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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, which predicts the marginal utility of consumption to rise when ambiguity is high. We further show that the ambiguity premium remains significant after controlling for exposures to expected real GDP growth, VIX, and financial market dislocations index.

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 owing to cognitive or informational constraints. The Ellsberg paradox (Ellsberg, 1961) and related experimental evidence demonstrate that decision makers are averse to uncertainty regarding future outcome not only with known probabilities (risk), but also with unknown probabilities (ambiguity or Knightian uncertainty). The literature on ambiguity and asset markets shows that ambiguity has important implications for the pricing of financial assets.[2] Most of the literature, however, has focused on theoretical aspects, presumably because it is more difficult to empirically quantify ambiguity than risk. The question of how ambiguity affects the cross-section of expected returns, in particular, has received scant 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 in which 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, our analyses consequently exhibit no look-ahead bias. 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 that predict ambiguity-averse investors to command a premium for bearing ambiguity (Epstein and Schneider, 2010; Ui, 2011; Ju and Miao, 2012; Brenner and Izhakian, 2018). 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

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[1] Cochrane (2008) reviews the limitations of extant asset pricing models in explaining asset market data.

[2] See Epstein and Schneider (2010) and Guidolin and Rinaldi (2013) for an excellent review of the implications of ambiguity for asset pricing.

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pricing puzzles.[3] In their model, the marginal utility of consumption rises when the economic model is unfavourable (i.e., when ambiguity is high). Investors must 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 returns when ambiguity is high, must have high expected returns to reward investors for bearing ambiguity. Stocks that deliver high returns when ambiguity is high (i.e., high ambiguity beta stocks), on the other hand, provide a good hedge and must thus have low expected returns.

Following Drechsler (2013) and Ulrich (2013), we measure level of ambiguity as the cross-sectional dispersion in real-time forecasts of next quarter's real GDP growth from the Survey of Professional Forecasters (SPF). Dispersion is computed simply as the standard deviation in the growth forecasts reported around the beginning of each 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 related to economic conditions is significantly priced in the cross-section of returns. We find that high ambiguity beta stocks earn lower future returns relative to 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 ambiguity beta sorted portfolios are likely to reflect expected returns. The 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 earns an annual return of 5.28%. 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 in ambiguity betas across stocks is associated with a 7.48% decline 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 known to predict cross-section returns. When we perform double portfolio sorts to control for size, book-to-market, past returns, co-skewness, and idiosyncratic volatility, the negative relation between the ambiguity beta and future returns remains significant. In Fama–MacBeth regressions that control for various stock characteristics simultaneously, the reward for bearing ambiguity is always negative, stable, and both economically and statistically significant in most specifications. These 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 et al. (2012), using expected real GDP growth as a proxy for business cycles, find that high business cycle beta stocks earn higher returns relative to low business cycle beta stocks. 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 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.

Our ambiguity measure could be correlated with other aggregate indices of stock market upheaval. We therefore need to distinguish the effect of our ambiguity measure from that of other aggregate indices of stock market upheaval including VIX and financial market dislocations index (MDI) proposed by Pasquariello (2014). Controlling for exposure to VIX and the MDI by means of conditional double sorts, we find the negative relation between the ambiguity beta and subsequent returns remains strongly significant. It thus suggests that the ambiguity premium is distinct from the negative volatility risk premium.

Finally, we consider various types of ambiguity including uncertainty about corporate profits, the state of the economy in the short and longer term, economic growth, and inflation, and investigate what kind of ambiguity is priced in the cross-section of returns. We compare their relative return predictive power by orthogonalizing various types of ambiguity betas with respect to each other. We find that the beta of ambiguity about corporate profits is not priced when orthogonalized to the beta of ambiguity about economic conditions, which remains a significant return predictor. We find that longer-term ambiguity betas lose return predictability power when orthogonalized to the short-term ambiguity beta, which suggests that investors care more about short-term (one-quarter-ahead) than longer-term ambiguity. We further show the ambiguity premium to remain significant after controlling for the effect of inflation, but to become smaller and statistically insignificant when we control for the effect of economic growth. It suggests that ambiguity regarding economic growth has more critical impact on the cross-section of stock returns, than does ambiguity regarding inflation. These results are confirmed by the Fama–MacBeth regressions that simultaneously include all orthogonalized ambiguity betas.

We build on Ju and Miao's (2012) model, 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, whereas Ju and Miao evaluate their model by performing 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 (2018) and Andreou et al. (2014) measure stock market ambiguity using financial market data and examine the intertemporal relation between ambiguity and the equity premium. Viale et al. (2014) construct an ambiguity measure by estimating a regime-switching model for a market return, and propose an uncertainty factor that helps explain the cross-section of stock returns. We differ from these studies in several important ways. First, we focus on the *predictive* cross-sectional relation between the ambiguity beta and future returns, instead of the intertemporal relation between ambiguity and stock returns. Although Viale et al. (2014) do study the cross-sectional relation by conducting asset pricing tests for the model in which ambiguity serves an additional risk factor, their

[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.

focus is on the *contemporaneous* relationship between ambiguity and stock returns. From an economic perspective, this difference in return predictability is particularly critical to investors looking to develop real-time implementable strategies. Second, whereas these studies examine stock market ambiguity or measure ambiguity using financial market data, we study ambiguity regarding the future prospect of the economy. We view the uncertainty associated with future return distributions to be related not only to firm fundamentals, but also to the course of events over which distributions occur. To the extent that future return distributions are affected by macroeconomic fundamentals, uncertainty about real economic activity is potentially important for asset returns.

Most closely related work to our study is Anderson et al. (2009), who measure ambiguity using the dispersion of forecasts for aggregate corporate profits and show that their ambiguity betas explain cross-sectional differences in returns. A critical difference between Anderson et al. (2009) and our work is that they do not estimate ambiguity out-of-sample, and therefore do not evaluate the predictive power of the ambiguity beta. Our additional analyses show that their ambiguity beta, unlike ours, is not a significant predictor of future stock returns when estimated out-of-sample. This further corroborates that investors seem to care more about ambiguity regarding macroeconomic fundamentals in general than regarding stock fundamentals (i.e., corporate profits).

The remainder of the paper is organized as follows. Section 2 describes the data and our empirical proxy for 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 provides additional results. Section 5 concludes.

2. Data and ambiguity measure

2.1. Data

Our initial sample consists of all common stocks in 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 book-to-market ratios. Following Fama and French (1993), we match book-to-market ratios with returns for July of year t to June of $t+1$, and match 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. Stocks with a price of $5 or less at the beginning of each holding period are excluded to minimize microstructure issues, such as illiquidity.

The Fama and French three factors, as well as the Carhart (1997) momentum factor, 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 the quarterly risk free rate. Our empirical analysis begins in the fourth quarter of 1968 and ends in the fourth quarter of 2013.

2.2. Measuring ambiguity

Ambiguity regarding economic conditions, our primary variable of interest, is measured by dispersion in beliefs among economists about future real GDP growth. Disagreement among economic agents can arise from two sources, differences in information and in prior models. Dispersion in beliefs among economists should not reflect information asymmetry, as information related to forecasting future economic conditions is widely accessible and routinely released to the public. This intuition is supported by Patton and Timmermann (2010), who argue that disagreement reflects heterogeneity in economists' models rather than information signals. Patton and Timmermann show that disagreement is greater for long-horizon forecasts than for short-horizon forecasts. That the contribution of the difference in information signals is stronger for short-horizon forecasts 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, a number of studies use disagreement among economists as the ambiguity related to economic conditions. Bansal and Shaliastovich (2010), for example, use cross-sectional dispersion in beliefs as a confidence measure. Ulrich (2013) uses dispersion in forecasts for inflation as a proxy for degree of inflation ambiguity. Drechsler (2013) argues that dispersion in economists' forecasts can be a proxy for degree of ambiguity. Anderson et al. (2009) use their theoretical model to measure ambiguity level based on the dispersion of the corporate profits.

