe, and Watanabe (2012).

3.5 Time-Variation of the Ambiguity Premium

To understand better what drives the ambiguity premium, we examine time variation of the ambiguity premium, that is, the return on the *LMH* portfolio. In particular, we are interested in whether the ambiguity premium systematically varies across different economic states and/or investor sentiment. Before proceeding formal regression tests, we plot the monthly returns on the *LMH* portfolio in Figure 2. Shaded areas indicate the recessionary periods classified by the National Bureau of Economic Research (NBER). We easily notice that the return spread (the ambiguity premium) soars sharply during the NBER recessionary periods. Other than the NBER recessionary periods, the ambiguity premium is high around the economic turbulence such as Market Crash (1987) and Gulf War (1991). On the contrary, during the periods of the economic boom such as the mid-90s and mid-2000s, the ambiguity premium is comparably small, and its fluctuation is relatively silent compared to bad times.

We define economic expansions and recessions, based on either the NBER business cycle classification (ex-post measure) or the Chicago Fed National Activity index (ex-ante measure).[7] We report the average return on the *LMH* portfolio conditional on these measures of economic states. We also test whether the difference in average returns across economic states is different. Table 6 reports the results. Panel A (Panel B) displays the return without (with) risk adjustment. The results show that the ambiguity premium is much higher during recessionary states than during expansionary states. Regardless of risk adjustment, the ambiguity premium is at least three times larger during recessionary states than during expansionary states. For instance, when the economic

[7] As suggested by the Chicago Fed, we define the recessionary states as the periods in which three-month moving average of the Chicago Fed National Activity index is below -0.7, and expansionary states for otherwise periods.

states are identified by the Chicago Fed index, the ambiguity premium is on average 1.08% during recessionary states, but only 0.25% during expansionary states. The difference of the ambiguity premium across both states is statistically significant with a *t*-statistic of 2.42. This counter-cyclical ambiguity premium reinforces our interpretation that the return spread between low and high ambiguity beta stocks reflects a compensation that ambiguity averse investors command for bearing ambiguity.

In a sharp contrast, we find that the ambiguity premium is unaffected by the investor sentiment. If the ambiguity premium is caused by mispricing or behavioral biases, the premium are likely to be greater during high sentiment periods, because mispricing are likely to be stronger during high level of investor sentiment (Stambaugh, Yu, and Yuan, 2012). We classify high sentiment periods when the sentiment index in the previous month is above the median value of the whole sample period. The otherwise periods are defined as low sentiment periods. We report the average returns on the *LMH* portfolios across high and low sentiment periods, in the last three columns of the table. The results show that the ambiguity premium is invariant across different sentiment periods. The results suggest that the ambiguity premium is unlikely to be related to mispricing or behavioral biases.

4 Additional Results

4.1 Determinants of the Ambiguity Beta

In the previous section, we show that low ambiguity beta stocks have higher expected returns than high ambiguity beta stocks by using both portfolio sorts and firm-level cross-sectional regressions. The predictive power of ambiguity betas is distinct from other risk factors as well as the expected business conditions.

In this subsection, we further show that the ambiguity betas are not correlated with other firm characteristics. Specifically, we cross-sectionally regress the ambiguity betas at quarter t on the market beta at quarter t ($\beta_{MKT,t}$), the ambiguity beta at the previous quarter ($\beta_{AMB,t-1}$), and the beta on the expected real GDP growth at quarter t ($\beta_{EGDP,t}$) as well as several firm characteristics. The betas on ambiguity, EGDP, and MKT are estimated simultaneously from a 20-quarter rolling window time-series regressions. The firm characteristics include the natural log of firm size (SIZE), the natural log of the book-to-market ratio (BTM), and the past returns from $t-12$ to $t-2$ months (PRET). For visibility, we multiply the ambiguity beta by 100 before estimation.

The results in Table 7 show that the ambiguity beta is not much correlated with firm characteristics as well as the loadings on MKT and EGDP. First, the betas on EGDP and the market factor are distinct from the ambiguity betas. The average coefficients for the betas on EGDP and the market factor are positive, but statistically insignificant at any conventional level. Also, the firm characteristics are not correlated with ambiguity betas. The average coefficients for SIZE, BTM, and PRET are statistically insignificant at all. Thus, the results bolster the argument that the predictive power of ambiguity betas is distinct from betas for EGDP and the market factor, and other firm characteristics known to predict stock returns.

The interesting point is that the ambiguity beta tends to have high autocorrelation. For instance, in the first row, the estimated coefficient for the past ambiguity beta is 0.928 with a *t*-statistic of 92.13, which is positive and highly statistically significant. This potentially suggests that the predictive power of the ambiguity betas might be persistent over longer horizons, which we explore in the later subsection.

4.2 Long-term Predictive Power of the Ambiguity Beta

Hinted by the previous evidence that the ambiguity betas are positively autocorrelated, we further examine whether the ambiguity premium persists over longer horizons. We hold a stock in the quintile portfolio formed on the ambiguity beta for longer than one quarter. Table 8 reports the results for different holding periods up to four quarters ahead. Note that the results in the first two columns indicate the one-quarter-ahead portfolio returns, which is identical to the baseline results in Table 2.