Following the aforementioned studies, we measure ambiguity regarding economic conditions as the cross-sectional dispersion in professional forecasters' forecasts of real GDP growth rates, obtained from the Survey of Professional Forecasters (SPF) 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 four quarters ahead. 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 quarter $t+k$ for each economist i as follows,

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

where $RGDP^i_{t,t+k}$ is the forecast made by economist i at time t for the level of real GDP at time $t+k$. Dispersion in beliefs among economists is then defined as the cross-sectional standard deviation of the forecasted economic growth (above), denoted as $AMB_{t,t+k}$. Our main results are based on $AMB_{t,t+1}$, the ambiguity related to the one-quarter-ahead real GDP growth rate. This simple measurement has the advantage that it does not rely on specific econometric models. If econometric models are misspecified, conclusions inferred from their use are incorrect as well. More importantly, the proposed measure is fully ex-ante information. This is

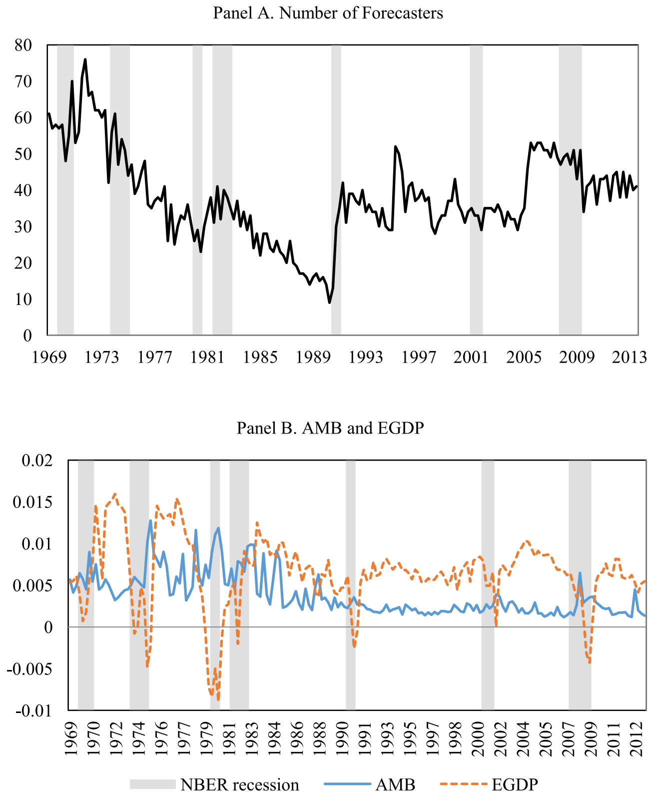

Fig. 1. Ambiguity measure. The graph in Panel A reports the number of forecasters used in calculating the ambiguity measure. The second figure plots the level of ambiguity (AMB) as well as the expected real GDP growth (EGDP). The shaded area indicates the NBER recessionary periods.

particularly important because our empirical analyses do not incur any look-ahead bias. Hereafter, we denote dispersion in forecasts of future real GDP growth as the ambiguity measure.

We measure expected real GDP growth (*EGDP*) as the cross-sectional median of forecasts of future real GDP growth, which Goetzmann et al. (2012) show to be priced in the stock market. We examine in Section 3.3 whether our results are affected by the impact of *EGDP*.

We plot the number of forecasts per each period in Panel A of Fig. 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 of forecasters had been greater than 30 until the early 1980s. Although the number decreased to around 10 in the ten years hence, since the early 1990s it has stabilized again at around 30.

2.3. Summary statistics

Table 1 presents summary statistics for our ambiguity measure (*AMB*) together with expected real GDP growth. The left-hand side reports mean, standard deviation, first-order autocorrelation, and augmented Dickey–Fuller test statistics. The *AMB* and *EGDP* averages of 0.384 and 0.646, respectively, imply that the majority of forecasts lie between 0.262% and 1.03% in cross-section, which suggests that forecasts of real GDP growth rate vary widely across economists. Time-variation is also high for both *AMB* and *EGDP*, their standard deviations across time being 0.254 and 0.429, respectively. Lastly, these variables are highly persistent, albeit statistically stationary.

To explore how ambiguity changes over time, we report on the right-hand side of the table the correlations between *AMB* and two economic states, the NBER recession dummy and investor sentiment. Noteworthy 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. This is consistent with Van Nieuwerburgh and Veldkamp (2006), who suggest that dispersion in beliefs should be greater during recessions, when fewer information signals are present. 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 the countercyclicality of ambiguity. Correlation of ambiguity with investor sentiment, on the other hand, is statistically insignificant, which implies that ambiguity is not associated with investors' behavioural biases.

For further illustration, we plot *AMB* and *EGDP* in Panel B of Fig. 1. We see that the AMB measure fluctuates in a countercyclical manner. Investors' ambiguity begins to rise at the onset of the NBER recessions and spikes during those periods, especially in the

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).

					Correlations	
	Mean	Standard deviation	Auto-correlation	ADF test	AMB	EGDP
AMB	0.384	0.254	0.742	−5.075***		
EGDP	0.646	0.429	0.804	−4.384***	−0.182**	
NBER					0.320***	−0.510***
SENT					−0.036	−0.179**

**Statistical significance level at 5%.

***Statistical significance level at 1%.

late 1960s, mid-1970s, 1980s, early 2000s, and 2008. It is also obvious that *EGDP* and *AMB* fluctuate in the opposite manner. Such countercyclicality of ambiguity is consistent with Patton and Timmermann (2010).

3. Empirical results

We investigate in this section our 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 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 out-of-sample predictability.

3.1. Portfolios sorted on the ambiguity beta

We examine our main hypothesis using a standard portfolio sorting approach. We estimate the sensitivity of each stock i on the ambiguity related to economic conditions via rolling windows regressions. For each stock i and for each quarter t, we run the 20 quarters rolling time-series regression as follows

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{AMB} AMB_{t-1,t} + \beta_{i,t}^{MKT} MKT_t + \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t}$ is the return on stock i , MKT_t is the excess market return at quarter t, and $AMB_{t-1,t}$ denotes the ambiguity measure based on forecasts at quarter $t-1$ for the real GDP growth rate for quarter t.[4] We require a minimum of two years of observations for estimating the ambiguity betas. For each quarter, we estimate $\beta_{i,t}$, that is, the ambiguity beta of stock i. We then form both equal- and value-weighted quintile portfolios at the end of each quarter t by sorting the stocks into portfolios based on the ambiguity beta. Portfolios are held until the end of the subsequent quarter. For notational convenience, we refer to the portfolio of stocks with the highest (lowest) ambiguity beta as the *High* (*Low*) portfolio. We form the *LMH* portfolio as a zero-investment portfolio that buys the *Low* portfolio and sells the *High* portfolio. The return spread on the *LMH* portfolio represents the ambiguity premium. Panel A of Table 2 reports results for the equal-weighted portfolios. 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 0.92% for the *Low* portfolio, and decreases to 0.49% for the *High* portfolio. The difference between average excess returns on the *Low* and *High* portfolios is 0.42% per month (equivalently, 5.04% per annum without compounding), with a t-statistic of 3.80. Our results are consistent with Ju and Miao (2012), who predict the marginal utility of consumption to rise 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 returns when ambiguity is high (i.e., high ambiguity beta stocks) provide a good hedge, and thus must have low expected returns. Our results strongly support these predictions.

We further examine whether the ambiguity premium remains significant after controlling for the Carhart (1997) four factors, namely, the excess market return (MKT), the size factor (SMB), the book-to-market factor (HML), and the momentum factor (UMD). Most importantly, the FF4 alpha of the long-short portfolio is 0.40%, and highly statistically significant at the 1% level. With respect to R^2, the risk factors explain only 17.2% of the fluctuation in the return on the *LMH* portfolio. The FF4 alphas of quintile portfolios also tend to decline with the ambiguity betas, and the loadings on the risk factors do not display any systematic pattern across the portfolios.

Panel B of Table 2 reports results for the value-weighted portfolios. Fama (1998) points out that value-weighted portfolio results more accurately reflect the wealth effect experienced by investors. Fama and French (2008) show that equal-weighted portfolio results are heavily affected by microcaps. Because of high transaction costs and illiquidity, trading strategy using microcaps are unlikely to be exploitable in practice. As such, value-weighted portfolio results are important. Consistent with the equal-weighted results, the

[4] Results (available upon request) are similar when MKT is excluded from the regressions.

Table 2
Univariate portfolios sorts on the ambiguity beta. The table reports the monthly excess returns and the Carhart (1997) four-factor alphas 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 quintile 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. *Low–High* indicates a long-short strategy that 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	Excess returns	Intercept	MKT	SMB	HML	MOM	Adj R^2
Panel A. Equal-weighted portfolios							
Low	0.92%	0.17%	1.04	0.65	0.26	−0.06	92.6%
	(3.35)	(2.23)	(43.61)	(8.42)	(4.30)	(−1.55)	
2	0.93%	0.25%	0.90	0.48	0.35	−0.04	94.1%
	(4.14)	(4.12)	(48.87)	(8.07)	(6.43)	(−1.27)	
3	0.84%	0.18%	0.88	0.44	0.36	−0.06	94.1%
	(3.72)	(3.16)	(42.45)	(7.39)	(7.27)	(−2.02)	
4	0.73%	0.07%	0.90	0.55	0.32	−0.08	94.9%
	(3.09)	(1.34)	(43.14)	(9.46)	(6.91)	(−2.23)	
High	0.49%	−0.23%	1.03	0.91	0.04	−0.05	94.8%
	(1.66)	(−2.91)	(47.79)	(31.27)	(0.92)	(−1.48)	
Low–High	0.42%	0.40%	0.01	−0.25	0.22	−0.01	17.2%
	(3.80)	(3.31)	(0.33)	(−2.90)	(2.47)	(−0.14)	
Panel B. Value-weighted portfolios							
Low	0.68%	0.16%	1.06	0.06	−0.16	0.00	84.6%
	(2.88)	(1.38)	(29.80)	(0.80)	(−2.45)	(−0.04)	
2	0.66%	0.11%	0.99	−0.14	0.12	0.01	91.1%
	(3.26)	(1.48)	(51.55)	(−3.48)	(2.78)	(0.51)	
3	0.60%	0.08%	0.94	−0.14	0.17	−0.04	92.0%
	(2.99)	(1.46)	(49.64)	(−3.03)	(3.86)	(−1.25)	
4	0.55%	0.00%	0.96	−0.01	0.16	−0.02	91.1%
	(2.55)	(−0.04)	(41.39)	(−0.20)	(3.41)	(−0.61)	
High	0.23%	−0.39%	1.18	0.31	0.00	−0.11	87.1%
	(0.75)	(−2.98)	(30.43)	(6.46)	(0.06)	(−2.41)	
Low–High	0.44%	0.55%	−0.12	−0.25	−0.16	0.10	9.0%
	(2.46)	(2.62)	(−1.96)	(−2.29)	(−1.51)	(1.25)	

average return spreads between the value-weighted low and high ambiguity beta portfolios are positive and statistically significant; 0.44% per month with a t-value of 2.46, which is similar in magnitude to their corresponding equal-weighted returns of 0.42% per month. Risk-adjusted return difference between the value-weighted low and high ambiguity betas using the four-factor model is also positive and significant; 0.55% per month, with a t-value of 2.62.

In summary, we provide evidence that low ambiguity beta stocks earns higher returns than high ambiguity beta stocks. We form the quintile portfolios based on the ambiguity beta, and find that average excess returns on those portfolios decrease monotonically 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 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 cannot be explained by the Carhart four factors.

3.2. Portfolio sorts controlling for firm characteristics

In this section, we examine the relation between the ambiguity beta and subsequent stock returns after controlling for the well-known return predictors in the cross-section, including the log firm size, log book-to-market ratio, past 12-month returns (skipping 1-month), co-skewness, and idiosyncratic volatility. We perform conditional bivariate portfolio sorts, as in Bali et al. (2011) and Bali et al. (2017).[5] Specifically, at the end of each month, we first sort all firms in the sample into quintiles based on one of the control variables. Then, within each control variable quintile, we sort firms into quintile portfolios based on the ambiguity beta. This exercise produces a set of the ambiguity beta portfolios with similar levels of the control variable, thereby controlling for the effect of the control variable. We obtain co-skewness as the slope coefficient on the squared excess market return term from a regression of excess stock returns on the squared excess market return as well as excess market return (using the monthly return observations over the prior 60 months). We measure idiosyncratic volatility (IVOL) as the standard deviation of the residuals from a regression of excess stock returns on the Fama–French three factors using daily return data in month t.

Table 3 presents average portfolio returns across the five control portfolios within each quintile of the ambiguity beta. Results show that none of the control variables considered explains the ambiguity beta-return relation. For instance, after controlling for idiosyncratic volatility (reported in the fifth column), equal (value)-weighted average return on the low-minus-high ambiguity beta

[5] Results from independent bivariate sorts are similar to those from conditional bivariate sorts. We note that independent bivariate portfolio sorts could be problematic (not sufficiently control for the control variable) when the sorting variables are highly correlated. As such, we report results for conditional bivariate sorts only.

Table 3

Portfolios sorts on the ambiguity beta controlling for firm characteristics. The table reports monthly excess returns of portfolios formed on the ambiguity betas controlling for the firm size (SIZE), book-to-market ratio (BTM), 12-months past returns skipping 1-month (PRET), co-skewness (COSKEW), and idiosyncratic volatility (IVOL). We first sort the stocks into quintiles based on the firm characteristics, and within each quintile, we form quintile portfolios using the ambiguity betas, which are estimated by 20 quarters rolling time-series regressions along with the market factor. We report the average returns of the portfolios formed on the ambiguity beta across the quintiles formed on each firm characteristic. *Low–High* indicates a long-short strategy that buys the *Low* portfolio and sells the *High* portfolio. The *t*-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

	Excess returns					FF4 alphas				
	SIZE	BTM	PRET	CO-SKEW	IVOL	SIZE	BTM	PRET	CO-SKEW	IVOL
Panel A. Equal-weighted portfolios										
Low	0.89%	0.90%	0.84%	0.91%	0.94%	0.16%	0.17%	0.14%	0.15%	0.22%
	(3.31)	(3.40)	(3.23)	(3.32)	(3.55)	(2.11)	(2.23)	(2.08)	(2.06)	(3.16)
2	0.92%	0.90%	0.90%	0.94%	0.88%	0.23%	0.23%	0.22%	0.25%	0.19%
	(4.06)	(3.98)	(3.89)	(4.17)	(3.76)	(3.67)	(3.57)	(3.63)	(4.28)	(3.31)
3	0.84%	0.80%	0.80%	0.84%	0.83%	0.19%	0.17%	0.13%	0.19%	0.17%
	(3.73)	(3.60)	(3.48)	(3.77)	(3.55)	(3.19)	(3.09)	(2.41)	(3.26)	(3.20)
4	0.73%	0.70%	0.74%	0.73%	0.71%	0.08%	0.06%	0.09%	0.08%	0.03%
	(3.15)	(2.95)	(3.15)	(3.09)	(2.95)	(1.34)	(1.06)	(1.70)	(1.47)	(0.70)
High	0.51%	0.59%	0.61%	0.51%	0.58%	−0.17%	−0.13%	−0.09%	−0.20%	−0.16%
	(1.77)	(2.08)	(2.17)	(1.76)	(2.10)	(−2.10)	(−1.82)	(−1.15)	(−2.76)	(−2.34)
Low–High	0.38%	0.31%	0.23%	0.40%	0.36%	0.33%	0.30%	0.23%	0.36%	0.38%
	(3.54)	(3.17)	(2.61)	(3.73)	(3.71)	(2.89)	(2.72)	(2.41)	(3.08)	(3.61)
Panel B. Value-weighted portfolios										
Low	0.86%	0.74%	0.57%	0.76%	0.70%	0.11%	0.07%	0.03%	0.16%	0.13%
	(3.32)	(3.15)	(2.39)	(3.23)	(2.78)	(1.61)	(0.78)	(0.37)	(1.66)	(1.33)
2	0.87%	0.70%	0.62%	0.73%	0.57%	0.17%	0.09%	0.10%	0.16%	−0.02%
	(4.00)	(3.54)	(2.83)	(3.63)	(2.37)	(2.98)	(1.26)	(1.58)	(2.30)	(−0.25)
3	0.81%	0.69%	0.60%	0.65%	0.61%	0.14%	0.10%	0.06%	0.08%	0.03%
	(3.75)	(3.41)	(2.74)	(3.09)	(2.59)	(2.76)	(1.57)	(0.89)	(1.20)	(0.55)
4	0.70%	0.59%	0.51%	0.57%	0.47%	0.02%	−0.01%	−0.04%	0.02%	−0.12%
	(3.12)	(2.74)	(2.28)	(2.61)	(1.88)	(0.43)	(−0.15)	(−0.65)	(0.34)	(−1.71)
High	0.49%	0.40%	0.33%	0.25%	0.32%	−0.24%	−0.33%	−0.31%	−0.40%	−0.35%
	(1.73)	(1.41)	(1.15)	(0.83)	(1.04)	(−3.13)	(−3.17)	(−2.81)	(−3.50)	(−2.90)
Low–High	0.36%	0.33%	0.24%	0.51%	0.37%	0.35%	0.39%	0.34%	0.56%	0.47%
	(3.25)	(2.40)	(1.71)	(3.25)	(2.39)	(3.06)	(2.43)	(2.23)	(3.04)	(2.58)