We find that the ambiguity premium persists up to three quarters ahead. The stocks with low ambiguity betas still outperform those with high ambiguity betas. For instance, two quarters ahead monthly excess return monotonically decreases from 1.04% on the *Low* portfolio to 0.67% on the *High* portfolio, and the return difference between the *Low* and *High* portfolios is statistically significant. The risk adjustment does not affect the results. Moreover, the magnitudes of two-quarter-ahead returns on each portfolio are comparably similar to one-quarter ahead portfolio returns.

The underperformance of the high ambiguity stocks is also preserved three quarters ahead. The portfolio excess return is 1.06% on the *Low* portfolio, and 0.78% on the *High* portfolio. The *LMH* portfolio earns on average 0.27% per month with a *t*-statistic of 2.36. However, the predictive power of the ambiguity betas becomes much weaker for three-quarter ahead in that the average return on the *LMH* portfolio is much lower compared to those for one- and two-quarter ahead, and it is statistically insignificant after risk adjustment. After four-quarter ahead, the ambiguity premium dissipates away. The return on the *LMH* portfolio is positive, but turns to be statistically insignificant. In summary, we show that the predictive power of ambiguity betas prolongs up to three quarters ahead.

4.3 Ambiguity about Longer-term Future Economy

The SPF dataset provides the forecasts for economic variables up to four quarters ahead, which enable us to gauge ambiguity of economic agents about longer term future economy. So far, we provide the evidence that low ambiguity beta stocks have higher expected returns using the one-quarter ahead forecasts made by professions. Meanwhile, there is no reason to expect that ambiguity about only short-term future economy should be priced in the stock market. If investors are averse to ambiguity about the longer-term future economy, they would also require high expected returns on stocks that deliver low returns when they are ambiguous about the longer-term future. Thus, we examine whether the ambiguity about longer-term future economy is negatively priced in the stock market.

Specifically, in this subsection, we investigate whether there exists the premium on the ambiguity about longer-term economic conditions. To this end, we measure ambiguity about the future real GDP growth from now up to *k* quarters ahead where *k* = 1, 2, 3, or 4. We estimate the ambiguity beta by the 20-quarter rolling windows regressions as follows:

$$R_{i,t+1,t+k} = \alpha_i + \gamma MKT_{t+1,t+k} + \beta_k AMB_{t,t+k} + \varepsilon_{i,t+1,t+k}, \tag{5}$$

where $R_{i,t+1,t+k}$ is an excess return on the stock *i* during the periods from the beginning of the quarter $t + 1$ to the end of quarter $t + k$, $MKT_{t+1,t+k}$ is an excess market return during the periods from quarter $t + 1$ to quarter $t + k$, and $AMB_{t,t+k}$ is the ambiguity measure based on the forecasts at time t for future real GDP growth from quarter $t + 1$ to quarter $t + k$. Based on the estimated ambiguity betas β_k, we sort stocks into quintile portfolios at the end of the quarter $t + k$, and examine the portfolio returns during the subsequent quarter. Table 9 reports the average excess returns for the quintile portfolios formed on the ambiguity about longer-term future economic conditions. To facilitate comparison, we also present the results when *k* equals 1, identical to the benchmark case in Table 2. The evidence shows that betas on the ambiguity about the longer-term economic conditions negatively predicts stock returns. When the portfolios are formed on the ambiguity about economic conditions up to two quarters ahead, we see that the monthly excess returns decrease from 1.01% for the *Low* portfolio to 0.78% for the *High* portfolio. As such, the *LMH* portfolio reveals the premium 0.23%, which is statistically significant at the 10% significance level. The ambiguity betas from using forecasts for economic growths up to three-quarter ahead negatively predict stock returns. The portfolio excess returns monotonically decrease across the portfolios from 1.09% for the *Low* portfolio to 0.82% to the *High* portfolio, yielding the long-short spread of 0.27% per month with a *t*-statistic of 2.07. Lastly, the ambiguity about the future economy up to four quarters ahead fails to deliver the meaningful premium in that the return on the *LMH* portfolio is statistically insignificant, and its magnitude is much smaller than other cases.

4.4 Alternative Ambiguity Measure Using Implied Real GDP Growth

The SPF provides the forecasts for the level of nominal GDP as well as the annual growth rate of CPI (i.e., inflation). As a robustness check, we combine forecasts for nominal GDP and CPI to obtain the implied real GDP, and construct an alternative measure of ambiguity using this implied real GDP growth. Specifically, we define the forecast for one-quarter ahead (implied) real GDP growth rate per each economist *i* as follows:

$$Implied\ real\ GDP\ growth_{t,t+1}^{i} = log\left[\frac{1}{\left(1 + CPI_{t,t+1}^{i}\right)^{1/4}} \frac{NGDP_{t,t+1}^{i}}{NGDP_{t,t}^{i}}\right], \tag{7}$$

where $NGDP_{t,t}^{i}$ ($NGDP_{t,t+1}^{i}$) denotes the forecast at time *t* from the economist *i* for nominal GDP level for quarter *t* (*t* + 1), and $CPI_{t,t+1}^{i}$ is the forecast for the annualized growth rate of the CPI level from quarter *t* to quarter *t* + 1. We convert the forecasted annualized inflation growth rate into quarterly frequency by taking fourth root. Once we calculate the implied real GDP growth rate forecasts, we measure the ambiguity about future economic conditions as the cross-sectional standard deviation of those forecasts. We then perform univariate quintile portfolios using this alternative ambiguity measure. Since the forecasts for the CPI growth rate starts in the third quarter of 1981, the quintile portfolios are constructed from the first quarter of 1982.