portfolio is 0.36% (0.37%) per month with a corresponding t -value of 3.71 (2.39). Results are similar for the four-factor alpha. The four-factor alphas of the low-minus-high ambiguity beta portfolio after controlling for idiosyncratic volatility, reported in the last column, are 0.38% and 0.47% for equal-weighted and value-weighted results, respectively, and significant at the 1% level.

Panel A, Table 3 demonstrates that after controlling for other firm characteristics (log firm size, log book-to-market ratio, momentum, and co-skewness), the average returns and alphas for the equal-weighted low-minus-high ambiguity beta portfolios ranges between 0.23% and 0.40% per month and are all strongly significant at the 1% level. From results reported in Panel B of Table 3, we can see that similar results are obtained for the value-weighted results. In sum, we show that the ambiguity premium is not driven by firm characteristics known to predict cross-section returns.

Harvey et al. (2016, HLZ hereafter) suggest that t -statistics of 3.0 should be used as new cutoff levels of statistical significance for newly discovered factors. Our main results from the equal-weighted univariate portfolio sorts for the low-minus-high ambiguity beta (reported in Panel A of Table 2) have t-statistics greater than 3.0 (for both raw return and FF4 alpha),[6] but some of the results from the equal-weighted bivariate portfolio sorts (reported in Panel A of Table 3) are significant only at the conventional 5% level, their t-statistics being greater than 1.96 but less than 3.0. HLZ, however, note that newly suggested higher statistical cutoffs should be treated differently for tests that, like ours, are heavily motivated by economic theory.[7] Given that our motivation of empirical analyses are guided by theoretical predictions of Ju and Miao (2012) that low ambiguity beta stocks should have higher returns than high ambiguity beta stocks, our findings are less likely driven by data mining.

Relatedly, Hou et al. (forthcoming, HXZ hereafter) raise a concern for p -hacking in the anomalies literature.[8] HXZ conclude that p-hacking is mainly driven by overweighting microcaps. HXZ suggest value-weights in portfolio sorts to control for microcaps. Results from value-weighted returns show that the average return spreads between the low and high ambiguity beta portfolios are similar in magnitude to equal-weighted returns and statistically significant at the conventional 5% level. For instance, results from univariate portfolio sorts reported in Table 2 show that the raw return (FF4 alpha) of the difference between the low and high

[6] The average slope coefficient on the ambiguity beta from the Fama–MacBeth cross-sectional regression, as shown in the next section (Table 5), has a t-statistic of 4.12.

[7] HLZ (2016, p.7) write: “There are limitations to our framework. First, should all factor discoveries be treated equally? We think no. A factor derived from a theory should have a lower hurdle than a factor discovered from a purely empirical exercise. Economic theories are based on a few economic principles and, as a result, there is less room for data mining”.

[8] Attempting to replicate hundreds of the anomalies literature by using a consistent set of replication procedures, HXZ find that 64% of anomalies are insignificant at the conventional 5% level (t-value < 1.96).

ambiguity beta value-weighted portfolios is 0.44% (0.55%) per month with a Newey–West *t*-statistic of 2.46 (2.62). This return spread is similar in magnitude to equal-weighted returns: the raw return (FF4 alpha) of the difference between the low and high ambiguity beta equal-weighted portfolios is 0.42% (0.40%) per month with a *t*-statistic of 3.80 (3.31). Nevertheless, we note that the statistical significance from value-weighted returns are weaker than equal-weighted returns, indicating that microcaps could inflate *t*-statistics for the average return spreads. That value-weighted returns earns significant (at the conventional 5% level) average return spread is observed throughout all Table with few exceptions. Finally, HXZ also highlight the importance of economic theory for newly uncovered determinants of the cross-section of returns.[9] The predictive power of the ambiguity beta for the cross-section of stock returns is theoretically motivated based on economic first principles, and therefore the pricing power of the ambiguity beta is relatively less concerned about credibility.[10]

3.3. Portfolio sorts controlling for 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 et al. (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 counter-cyclical stocks. We want to ensure that the cross-sectional predictive power of ambiguity, which is inherently the second moment of the cross-section of economists' forecasts, is distinct from expected real GDP growth.

Table 4

Portfolio sorts on the ambiguity beta controlling for the EGDP beta. The table presents the predictive power of the ambiguity betas controlling for the loading on the expected real GDP growth (i.e., EGDP beta) in two ways. We estimate the EGDP betas by 20 quarters rolling time-series regressions along with the market factor. We then form quintile portfolios for the next quarter based on the estimated EGDP betas. Within each quintile, we sort the stocks into quintiles using the ambiguity betas. In the left half of the table, we report the average returns of the portfolios formed on the ambiguity beta across the EGDP beta quintiles. In the right half, we report the returns on the quintile portfolios formed on the residuals plus the intercept from the cross-sectional regressions of the ambiguity betas on the EGDP betas per each quarter. *Low–High* indicates a long-short strategy that buys the *Low* portfolio and sells the *High* portfolio. The *t*-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

	Conditional sorts				Univariate sorts			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
Portfolio	Excess returns	FF4 alpha	Excess returns	FF4 alpha	Excess returns	FF4 alpha	Excess returns	FF4 alpha
Low	0.88%	0.10%	0.70%	0.13%	0.88%	0.10%	0.13%	0.06%
	(3.29)	(1.28)	(2.90)	(1.60)	(3.21)	(1.16)	(1.73)	(0.70)
2	0.89%	0.16%	0.72%	0.14%	0.91%	0.24%	0.22%	0.09%
	(3.84)	(2.31)	(3.35)	(2.41)	(3.98)	(3.67)	(3.68)	(1.27)
3	0.83%	0.10%	0.64%	0.02%	0.83%	0.19%	0.17%	0.11%
	(3.64)	(1.69)	(3.01)	(0.41)	(3.71)	(3.18)	(3.12)	(1.75)
4	0.75%	0.02%	0.59%	−0.03%	0.74%	0.09%	0.08%	0.01%
	(3.14)	(0.27)	(2.60)	(−0.52)	(3.16)	(1.78)	(1.51)	(0.25)
High	0.54%	−0.22%	0.32%	−0.40%	0.54%	−0.17%	−0.16%	−0.37%
	(1.91)	(−3.46)	(1.07)	(−4.39)	(1.86)	(−2.04)	(−2.01)	(−2.75)
Low–High	0.34%	0.32%	0.38%	0.53%	0.34%	0.28%	0.29%	0.43%
	(3.16)	(2.99)	(2.55)	(3.64)	(3.06)	(2.11)	(2.35)	(2.25)

We investigate whether the predictive power of the ambiguity betas for future returns remains significant after controlling for exposure to expected real GDP growth. We estimate the EGDP beta in a manner similar to the estimation of the ambiguity beta, except that the ambiguity measure in Eq. (1) is replaced by expected real GDP (EGDP) growth. We form the quintile portfolios based on the ambiguity beta, controlling for the EGDP beta. Specifically, we form quintile portfolios ranked on the basis of the EGDP beta, and within each quintile, sort stocks into quintile portfolios ranked on the basis of the ambiguity beta.

The first four columns of Table 4 report average portfolio returns across the five EGDP beta portfolios within each quintile of the ambiguity beta. The equal-weighted return difference between the Low and High portfolios is 0.34% per month with a *t*-statistic 3.16. The FF4 alpha of the equal-weighted low-minus-high ambiguity portfolio is 0.32% per month and highly significant, with a *t*-value of 2.99. Results for the value-weighted portfolio are qualitatively similar. Thus, the predictive power of the ambiguity beta is not subsumed by the EGDP beta.

To further assure the robustness of our results, we orthogonalize the ambiguity beta to the EGDP beta and examine its return predictive power. Specifically, for each quarter we run the cross-sectional regression of the ambiguity beta on the intercept and EGDP beta. The intercept plus residual is computed as the orthogonalized ambiguity beta. We then form quintile portfolios ranked on the basis of the orthogonalized ambiguity beta. Results are reported in the last four columns of Table 4. Average returns and alphas for the equal-weighted low-minus-high orthogonalized ambiguity beta portfolios are 0.34% and 0.28% per month, respectively, and statistically significant at the 5% level or higher. Similar results are obtained for value-weighted portfolios. Collectively, these results suggest that the ambiguity premium is distinct from the procyclicality premium.

9 HXZ write (p. 38): "Perhaps most important, the credibility of the anomalies literature can improve via a closer connection with economic theory".

10 HXZ further suggest NYSE breakpoints (rather than NYSE-Amex-NASDAQ breakpoints) in portfolio sorts to alleviate microcaps. Our unreported results show that when forming portfolios with NYSE breakpoints and value-weighted returns, the low-minus-high ambiguity beta portfolios still earn positive abnormal returns, significant at the conventional 5% level.

3.4. Firm-level cross-sectional regressions

Although an intuitive and powerful tool for evaluating the economic significance of predictive relations, the portfolio sorting approach focuses on extreme portfolios and is often difficult to control for many variables. Fama–MacBeth cross-sectional regression, in contrast, can take many control variables into account simultaneously and examine the average effect. We therefore perform cross-sectional regressions to confirm our main finding that the ambiguity betas negatively predict the cross-section of stock returns. We run monthly cross-sectional regressions as follows:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_t^{AMB} \beta_{i,t}^{AMB} + \gamma_t^{EGDP} \beta_{i,t}^{EGDP} + \gamma_t^{X'} \boldsymbol{X}_{i,t} + \eta_{i,t+1}, \tag{3}$$

where $R_{i,t+1}$ is the return of stock i in month $t+1$, $\beta_{i,t}^{AMB}$ and $\beta_{i,t}^{EGDP}$ denote the quarterly ambiguity (expected real GDP growth) beta of stock i in months t, $t-1$, and $t-2$, and $\boldsymbol{X}_{i,t}$ denote a vector of firm-specific control variables at time t of stock i (market beta, firm size, book-to-market, momentum, co-skewness, and idiosyncratic volatility). We report the time-series averages of the slope coefficients in Table 5. T-statistics (in parentheses) are adjusted by the Newey and West (1987) *HAC* estimator.

Table 5

Fama–MacBeth cross-sectional regressions. This table reports the results of Fama–MacBeth (1973) cross-sectional regressions of monthly excess returns on the ambiguity betas and other control variables. The regression specification is the following:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_t^{AMB} \beta_{i,t}^{AMB} + \gamma_t^{EGDP} \beta_{i,t}^{EGDP} + \gamma_t^{X'} \boldsymbol{X}_{i,t} + \eta_{i,t+1},$$

where $R_{i,t+1}$ is the return of stock i in month $t+1$, $\beta_{i,t}^{AMB}$ and $\beta_{i,t}^{EGDP}$ denote the quarterly ambiguity (expected real GDP growth) beta of stock i in months t, $t-1$, and $t-2$, and $\boldsymbol{X}_{i,t}$ denote a vector of firm-specific control variables at time t of stock i (market beta, firm size, book-to-market, momentum, co-skewness, and idiosyncratic volatility). The time-series averages of the coefficients are reported. T-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

	Intercept	β_{AMB}	β_{MKTRF}	ME	BTM	PRET	COSKEW	IVOL	β_{EGDP}	Adj R^2
(1)	0.798	−0.432								0.51%
	(3.32)	(−4.12)								
(2)	0.737	−0.452	0.060							2.03%
	(3.96)	(−3.94)	(0.69)							
(3)	1.010	−0.224	0.077	−0.033	0.265	0.803				4.35%
	(2.36)	(−2.65)	(1.04)	(−1.15)	(3.89)	(5.41)				
(4)	1.558	−0.213	0.115	−0.068	0.228	0.783	−0.158	−0.037		4.77%
	(3.79)	(−2.57)	(1.60)	(−2.52)	(3.51)	(5.29)	(−1.40)	(−9.62)		
(5)	1.524	−0.194	0.120	−0.066	0.226	0.776	−0.153	−0.037	0.188	4.91%
	(3.74)	(−2.16)	(1.64)	(−2.46)	(3.49)	(5.45)	(−1.39)	(−9.66)	(1.03)	

The univariate regression results reported in row (1) show a negative and statistically significant relation between the ambiguity beta and subsequent returns in the cross-section. The average slope coefficient on the ambiguity beta is −0.432, and highly significant with a t-statistic −4.12. This average slope coefficient is economically significant; it implies that a two-standard-deviation increase across stocks in the ambiguity beta is associated with a 7.48% decline in expected annual returns.[11]

Rows (2)–(5) report the results after controlling for a host of control variables. The results in row (2) show that the predictive power of the ambiguity beta is robust to controlling for the market beta. The average slope on the ambiguity beta is −0.452, similar to the corresponding estimate in row (1), and highly significant, with a t-value of −3.94. We control for firm size, book-to-market, and past returns in row (3). In this specification, the average slope on the ambiguity beta is reduced to −0.224, but still statistically significant with a t-statistic −2.65. This coefficient is still economically significant, a two-standard-deviation increase across stocks in the ambiguity beta being associated with a 3.35% decline in expected annual returns.

Results reported in row (4) show the predictive power of the ambiguity beta to be robust to two additional control variables, co-skewness and idiosyncratic volatility. The average slope on the ambiguity beta is negative, −0.213, and strongly significant, with a t-value −2.57. We further confirm that the EGDP beta does not drive away the predictive power of the ambiguity beta. Row (5) presents the results for the full specification, simultaneously controlling for all variables, including size, book-to-market, momentum, co-skewness, idiosyncratic volatility, and EGDP beta. The estimated average slope coefficient for the ambiguity beta remains negative and statistically significant. Evidence from the firm-level cross-sectional regressions lends further support to the main hypothesis that low ambiguity beta stocks earn higher returns.

3.5. Controlling for exposures to aggregate indices of stock market upheaval

Our ambiguity measure could be correlated with other aggregate indices of stock market upheaval. One may have a concern that our ambiguity measure could be highly correlated with other aggregate indices of stock market upheaval (such as volatility), which is not necessarily related to ambiguity. In this section, we investigate whether the effect of the ambiguity measure can be distinguished from other aggregate measures of stock market upheaval. We examine the relation between the ambiguity beta and subsequent stock returns after controlling for the betas with respect to the VIX and financial market dislocations index (MDI, hereafter) of Pasquariello (2014).[12] We control for the MDI beta by performing conditional double sorts. Specifically, at the end of each month, we first sort all firms in the sample into quintiles based on the MDI beta. Then, within each MDI beta quintile, we sort firms into quintile portfolios based on the ambiguity beta.

[11] The time-series mean of the cross-sectional standard deviations of the ambiguity beta is 72.17. The expected decrease by two-standard-deviation increase in the ambiguity beta is calculated as 2 * (−0.432/100) * 72.17 * 12.

[12] MDI is designed to capture widespread mispricing of traded financial securities. It is constructed as a composite index of relative mispricing in global stock, foreign exchange, and money markets. We appreciate Pasquariello for kindly providing the MDI data to us.