The results in Table 10 show that the betas on this alternative measure of ambiguity negatively predicts stock returns. The portfolio excess return is 0.96% per month on the *Low* portfolio, and monotonically declines to 0.73% on the *High* portfolio. The return spread between the *Low* and *High* portfolios is positive, 0.22%, and statistically significant with a *t*-statistic of 2.11. Such monotonicity in portfolio returns is also preserved with risk adjustment. The risk-adjusted returns decline from 0.20% on the *Low* portfolio to 0.01% on the *High* portfolio, and the return difference is 0.19%, statistically positive at the 10% significance level. Finally, the portfolio characteristics do not show any patterns, suggesting that the ambiguity premium is also not subsumed by firm characteristics which are known to predict stock returns.

5 Conclusion

Motivated by recent asset pricing models that predict ambiguity averse investors command a premium for bearing ambiguity, we investigate the pricing implications of ambiguity for the cross-section of expected stock returns. We measure ambiguity as the cross-sectional dispersion in real-time forecasts of real GDP growth from SPF. We find strong evidence that ambiguity regarding economic conditions is significantly negatively priced in the cross-section of returns; high ambiguity beta stocks earn lower future returns. A real-time implemental long-short strategy using the portfolios formed on the ex-ante measure of the ambiguity beta generates an ambiguity premium that is statistically and economically significant.

The negative predictive relation between the ambiguity beta and future returns is consistent with theory that predicts the marginal utility of consumption rises when ambiguity is high. Stocks that deliver low returns when marginal utility rises (i.e., low ambiguity beta stocks) must have high expected returns to reward investors for bearing ambiguity. On the other hand, stocks that deliver high return when ambiguity is high (i.e., high ambiguity beta stocks) provide a good hedge and therefore must have low expected returns.

We further report several interesting findings. First, we show that the ambiguity premium is different from the procyclicality premium, the finding that high business cycle beta stocks earn higher returns relative to low business cycle betas, reported by of Goetzmann, Watanabe, and Watanabe (2012). Second, time variation of the ambiguity premium is systematically related to changing economic conditions, but is not related to the investor sentiment index. Third, the predictive power of the ambiguity beta for future stock returns is not subsumed by stock characteristics that are known to predict cross-section returns. Lastly, we obtain the similar results for alternative measures of ambiguity.

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Table 1
Summary Statistics for Ambiguity Measure

The table shows the summary statistics for the ambiguity measure. The left half of the table reports the mean, standard deviation, 1st order autocorrelation, and Augmented Dickey-Fuller (ADF) test statistics. AMB indicates the ambiguity measure, which is measured as the standard deviation of real GDP growth forecasts among economists. EGDP is the expected real GDP growth, which we calculate as the median value of real GDP growth forecasts. The right half of the table reports the Pearson correlations among AMB, EGDP, and the NBER recession periods (NBER) as well as investor sentiment (SENT). '**' and '***' mean the statistical significance level at 5% and 1% respectively.

					Correlations	
	Mean	Standard Deviation	Auto-correlation	ADF Test	AMB	EGDP
AMB	0.384	0.254	0.742	-5.08***		
EGDP	0.646	0.429	0.804	-4.39***	-0.182**	
NBER					0.32***	-0.51***
SENT					-0.036	-0.179**

Table 2

Univariate Portfolios Sorts on theAmbiguity Beta

The table reports the monthly excess returns and characteristics of quintile portfolios sorted by the ambiguity beta. We estimate the ambiguity beta on individual stocks from 20 quarters rolling time-series regressions along with the market factor, and form five portfolios for the next quarter based on the estimated beta. The quintile *Low* contains stocks with the lowest ambiguity beta, and the quintile *High* contains stocks with highest ambiguity beta during the previous quarter. The left half of the table displays the equal-weighted excess returns as well as the Carhart (1997) four-factor alpha of each portfolio. The right half of the table reports the average characteristics such as the ambiguity beta (Beta), firm size (SIZE), book-to-market ratio (BTM), and the past return from month t - 12 to t – 2 (PRET). *LMH* indicates a long-short strategy which buys the *Low* portfolio and sells the *High* portfolio. The t-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