Table 6
Controlling for exposure to aggregate indices of stock market upheaval. The table reports monthly excess returns of portfolios formed on the ambiguity betas controlling for exposure on the VIX index and Pasquariello's (2014) market dislocation index. The beta of each stock on the VIX index is estimated from the regressions of excess stock returns on MKTRF and changes in the VIX index using daily data for one month. We sort the stocks into quintiles based on the betas on the VIX and MDI indices and, within each quintile, form quintile portfolios using the ambiguity betas. We report the average returns of the portfolios formed on the ambiguity beta across the quintiles formed on each firm characteristic. *Low–High* indicates a long-short strategy that 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: Sort by β_{MDI}				Panel B: Sort by $\beta_{\Delta VIX}$			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
	Excess returns	FF4 alpha	Excess returns	FF4 alpha	Excess returns	FF4 alpha	Excess returns	FF4 alpha
Low	0.99%	0.19%	0.78%	0.13%	1.00%	0.21%	0.75%	0.15%
	(3.29)	(2.51)	(2.75)	(1.34)	(2.70)	(1.96)	(2.34)	(1.34)
2	0.94%	0.22%	0.74%	0.13%	0.98%	0.29%	0.78%	0.16%
	(3.77)	(3.07)	(3.13)	(1.69)	(3.37)	(3.19)	(2.91)	(1.55)
3	0.88%	0.19%	0.71%	0.15%	0.88%	0.22%	0.70%	0.09%
	(3.60)	(2.80)	(3.21)	(2.02)	(3.11)	(2.82)	(2.69)	(1.14)
4	0.71%	0.03%	0.52%	−0.08%	0.82%	0.12%	0.58%	−0.03%
	(2.82)	(0.45)	(2.15)	(−1.13)	(2.76)	(1.95)	(2.03)	(−0.42)
High	0.57%	−0.16%	0.29%	−0.36%	0.67%	−0.17%	0.40%	−0.41%
	(1.86)	(−2.10)	(0.85)	(−2.45)	(1.78)	(−1.69)	(0.96)	(−2.81)
Low–High	0.42%	0.36%	0.50%	0.49%	0.32%	0.37%	0.35%	0.56%
	(3.76)	(3.02)	(2.79)	(2.36)	(1.97)	(2.33)	(1.68)	(2.61)

The first four columns of Table 6 report average portfolio returns across the five MDI beta portfolios within each quintile of the ambiguity beta. Results show that, after controlling for the MDI beta, the average return (FF4 alpha) of the difference between the low and high ambiguity beta equal-weighted portfolios is 0.42% (0.36%) per month with a *t*-statistic of 3.76 (3.02). Similar results are obtained from value-weighted portfolios. The third and fourth columns Table 6 show that after controlling for the MDI beta, the raw return (FF4 alpha) of the difference between the low and high ambiguity beta value-weighted portfolios is 0.50% (0.49%) per month with a *t*-statistic of 2.79 (2.36). Thus, the ambiguity premium remains strong after controlling for the effect of the MDI. The last four columns of Table 6 show that after controlling for the betas with respect to the changes in the VIX, the raw return as well as FF4 alphas of the difference between the low and high ambiguity beta portfolios range between 0.35% and 0.56% per month and remain significant, although the statistical significances become weaker. In sum, these results indicate that the ambiguity premium persists after controlling for the effect of other aggregate indices of stock market upheaval.

4. Additional results

4.1. Ambiguity measure using forecasts for aggregate corporate profits

Anderson et al. (2009, AGJ hereafter) measure ambiguity using forecasts of aggregate corporate profits, and show that ambiguity betas can explain cross-sectional differences in returns. AGJ's measure of uncertainty is constructed with a flexible weighting scheme to accommodate assigning more or less weight to extreme forecasts, which, albeit novel, because it relies on the full sample to estimate parameters (and consequently ambiguity) is subject to look-ahead bias in the portfolio construction. In contrast, our measure of ambiguity, as the cross-sectional dispersion in forecasts of future real GDP growth, exploits the availability of real-time data. There being no modelling assumption involved and the requisite information being available, the simple standard deviation is suitable for the predictability exercise and avoids look-ahead bias in forming portfolios.

In this section, we evaluate the out-of-sample performance of the beta with respect to AGJ's ambiguity measure, constructed from forecasts of aggregate corporate profits, in predicting the cross-section of future stock returns. It requires us to recursively estimate AGJ's ambiguity measure using only the information available up to portfolio formation date. Specifically, the recursive out-of-sample estimates for AGJ's ambiguity measure and its betas are computed as follows. We first estimate parameters for the flexible weighting scheme on the extending windows, which always start at 1969:Q1 and end at each time t, by performing the quasi-maximum likelihood estimation of Eq. (28) in AGJ. Next, for each firm we obtain the AGJ ambiguity beta by estimating Eq. (39) in AGJ over the most recent 20 quarters (i.e., the period from time t−19 to time t). Stocks are then sorted into quintile portfolios at the end of the time t based on the estimated AGJ ambiguity betas. Quintile portfolios are held during the subsequent quarter. This procedures is repeated for each additional quarter until the end of 2013:Q4. To ensure a sufficient number of observations for estimation, the initial parameters estimates are obtained for the ten-year period from 1969:Q1 to 1978:Q4. Portfolio returns consequently begin at 1979:Q1.

Table 7 reports monthly average excess returns and alphas for the equal-weighted and value-weighted quintile portfolios formed on the out-of-sample estimated AGJ ambiguity measure. Results show that, when the AGJ ambiguity measure is recursively estimated out-of-sample, it fails to predict future stock returns. The average return spreads between the low and high ambiguity beta portfolios are close to zero and statistically insignificant: −0.06% (−0.02%) per month for equal-weighted (value-weighted) returns.[13]

[13] To ensure that our results are not induced by using the extended sample period, we also examine AGJ's original, shorter sample period from 1979:Q1 to 2003:Q4. Unreported results show that there is no out-of-sample predictive power of the AGJ ambiguity betas for the future stock returns in the shorter sample period.

Table 7

Portfolios sorts on the ambiguity measure using forecasts of corporate profits. The table reports monthly excess returns and the Carhart (1997) four-factor alphas of quintile portfolios sorted by the betas on the ambiguity measure of Anderson et al. (2009, AGJ hereafter) on an out-of-sample basis. Recursive out-of-sample estimates of AGJ's ambiguity measure and its betas are computed as follows. We perform the quasi-maximum likelihood estimation of Eq. (28) in AGJ to estimate parameters for a flexible weighting scheme on the extending windows, which always start at 1969:Q1 and end at each time t. Then, for each firm we obtain AGJ's ambiguity beta by estimating Eq. (39) in AGJ over the most recent 20 quarters (i.e., the period from time t−19 to time t). Stocks are then sorted into quintile portfolios at the end of time t based on the estimated AGJ's ambiguity betas. Quintile portfolios are held during the subsequent quarter. The procedures above are repeated for each additional quarter to the end of 2013:Q4. To ensure a sufficient number of observations for estimation, the initial parameters estimates are obtained over the ten-year period from 1969:Q1 to 1978:Q4. The portfolio returns consequently begin at 1979:Q1. The quintile *Low* contains stocks with the lowest sensitivities, and the quintile *High* contains stocks with highest sensitivities during the previous quarter. *Low–High* indicates a long-short strategy that buys the *Low* portfolio and sells the *High* portfolio. The *t*-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

	Equal-weighted		Value-weighted	
Portfolio	Excess returns	FF4 alpha	Excess returns	FF4 alpha
Low	0.75%	0.02%	0.76%	0.11%
	(2.47)	(0.22)	(2.76)	(0.80)
2	0.86%	0.15%	0.76%	0.14%
	(3.69)	(2.48)	(3.69)	(2.20)
3	0.90%	0.16%	0.65%	−0.02%
	(3.83)	(2.49)	(2.95)	(−0.38)
4	0.91%	0.12%	0.67%	−0.03%
	(3.48)	(1.83)	(2.55)	(−0.36)
High	0.81%	−0.06%	0.78%	0.05%
	(2.51)	(−0.83)	(2.31)	(0.37)
Low–High	−0.06%	0.08%	−0.02%	0.07%
	(−0.57)	(0.63)	(−0.12)	(0.31)

One may point out that the poor predictability power of the out-of-sample estimated AGJ ambiguity measure, reported in Table 7, could be driven by the use of flexible weighing schemes, rather than forecasts of corporate profits. To evaluate this possibility, we compute an alternative ambiguity measure as the simple standard deviation in forecasts of future aggregate corporate profits and examine the out-of-sample predictive power of its betas for future stock returns. Unreported results show that corporate profits-based ambiguity betas do not yield a meaningful premium regardless how the cross-sectional dispersion is calculated. The return spreads between the low and high ambiguity portfolios are economically small and statistically insignificant. It therefore corroborates that the betas with respect to ambiguity regarding future aggregate corporate profits fail to predict stock returns in the cross-section.