		Controlling for FF4 Factors						Portfolio Characteristics			
Portfolio	Excess Returns	Intercept	MKT	SMB	HML	UMD	Adj R^2	Beta	SIZE	BTM	PRET
Low	1.07%	0.23%	1.03	0.55	0.33	-0.07	91.3%	-0.83	2,512,391	0.78	0.19
	(4.02)	(2.82)	(42.57)	(6.57)	(4.65)	(-1.68)					
2	1.02%	0.26%	0.90	0.42	0.39	-0.04	93.1%	-0.29	3,056,605	0.83	0.16
	(4.49)	(3.90)	(43.19)	(6.44)	(6.63)	(-1.43)					
3	0.95%	0.22%	0.88	0.38	0.40	-0.05	93.4%	-0.04	3,230,394	0.85	0.15
	(4.26)	(3.45)	(40.28)	(6.43)	(7.52)	(-1.74)					
4	0.87%	0.12%	0.90	0.45	0.36	-0.05	94.5%	0.22	2,761,971	0.86	0.15
	(3.78)	(2.40)	(42.80)	(8.31)	(7.36)	(-1.66)					
High	0.69%	-0.13%	1.02	0.75	0.15	-0.07	95.0%	0.84	1,874,167	0.83	0.18
	(2.46)	(-1.63)	(52.11)	(28.58)	(3.47)	(-2.13)					
LMH	0.38%	0.36%	0.01	-0.20	0.18	0.00	12.6%				
	(3.34)	(2.95)	(0.21)	(-2.40)	(1.90)	(0.03)					

Table 3
Double-Sorted Portfolios by the Ambiguity Beta and Firm Characteristic

The table reports equal-weighted monthly excess returns of portfolios formed on firm characteristics and ambiguity betas on individual stocks. We estimate the ambiguity beta by 20 quarters rolling time-series regressions along with the market factor. We sort stocks independently into the 3-by-3 portfolios based on the ambiguity beta and firm characteristics including the book-to-market ratio, firm size, and past returns from t - 12 to t - 2. *LMH* indicates a long-short strategy which buys the *Low* portfolio and sells the *High* portfolio. The t-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

	Firm Characteristics							
	Excess Returns				4-Factor Alpha			
	Low	Mid	High	L - H	Low	Mid	High	L - H
Panel A. Sorted by Book-to-Market Ratio								
Low	0.85%	1.07%	1.21%	-0.36%	0.21%	0.23%	0.30%	-0.09%
	(3.20)	(4.34)	(4.87)	(-2.70)	(2.22)	(2.83)	(4.15)	(-1.18)
	0.78%	0.93%	1.08%	-0.31%	0.14%	0.18%	0.28%	-0.14%
	(3.27)	(4.07)	(4.86)	(-2.63)	(1.85)	(2.69)	(4.02)	(-1.91)
High	0.62%	0.82%	0.94%	-0.31%	0.00%	0.03%	0.00%	0.00%
	(2.24)	(3.22)	(3.63)	(-2.08)	(-0.03)	(0.43)	(-0.01)	(-0.02)
LMH	0.23%	0.24%	0.28%		0.21%	0.20%	0.30%	
	(2.21)	(2.88)	(3.00)		(2.03)	(2.03)	(2.69)	
Panel B. Sorted by Firm Size								
Low	1.17%	1.10%	0.86%	0.31%	0.32%	0.19%	0.22%	0.10%
	(4.56)	(4.09)	(3.52)	(2.28)	(3.89)	(2.36)	(2.24)	(0.94)
	1.06%	0.99%	0.79%	0.27%	0.32%	0.18%	0.15%	0.17%
	(4.50)	(4.21)	(3.61)	(2.28)	(3.61)	(2.59)	(2.02)	(1.96)
High	0.90%	0.78%	0.64%	0.25%	0.06%	-0.05%	-0.02%	0.08%
	(3.46)	(2.85)	(2.44)	(2.00)	(0.60)	(-0.65)	(-0.31)	(0.78)
LMH	0.28%	0.32%	0.22%		0.26%	0.24%	0.24%	
	(3.41)	(3.01)	(2.03)		(2.76)	(2.26)	(2.01)	
Panel C. Sorted by Past Returns								
Low	0.77%	1.07%	1.19%	-0.42%	0.16%	0.31%	0.22%	-0.06%
	(2.78)	(4.78)	(4.70)	(-2.63)	(2.00)	(3.93)	(2.44)	(-0.58)
	0.76%	0.90%	1.18%	-0.42%	0.17%	0.20%	0.26%	-0.09%
	(2.80)	(4.32)	(5.21)	(-2.84)	(2.32)	(2.66)	(3.22)	(-1.03)
High	0.54%	0.77%	1.11%	-0.57%	-0.06%	0.02%	0.14%	-0.20%
	(1.80)	(3.21)	(4.16)	(-3.49)	(-0.60)	(0.27)	(2.01)	(-2.29)
LMH	0.23%	0.30%	0.08%		0.22%	0.29%	0.08%	
	(2.21)	(3.67)	(0.94)		(1.87)	(3.41)	(0.80)	

Table 4

Double-Sorted Portfolios by the Ambiguity Beta and EGDP Beta

This table reports the equal-weighted portfolios by sorting stocks based on the ambiguity beta which is estimated with the market factor and the expected real GDP growth (EGDP). In Panel A, we sort stocks based on the estimated ambiguity betas into the quintile portfolios, and report the equal-weighted excess returns as well as the Carhart (1997) four-factor alpha of each portfolio. Panel B reports the excess returns on the 3-by-3 equal-weighted portfolios by sorting stocks based on the ambiguity beta and the beta on EGDP. *LMH* indicates a long-short strategy which buys the *Low* portfolio and sells the *High* portfolio. The *t*-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