We further compare our ambiguity measure (regarding economic conditions) with (out-of-sample estimated) AGJ's ambiguity measure by orthogonalizing the ambiguity betas with respect to each other. Specifically, for each quarter we run a cross-sectional regression of AGJ's ambiguity beta on the intercept and our ambiguity beta. The intercept plus residual is computed as the orthogonalized AGJ ambiguity beta. We run Fama–MacBeth cross-sectional regressions of one-month ahead stock returns on our ambiguity beta, the orthogonalized AGJ ambiguity beta, and other control variables (market beta, firm size, book-to-market, past return, coskewness, and IVOL).

Table 8 presents the time-series averages of the slope coefficients on these ambiguity betas. Results show that the orthogonalized AGJ ambiguity is not priced in the cross-section of stock returns. The average slope coefficient on the orthogonalized AGJ ambiguity beta is insignificant, while that on our ambiguity beta is significant. This is somewhat expected from the above results that the AGJ ambiguity beta turns out to be an insignificant return predictor when estimated out-of-sample. When we reverse the order of orthogonalizing betas (i.e., orthogonalize our ambiguity beta with respect to the AGJ ambiguity beta), the orthogonalized our ambiguity beta is a significant predictor for subsequent stock returns (not reported).

In sum, our analyses show that, unlike our ambiguity beta, the AGJ ambiguity beta is not a significant predictor of future stock returns when estimated out-of-sample. It suggests that investors seem to care more about ambiguity about macroeconomic fundamentals in general than about stock fundamentals (i.e., corporate profits). From an economic perspective, this difference in return predictability is particularly critical to investors seeking to develop real-time implementable strategies.

4.2. Ambiguity about prospects for the future economy over a longer horizon

In this section, we compare the relative return predictive power of the betas for ambiguity about short- and longer-term economic conditions. Our baseline ambiguity measure is constructed using one-quarter-ahead forecasts of future GDP. The SPF dataset provides forecasts for economic variables up to four quarters ahead, enabling us to gauge ambiguity related to longer-term economic conditions. The evidence provided thus far that low ambiguity beta stocks have higher expected returns use one-quarter-ahead forecasts made by professionals. There is no reason, however, to expect ambiguity regarding only short-term (one-quarter-ahead) economic condition

Table 8

Fama–MacBeth regressions that include the orthogonalized AGJ ambiguity betas. This table reports the results of Fama–MacBeth (1973) cross-sectional regressions of monthly excess returns on the ambiguity betas, betas on the ambiguity measure of Anderson et al. (2009, AGJ hereafter), and control variables. We first estimate AGJ's ambiguity measure on an out-of-sample basis. The AGJ's ambiguity betas are calculated by means of a 20 quarters rolling window regression, as in calculating our ambiguity beta. We next run, for each time, a cross-sectional regression of AGJ's ambiguity betas on the intercept and our ambiguity beta. The intercept plus residual is computed as the orthogonalized AGJ ambiguity beta (β^{OOS}_{AGJ}). We then run cross-sectional regressions following the specification in Table 5, with the orthogonalized AGJ ambiguity betas as additional regressors. Time-series averages of the coefficients are reported, and the t-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator.

	Intercept	β_{AMB}	β^{OOS}_{AGJ}	β_{MKTRF}	ME	BTM	PRET	COSKEW	IVOL	Adj R^2
(1)	0.798	−0.432								0.5%
	(3.32)	(−4.12)								
(2)	0.821		0.016							0.3%
	(3.30)		(1.12)							
(3)	0.835	−0.464	0.015							0.8%
	(3.35)	(−4.10)	(1.08)							
(4)	1.558	−0.213		0.115	−0.068	0.228	0.783	−0.037	−0.158	4.8%
	(3.79)	(−2.57)		(1.60)	(−2.52)	(3.51)	(5.29)	(−9.62)	(−1.40)	
(5)	1.392		0.011	0.110	−0.049	0.193	0.738	−0.033	−0.230	4.4%
	(3.22)		(1.14)	(1.53)	(−1.81)	(2.69)	(4.13)	(−8.77)	(−1.90)	
(6)	1.393	−0.236	0.008	0.129	−0.050	0.191	0.777	−0.033	−0.210	4.7%
	(3.28)	(−2.55)	(0.91)	(1.66)	(−1.85)	(2.74)	(4.77)	(−8.76)	(−1.73)	

Table 9

Fama–MacBeth regressions that include the orthogonalized longer-term ambiguity betas. We first estimate the betas for ambiguity about future real GDP growth from the present to k quarters ahead, where $k = 1, 2, 3$, or 4, and orthogonalize these ambiguity betas with respect to each other. The baseline short-term (one-quarter-ahead) ambiguity beta is unaffected. The orthogonalized two-quarter-ahead ambiguity beta (β_{AMB2}) is the component of the original two-quarter-ahead ambiguity beta orthogonal to the one-quarter-ahead ambiguity beta, the orthogonalized three-quarter-ahead ambiguity beta (β_{AMB3}) is the component of the original three-quarter-ahead ambiguity beta orthogonal to both the one- and two-quarter-ahead ambiguity betas, and so on. β_{AMB4}denotes the orthogonalized four-quarter-ahead ambiguity beta. Table 9 reports the time-series averages of the slope coefficients from the Fama–MacBeth regressions of one-month ahead stock returns on these orthogonalized longer-term ambiguity betas and control variables. For visibility, the coefficients for β_{AMB}, β_{AMB2}, β_{AMB3}, and β_{AMB4} are multiplied by 100.

	Intercept	β_{AMB}	β_{AMB2}	β_{AMB3}	β_{AMB4}	β_{MKTRF}	ME	BTM	PRET	COSKEW	IVOL	Adj R^2
(1)	1.558	−0.213				0.115	−0.068	0.228	0.783	−0.037	−0.158	4.8%
	(3.79)	(−2.57)				(1.60)	(−2.52)	(3.51)	(5.29)	(−9.62)	(−1.40)	
(2)	1.553	−0.215	−0.133			0.110	−0.068	0.227	0.779	−0.037	−0.200	4.9%
	(3.82)	(−2.62)	(−0.43)			(1.51)	(−2.55)	(3.53)	(5.37)	(−9.69)	(−1.84)	
(3)	1.552	−0.221		−0.143		0.125	−0.069	0.226	0.783	−0.037	−0.163	4.9%
	(3.75)	(−2.65)		(−0.32)		(1.77)	(−2.53)	(3.51)	(5.37)	(−9.69)	(−1.46)	
(4)	1.573	−0.222			0.906	0.113	−0.068	0.232	0.797	−0.037	−0.198	4.9%
	(3.80)	(−2.59)			(1.71)	(1.54)	(−2.49)	(3.49)	(5.40)	(−9.70)	(−1.78)	
(5)	1.553	−0.232	−0.237	−0.260	0.764	0.121	−0.069	0.228	0.791	−0.037	−0.245	5.1%
	(3.78)	(−2.71)	(−0.76)	(−0.60)	(1.36)	(1.64)	(−2.52)	(3.47)	(5.64)	(−9.81)	(−2.32)	

should be priced in the stock market. Investors could care more about ambiguity regarding the future economy longer-term (e.g., four-quarter-ahead). We therefore examine whether ambiguity regarding longer-term economic conditions has stronger (or weaker) power to predict stock returns in the cross-section.

We estimate the betas for ambiguity about future real GDP growth from the present up to k quarters ahead, where $k = 1$, 2, 3, or 4. We then orthogonalize these ambiguity betas with respect to each other: The baseline short-term (one-quarter-ahead) ambiguity beta is unaffected, the orthogonalized two-quarter-ahead ambiguity beta is the component of the original two-quarter-ahead ambiguity beta orthogonal to the one-quarter-ahead ambiguity beta, the orthogonalized three-quarter-ahead ambiguity beta is the component of the original three-quarter-ahead ambiguity beta orthogonal to both the one- and two-quarter-ahead ambiguity betas, and so on. Table 9 reports the time-series averages of the slope coefficients from the Fama–MacBeth regressions of one-month ahead stock returns on these orthogonalized longer-term ambiguity betas. Other control variables are included in the regressions.