Panel A. Univariate-sorted Portfolio Returns

		Controlling for FF4 factors					
Portfolio	Excess Returns	Intercept	MKT	SMB	HML	UMD	Adj R^2
Low	1.01%	0.18%	1.01	0.57	0.31	-0.05	91.0%
	(3.83)	(2.29)	(41.27)	(7.34)	(4.14)	(-1.31)	
2	1.01%	0.25%	0.91	0.42	0.37	-0.04	92.8%
	(4.41)	(3.56)	(46.39)	(7.05)	(6.19)	(-1.21)	
3	0.96%	0.21%	0.89	0.38	0.39	-0.04	93.3%
	(4.26)	(3.58)	(38.86)	(5.89)	(6.97)	(-1.26)	
4	0.88%	0.13%	0.91	0.44	0.38	-0.06	94.8%
	(3.82)	(2.22)	(40.47)	(7.80)	(8.29)	(-1.98)	
High	0.75%	-0.06%	1.02	0.74	0.18	-0.10	95.0%
	(2.67)	(-0.73)	(50.94)	(24.73)	(3.72)	(-2.56)	
LMH	0.26%	0.24%	-0.01	-0.17	0.13	0.04	8.1%
	(2.26)	(1.89)	(-0.17)	(-2.25)	(1.23)	(0.58)	

Panel B. Double-Sorted Portfolio Returns

	Excess Returns				FF4 Alphas			
Portfolio	Low EGDP	Mid EGDP	High EGDP	Low - High	Low EGDP	Mid EGDP	High EGDP	Low - High
Low	0.95%	1.00%	1.15%	-0.20%	0.18%	0.23%	0.34%	-0.16%
	(3.59)	(4.34)	(4.22)	(-1.85)	(1.54)	(2.88)	(3.57)	(-1.23)
	0.94%	0.91%	0.98%	-0.04%	0.17%	0.20%	0.22%	-0.05%
	(3.79)	(4.37)	(4.13)	(-0.44)	(1.92)	(3.01)	(3.17)	(-0.54)
High	0.74%	0.75%	0.78%	-0.03%	-0.02%	-0.03%	-0.03%	0.01%
	(2.72)	(3.16)	(2.79)	(-0.29)	(-0.18)	(-0.34)	(-0.26)	(0.06)
LMH	0.21%	0.25%	0.38%		0.19%	0.26%	0.36%	
	(1.99)	(2.79)	(3.11)		(1.90)	(2.36)	(2.59)	

Table 5
Fama-MacBeth Regressions

This table reports the results for the cross-sectional regressions of monthly excess returns on lagged estimated risk loadings. In the first stage, we estimate the loadings by regressing quarterly excess returns on the ambiguity measure, the Carhart (1997) four factors, and the expected real GDP growth rate (EGDP) over the previous 20 quarters, varying with specifications. Then, in the second stage, we cross-sectionally regress monthly subsequent excess returns on estimated loadings. The time-series averages of estimated risk premiums are reported. *t*-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

	Intercept	MKT	SMB	HML	EGDP	AMB
1	0.905					-0.004
	(4.03)					(-2.43)
2	0.723	0.173				-0.004
	(4.13)	(1.62)				(-2.79)
3	0.657	0.166	0.118	0.135		-0.004
	(3.88)	(1.67)	(1.94)	(2.16)		(-3.18)
4	0.842				0.009	-0.004
	(3.84)				(2.05)	(-2.42)
5	0.705	0.179			0.008	-0.004
	(4.01)	(1.68)			(1.76)	(-2.67)
6	0.652	0.176	0.117	0.127	0.007	-0.004
	(3.83)	(1.78)	(1.95)	(2.07)	(1.74)	(-2.92)

Table 6
Ambiguity Premium Conditional on Economic States

This table reports the excess returns and the Carhart (1997) four-factor alpha for the quintile portfolios formed on the ambiguity beta conditional on economic states. We form the equal-weighted quintile portfolios by sorting stocks based on the ambiguity beta which is estimated by 20-quarter rolling regression along with the market factor. We define the recessionary state (*Rec*) as the periods marked by the National Bureau of Economic Research (NBER) or those in which three-month moving average of the Chicago Fed National Activity Index (CFNAI) is below -0.7. The otherwise states are defined as the expansionary state (*Exp*). Based on investor sentiment, we classify periods into high sentiment periods (*High Sent*) in which the value of the sentiment index in the previous month is above the median value for the sample period. The otherwise states are defined as low sentiment periods (*Low Sent*).

	NBER			CFNAI (MA3)			Investor Sentiment		
Portfolio	Rec	Exp	Rec - Exp	Rec	Exp	Rec - Exp	High Sent	Low Sent	High Sent – Low Sent
Panel A. Raw Returns									
Low	0.92%	1.10%	-0.17%	2.68%	0.78%	1.90%	1.36%	0.75%	-0.61%
	(0.82)	(4.85)	(-0.15)	(2.40)	(3.16)	(1.65)	(3.64)	(1.90)	(-1.14)
2	0.71%	1.08%	-0.37%	2.25%	0.80%	1.45%	1.13%	0.84%	-0.28%
	(0.74)	(5.60)	(-0.39)	(2.51)	(3.63)	(1.56)	(3.46)	(2.48)	(-0.61)
3	0.65%	1.01%	-0.35%	2.07%	0.75%	1.31%	1.12%	0.69%	-0.42%
	(0.67)	(5.44)	(-0.36)	(2.22)	(3.55)	(1.37)	(3.49)	(2.08)	(-0.93)
4	0.46%	0.95%	-0.49%	1.92%	0.69%	1.23%	1.05%	0.59%	-0.46%
	(0.47)	(4.87)	(-0.50)	(2.04)	(3.10)	(1.27)	(3.11)	(1.74)	(-0.98)
High	0.06%	0.80%	-0.74%	1.60%	0.53%	1.07%	1.04%	0.19%	-0.85%
	(0.05)	(3.25)	(-0.64)	(1.41)	(1.97)	(0.92)	(2.71)	(0.46)	(-1.53)
LMH	0.86%	0.29%	0.57%	1.08%	0.25%	0.83%	0.32%	0.56%	-0.24%
	(2.63)	(2.45)	(1.61)	(3.37)	(2.19)	(2.42)	(2.31)	(3.13)	(-1.10)
Panel B. Four-Factors Alpha									
Low	0.57%	0.17%	0.40%	0.68%	0.15%	0.53%	0.22%	0.31%	0.09%
	(2.36)	(2.03)	(1.58)	(2.77)	(1.91)	(2.09)	(2.21)	(2.42)	(0.61)
2	0.43%	0.23%	0.20%	0.56%	0.21%	0.35%	0.12%	0.40%	0.28%
	(1.93)	(3.64)	(0.88)	(2.34)	(3.42)	(1.44)	(1.44)	(3.67)	(2.20)
3	0.41%	0.18%	0.22%	0.44%	0.18%	0.26%	0.14%	0.26%	0.12%
	(2.19)	(2.92)	(1.18)	(2.04)	(2.98)	(1.19)	(1.76)	(2.76)	(1.01)
4	0.16%	0.11%	0.04%	0.19%	0.11%	0.08%	0.04%	0.17%	0.12%
	(1.07)	(2.20)	(0.28)	(1.12)	(2.14)	(0.43)	(0.63)	(2.12)	(1.30)
High	-0.43%	-0.07%	-0.36%	-0.62%	-0.04%	-0.57%	-0.15%	-0.16%	-0.02%
	(-1.85)	(-1.05)	(-1.59)	(-2.53)	(-0.62)	(-2.43)	(-1.35)	(-1.55)	(-0.12)
LMH	1.00%	0.24%	0.76%	1.30%	0.19%	1.11%	0.37%	0.48%	-0.11%
	(3.01)	(2.06)	(2.22)	(4.04)	(1.73)	(3.40)	(2.18)	(2.93)	(-0.52)

Table 7
Determinants of the Ambiguity Beta

This table summarizes the results of Fama-Macbeth cross-sectional regression in which we regress the ambiguity beta at quarter t on the market beta at quarter t ($\beta_{MKT,t}$), the ambiguity beta estimated at the previous quarter ($\beta_{AMB,t-1}$), and the beta on the expected real GDP growth at quarter t ($\beta_{EGDP,t}$) as well as firm characteristics. The betas on ambiguity, EGDP, and market factor for each stock are estimated simultaneously by 20-quarter rolling regression. The firm characteristics include the natural log of firm size (SIZE), the natural log of the book-to-market ratio (BTM), and the past returns from t – 12 to t – 2 months (PRET). For visibility, we multiply the ambiguity beta by 100 before estimation.

	Intercept	$\beta_{AMB,t-1}$	$\beta_{EGDP,t}$	$\beta_{MKT,t}$	SIZE	BTM	PRET	Adj R^2
1	-0.544	0.928		0.597				86.92%
	(-0.95)	(92.13)		(1.34)				
2	5.630				-8.423	-2.463	-0.403	10.29%
	(0.64)				(-1.26)	(-1.27)	(-0.82)	
3	-0.302	0.925		0.562	-0.779	-0.282	-0.034	87.71%
	(-0.16)	(92.23)		(1.18)	(-0.93)	(-0.71)	(-0.29)	
4	-1.045	0.926	0.021	0.576				86.60%
	(-1.26)	(94.82)	(1.16)	(1.24)				
5	6.998				-3.096	-2.020	-0.753	8.35%
	(0.65)				(-0.53)	(-1.01)	(-1.32)	
6	-0.987	0.924	0.029	0.685	0.598	-0.009	-0.032	87.38%
	(-0.46)	(92.19)	(1.38)	(1.40)	(0.71)	(-0.03)	(-0.26)	

Table 8
LongerTerm Predictive Power of the Ambiguity Beta

We form the equal-weighted quintile portfolios by sorting stocks based on the ambiguity beta, and report the subsequent excess returns and the Carhart (1997) four-factor alpha of portfolios up to four quarters ahead. The ambiguity betas are estimated using 20-quarter rolling regression along with the market factor. The quintile *Low* contains stocks with the lowest ambiguity beta, and the quintile *High* contains stocks with highest ambiguity beta during the previous quarter. *LMH* indicates a long-short strategy which buys the *Low* portfolio and sells the *High* portfolio.