Results show that the average slope coefficient on the baseline (one-quarter-ahead) ambiguity beta is negative and significant, but those on the orthogonalized longer-term ambiguity betas are insignificant. Our analyses using the orthogonalized longer-term ambiguity betas indicate that investors care more about short-term (one-quarter-ahead) ambiguity than about longer-term ambiguity, since longer-term ambiguity betas lose return predictability power when orthogonalized to the short term ambiguity beta.

4.3. Ambiguity about economic growth and inflation

Real GDP growth consists of economic growth (nominal GDP growth) and inflation (CPI growth). In this section, we explore whether investors care more about ambiguity regarding economic growth or inflation. We do so by investigating the relation between our baseline ambiguity beta (obtained using real GDP growth) and subsequent stock returns, controlling separately for ambiguity about economic growth and inflation. Specifically, we measure the effect of inflation (economic growth) as the baseline ambiguity beta orthogonal to the beta of ambiguity regarding economic growth (inflation) and perform conditional bivariate portfolio sorts,

Table 10
Ambiguity beta controlling for the effects of inflation and economic growth. The table reports monthly excess returns of portfolios formed on the ambiguity betas, controlling for the effects of inflation and economic growth. We measure the effect of inflation (economic growth) as the ambiguity beta orthogonal to the beta of ambiguity about economic growth (inflation). We perform conditional bivariate portfolio sorts first by the effect of inflation (economic growth) and then by the baseline ambiguity beta. The left half of the table reports the ambiguity premium, controlling for the effect of inflation. Specifically, it presents average portfolio returns across the five portfolios formed on the effect of inflation within each quintile of the baseline ambiguity beta. The right half of the table reports the ambiguity premium, controlling for the effect of economic growth. *Low–High* indicates a long-short strategy that 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 the effect of inflation				Controlling for the effect of economic growth			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
	Excess returns	FF4 alpha	Excess returns	FF4 alpha	Excess returns	FF4 alpha	Excess returns	FF4 alpha
Low	0.90%	0.17%	0.70%	0.07%	0.88%	0.14%	0.71%	0.11%
	(3.47)	(2.77)	(2.96)	(1.12)	(3.33)	(2.19)	(2.93)	(1.41)
2	0.84%	0.16%	0.64%	0.03%	0.79%	0.11%	0.53%	−0.05%
	(3.61)	(2.91)	(3.06)	(0.58)	(3.29)	(2.05)	(2.38)	(−0.82)
3	0.76%	0.07%	0.63%	0.07%	0.75%	0.08%	0.59%	0.04%
	(3.23)	(1.21)	(2.96)	(1.19)	(3.20)	(1.61)	(2.74)	(0.77)
4	0.72%	0.05%	0.51%	−0.08%	0.73%	0.06%	0.55%	−0.06%
	(3.02)	(1.12)	(2.18)	(−1.51)	(3.04)	(1.02)	(2.35)	(−0.94)
High	0.70%	0.01%	0.46%	−0.15%	0.77%	0.07%	0.51%	−0.07%
	(2.52)	(0.09)	(1.64)	(−2.06)	(2.96)	(1.19)	(2.01)	(−0.92)
Low–High	0.20%	0.17%	0.24%	0.22%	0.11%	0.08%	0.19%	0.17%
	(2.27)	(1.94)	(2.01)	(2.10)	(1.47)	(0.90)	(1.86)	(1.43)

first by the effect of inflation (economic growth), then by the baseline ambiguity beta. The first four columns of Table 10 report the ambiguity premium, controlling for the effect of inflation. That is, it presents average portfolio returns across the five portfolios formed on the effect of inflation within each quintile of the baseline ambiguity beta. Results show that the ambiguity premium, controlling for the effect of inflation, remain significant. In contrast, results reported in the last four columns of Table 10, show that the ambiguity premium, controlling for the effect of economic growth, becomes smaller and statistically insignificant. This suggests that ambiguity regarding economic growth has more critical impact on the cross-section of stock returns, than does ambiguity regarding inflation. Our results do not necessarily mean, however, that ambiguity regarding inflation is not important; it could play an important role in other asset classes, such as fixed income and housing markets. Ulrich (2013), for instance, shows that investors' concern for inflation ambiguity can account for the upward sloping term premium in nominal U.S. Government bond yields.

4.4. Controlling simultaneously for the various types of ambiguity betas

In this section, we control simultaneously for the various types of ambiguity betas by running the Fama–MacBeth regressions including all the orthogonalized ambiguity betas discussed above. Specifically, the cross-sectional regressions are run on the orthogonalized betas of ambiguity about corporate profits, longer-term economic conditions, economic growth, and inflation as well as on our baseline ambiguity beta. Other firm characteristics control variables are included in the regressions but not reported for the sake of brevity.

Table 11 reports the results. In this more general specification, the average slope coefficients on the baseline ambiguity beta remains negative and statistically significant in all cases. The average slope coefficients on the various types of orthogonalized ambiguity betas are all statistically insignificant, consistent with our earlier results. It thus corroborates that investors care more about ambiguity regarding economic conditions than corporate profits, more about ambiguity regarding the state of the economy in the short rather than long term, and more about ambiguity regarding economic growth than inflation.

5. Conclusion

Motivated by recent asset pricing models that predict that ambiguity-averse investors command a premium for bearing ambiguity, we investigate the pricing implications of ambiguity for the cross-section of expected stock returns. Measuring ambiguity as the cross-sectional dispersion in real-time forecasts of real GDP growth from SPF, we find strong evidence that ambiguity related to economic conditions is significantly negatively priced in the cross-section of returns, that is, high ambiguity beta stocks earn lower future returns. A real-time, implementable 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. Stocks that deliver high returns when ambiguity is high (i.e., high ambiguity beta stocks), on the other hand, provide a good hedge and must thus have low expected returns.

We further document several interesting findings. First, we show that the ambiguity premium is distinct from the procyclicality premium, the finding of Goetzmann et al. (2012) that high business cycle beta stocks earn higher returns relative to low business cycle betas. Second, the ambiguity premium persists after controlling for the effect of other aggregate indices of stock market upheaval,

Table 11
Fama–MacBeth regressions that include various types of the orthogonalized ambiguity betas. We control for various types of ambiguity betas simultaneously by running the Fama–MacBeth regressions with all of the orthogonalized ambiguity betas included. The cross-sectional regressions are run on the orthogonalized betas of ambiguity about corporate profits, longer-term economic conditions, economic growth, and inflation as well as our baseline ambiguity beta. Other firm characteristics control variables including the market beta, logarithms of firm size and book-to-market ratio, 12-month past returns skipping 1-month, co-skewness, and idiosyncratic volatility are included in the regressions, but not reported for the sake of brevity. The table reports the time-series averages of the coefficients. The t-statistics in parentheses are adjusted by the Newey and West (1987) HAC estimator. Results for the control variables and intercepts are omitted for the sake of brevity.

	β_{AMB}	β_{AGJ}^{OOS}	β_{AMB2}	β_{AMB3}	β_{AMB4}	β_{NGDP}	β_{PGDP}	Adj R^2
(1)	−0.236	0.820						4.7%
	(−2.55)	(0.91)						
(2)	−0.232		−0.237	−0.260	0.764			5.1%
	(−2.71)		(−0.76)	(−0.60)	(1.36)			
(3)	−0.213					−0.010	0.078	5.0%
	(−2.59)					(−0.11)	(1.32)	
(4)	−0.231	0.474	−0.636	−0.234	0.852	0.088	0.078	5.2%
	(−2.53)	(0.47)	(−1.91)	(−0.88)	(1.80)	(1.02)	(1.38)	

including VIX and financial market dislocations index. Third, the beta of ambiguity about corporate profits is not a significant predictor of future stock returns when estimated out-of-sample, suggesting that investors seem to care more about ambiguity about macroeconomic fundamentals in general than about stock fundamentals (corporate profits). Finally, we compare the relative return predictive power of various types of ambiguity betas by orthogonalizing ambiguity betas with respect to each other. Our results suggest that investors seem to care more about ambiguity about the state of the economy in the short-term, rather than long-term, and more about ambiguity about economic growth than inflation.

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