	# of quarters ahead							
	1		2		3		4	
Portfolio	Excess Returns	FF4 Alpha	Excess Returns	FF4 Alpha	Excess Returns	FF4 Alpha	Excess Returns	FF4 Alpha
Low	1.07%	0.23%	1.04%	0.21%	1.06%	0.17%	1.07%	0.13%
	(4.02)	(2.82)	(3.97)	(2.71)	(4.00)	(2.24)	(4.10)	(1.74)
2	1.02%	0.26%	1.03%	0.28%	1.05%	0.25%	1.08%	0.22%
	(4.49)	(3.90)	(4.51)	(3.91)	(4.63)	(3.89)	(4.79)	(3.52)
3	0.95%	0.22%	0.96%	0.23%	1.00%	0.24%	1.01%	0.20%
	(4.26)	(3.45)	(4.32)	(3.79)	(4.65)	(4.36)	(4.66)	(3.47)
4	0.87%	0.12%	0.85%	0.10%	0.87%	0.10%	0.95%	0.12%
	(3.78)	(2.40)	(3.66)	(1.82)	(3.88)	(1.70)	(4.18)	(2.09)
High	0.69%	-0.13%	0.67%	-0.11%	0.78%	0.02%	0.90%	0.09%
	(2.46)	(-1.63)	(2.33)	(-1.25)	(2.84)	(0.24)	(3.30)	(1.28)
LMH	0.38%	0.36%	0.37%	0.32%	0.27%	0.15%	0.17%	0.04%
	(3.34)	(2.95)	(3.14)	(2.46)	(2.36)	(1.35)	(1.51)	(0.45)

Table 9
Portfolio Sorts on Longer-Term Forecasts

We measure the ambiguity as a cross-sectional standard deviation of forecasts for real GDP growth during the periods from the current quarter up to *k* quarters ahead where *k* = 1, 2, 3, 4. The ambiguity beta is estimated as follows:

$$R_{i,t+1,t+k} = \alpha_i + \gamma MKT_{t+1,t+k} + \beta_k AMB_{t,t+k} + \varepsilon_{i,t+1,t+k}$$

where $R_{i,t+1,t+k}$ is an excess return on the stock *i* during the periods from quarter $t + 1$ to quarter $t + k$, $MKT_{t+1,t+k}$ is an excess market return from quarter $t + 1$ to quarter $t + k$, and $AMB_{t,t+k}$ is the ambiguity measure based on the forecasts at time *t* for real GDP growth during the periods from quarter $t + 1$ to quarter $t + k$. We then form quintile portfolios by sorting stocks based on estimated β_k, and examine the portfolio excess returns during the subsequent quarter. We report monthly excess returns and the Carhart (1997) four-factor alpha for each portfolio.

	Forecasted Period for real GDP growth (1 ~ *k* qtrs)							
	1 Qtr		1 ~ 2 Qtrs		1 ~ 3 Qtrs		1 ~ 4 Qtrs	
Portfolio	Excess Returns	FF4 Alpha	Excess Returns	FF4 Alpha	Excess Returns	FF4 Alpha	Excess Returns	FF4 Alpha
Low	1.07%	0.23%	1.01%	0.18%	1.09%	0.22%	1.02%	0.16%
	(4.02)	(2.82)	(3.62)	(2.19)	(4.19)	(2.63)	(3.90)	(1.82)
2	1.02%	0.26%	0.99%	0.23%	0.97%	0.15%	0.95%	0.16%
	(4.49)	(3.90)	(4.31)	(3.56)	(4.30)	(2.44)	(4.28)	(2.58)
3	0.95%	0.22%	0.95%	0.22%	0.95%	0.17%	0.91%	0.14%
	(4.26)	(3.45)	(4.33)	(3.73)	(4.41)	(3.13)	(4.24)	(2.35)
4	0.87%	0.12%	0.86%	0.12%	0.96%	0.18%	0.94%	0.14%
	(3.78)	(2.40)	(3.72)	(2.05)	(4.22)	(3.40)	(4.15)	(2.23)
High	0.69%	-0.13%	0.78%	-0.02%	0.82%	0.03%	0.89%	0.07%
	(2.46)	(-1.63)	(2.79)	(-0.35)	(2.88)	(0.37)	(3.22)	(0.93)
LMH	0.38%	0.36%	0.23%	0.20%	0.27%	0.19%	0.13%	0.09%
	(3.34)	(2.95)	(1.86)	(1.75)	(2.07)	(1.50)	(1.01)	(0.68)

Table 10
Portfolio Sorts on the Implied Real GDP Growth

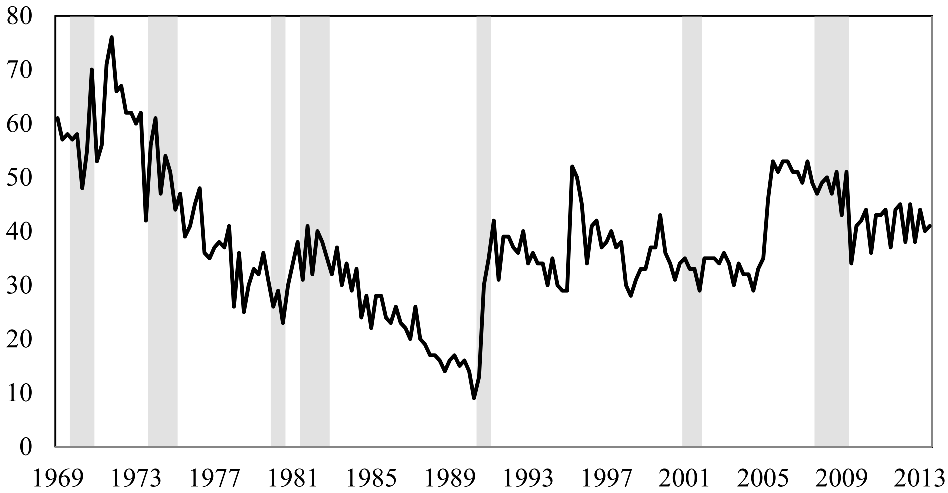
We alternatively measure the level of ambiguity using forecasts for nominal GDP level and CPI growth, and estimate the ambiguity beta by 20-quarter rolling regressions along with the market factor. We then report the monthly excess returns and characteristics of quintile portfolios formed based on such alternative ambiguity beta. The quintile *Low* contains stocks with the lowest ambiguity beta, and the quintile *High* contains stocks with highest ambiguity beta during the previous quarter. The left half of the table displays the equal-weighted excess returns as well as the Carhart (1997) four-factor alpha of each portfolio. The right half of the table reports the average characteristics such as the ambiguity beta (Beta), firm size (SIZE), book-to-market ratio (BTM), and the past return from month t - 12 to t – 2 (PRET). *LMH* indicates a long-short strategy which buys the *Low* portfolio and sells the *High* portfolio. The sample starts from 1980. The t-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

			Portfolio Characteristics			
Portfolio	Excess Returns	FF4 Alpha	Beta	SIZE	BTM	PRET
Low	0.96%	0.20%	-0.71	2,678,319	0.66	0.18
	(3.02)	(2.53)				
2	0.90%	0.23%	-0.29	4,308,681	0.69	0.13
	(3.39)	(3.33)				
3	0.83%	0.18%	-0.10	4,417,480	0.70	0.13
	(3.24)	(2.31)				
4	0.83%	0.15%	0.09	4,030,663	0.70	0.13
	(3.11)	(1.91)				
High	0.73%	0.01%	0.51	3,012,604	0.67	0.17
	(2.23)	(0.09)				
LMH	0.22%	0.19%				
	(2.11)	(1.89)				

Figure 1
Ambiguity Measure

The graph in Panel A reports the number of forecasters used in calculating the ambiguity measure. The second figure plots the level of ambiguity (AMB) as well as the expected real GDP growth (EGDP). The shaded area indicates the NBER recessionary periods.

Panel A. Number of Forecasters



Panel B. AMB and EGDP

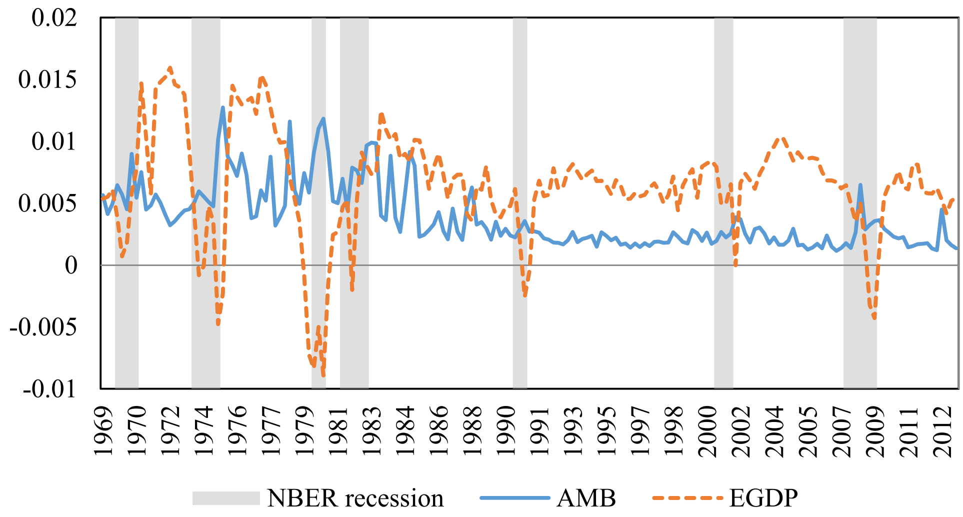


Figure 2

Ambiguity Premium

We form quintile portfolios by sorting stocks based on the ambiguity beta, which we calculate by 20 quarters rolling regression along with the market factor. We plot the ambiguity premium, which is the return spread between the portfolio of stocks with the lowest ambiguity beta, and the portfolio of stocks with the highest ambiguity beta. The shaded area indicates the NBER recessionary periods.