

Market Ambiguity and Returns

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Abstract: Using a GARCH-M model, we examine the effect of the *level of ambiguity* in the stock market on the conditional mean of market returns. Additionally, we investigate the predictive power of the *level of ambiguity* expected market returns. The results of the GARCH-M estimation indicate the presence of GARCH effects and show a positive risk-return tradeoff. Second, we find that the *level of ambiguity*, although orthogonal to risk, is correlated with market returns. On dividing our study period into expansion and recession subperiods, we find that there is an inverse relationship between the *level of ambiguity* and contemporaneous market returns only during recessions. Finally, the results of the forecast models indicate that the *level of ambiguity* is a strong predictor of future market returns. Specifically, our findings offer the first definite evidence of a positive relationship between the *level of ambiguity* and future market returns.

Keywords: market ambiguity, market returns, conditional mean, risk-return tradeoff, GARCH effects, return predictors, future market returns, Knightian uncertainty

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1. Introduction

The concept of risk-return tradeoff is a fundamental principle in Finance; central to asset pricing theory and can be expressed as a positive association between the conditional mean and the conditional variance of market returns. Merton [1] states that in equilibrium, a risk-averse investor will require higher returns from investing in riskier stocks. While the risk-return tradeoff concept is theoretically sound, the empirical evidence, though extensive, is contradictory and puzzling. A section of the previous studies finds a positive risk-return tradeoff (see Guo and Whitelaw [2]). Another section finds a negative or no relation between risk and returns (see Harvey [3]). Recently, a new explanatory factor: *ambiguity*, has been introduced into the risk-return relation literature (see Brenner and Izhakian [4]). Ambiguity is the variability of the probabilities of future returns, and it is orthogonal to risk. To illustrate the concept, consider the following example of a stock with two potential future returns: $a = 5\%$ and $b = 15\%$ with *known* probabilities $P(a) = 0.2$ and $P(b) = 0.8$. The expected return is simply $[0.2 \times 5\%] + [0.8 \times 15\%] = 13\%$ and the risk, measured by standard deviation of returns is $[(5\%-13\%)^2 \times 0.2 + (15\%-13\%)^2 \times 0.8]^{0.5} = 4\%$. In this example, the probabilities are known and so there is *no ambiguity*. Let's introduce a complication. Assume that $P(a) = 0.2$ and $P(b) = 0.8$, or $P(a) = 0.8$ and $P(b) = 0.2$ and these two alternative probability distributions are *equally possible*. Investors are now confronted with a variability of probabilities of future returns: *ambiguity*. With the alternative probability

distribution, the expected return is $[0.8 \times 5\%] + [0.2 \times 15\%] = 7\%$ and the standard deviation is $[(5\%-7\%)^2 \times 0.8 + (15\%-7\%)^2 \times 0.2]^{0.5} = 4\%$. Noticeably, the variability in expected returns due to the variability in probability of returns is not captured by the standard deviation of returns (risk) since the expected probabilities remain the same: $E[P(a)] = E[P(b)] = 0.5$. Brenner and Izhakian [4], developed a measure for the degree of ambiguity (A): the expected variability of the future return probabilities. Following Brenner and Izhakian [4], with *unknown* probabilities, $A = [\sum_i E[P(i)] \text{Var}[P(i)]]^{0.5} = [(E[P(a)] \times \text{Var}[P(a)]) + (E[P(b)] \times \text{Var}[P(b)])]^{0.5} = [(0.5 \times ((0.2-0.5)^2 \times 0.5 + (0.8-0.5)^2 \times 0.5) + (0.5 \times ((0.8-0.5)^2 \times 0.5 + (0.2-0.5)^2 \times 0.5))]^{0.5} = 0.3$. The ambiguity factor captures the dispersion in expected return due to the variability in probability distribution. Brenner and Izhakian [4], using OLS regressions, find that ambiguity is priced in equity markets and combining ambiguity with risk in asset pricing models improves the role of risk in explaining the risk-return tradeoff. We add to this literature by examining the effect of the ambiguity factor in the intertemporal risk-return relationship. In the conditional mean and conditional risk literature, time-varying risk has traditionally been modeled using GARCH models. Hence, we employ a GARCH-M framework, incorporate exogenous control variables and the ambiguity factor, to investigate the contemporaneous effects of ambiguity on the conditional mean of returns. Additionally, we examine the capacity of the ambiguity factor to predict future returns in univariate as well as bivariate regressions using the ambiguity factor and one of the established return predictors as a control variable. We find that results of the GARCH-M estimation indicate the presence of GARCH

effects and show a positive risk-return tradeoff. Second, we find that the *level of ambiguity*, although orthogonal to risk, is correlated with market returns. On dividing our study period into expansion and recession subperiods, we find that there is an inverse relationship between the *level of ambiguity* and contemporaneous market returns only during recessions, indicating that ambiguity-averse investors tend to overweight the likelihood of negative returns during recessions, lowering the perceived expected returns to investments. Finally, the results of the forecast models; univariate as well as bivariate tests, indicate that the *level of ambiguity* is a strong predictor of future market returns. Specifically, our findings offer the first definite evidence of a positive relationship between the *level of ambiguity* and future market returns.

2. Literature Review

Merton [1] asserts that in equilibrium, a risk-averse investor will demand a higher reward from investing in riskier stocks. However, extant theoretical research suggests that there are fluctuations in the risk-return relation. These fluctuations could be attributable to various shocks, such as Poisson shocks to expected mean and variance of aggregate consumption (Drechsler and Yaron [5]), time-varying risk aversion (Bekaert and Engstrom [6]), and Knightian uncertainty shocks (Miao, Wei, and Zhou [7]). Hence, one contribution of this study is to expand the literature in this area by presenting additional evidence on a new economic factor in the risk-return relation: the effect of *ambiguity*. Numerous empirical studies have examined the risk-return relation for evidence of a linear and positive relation between risk and return. However, the results are conflicting. Fama and French [8] examining cross-sectional returns, document that the relation between risk, measured by beta, and return is weak. Later studies attempt to explain the risk-return relation by decomposing beta into its components. For instance, Jacobs and Wang [9] decompose beta into aggregate consumption risk and idiosyncratic consumption risk and Guo and Whitelaw [2] decompose beta into a risk component and a hedge component. These enhancements add some statistical power for risk in explaining returns, however, the validity of these risk measures is debatable. Studies such as Black [10], Campbell [11], Nelson [12], and Harvey [3] find a negative risk-return relation. Other studies such as French et al. [13], Campbell and Hentschel [14], and Guo and Whitelaw [2] find a positive relation. The conflicting findings have necessitated a strand of literature attempting to explain the differences. Some studies propose other measures of risk [15], while others, such as Harvey [3], suggest a change to the methodology used to determine the conditional variance in the risk-return relation. Another branch of literature on the risk-return relation includes time-varying risk aversion modeled as conditional moments of returns: conditional mean and conditional variance [16]. In the conditional mean and conditional variance literature, the time-varying risk and return relation is traditionally estimated using GARCH models. GARCH models originated from the autoregressive conditional heteroskedasticity (ARCH)

models. Extant research such as Nelson [12] has established that negative returns tend to trigger higher volatility than positive returns, and Engle and Ng [17] show that GARCH models which account for this asymmetry in volatility are better predictors of the market variance. Conversely, Glosten, Jagannathan, and Runkle [18] find that testing the risk-return tradeoff with asymmetric GARCH models, yields a negative coefficient estimate, which contrasts with symmetric GARCH model tests which find a positive coefficient estimate. Our study adds to the literature on the use of GARCH models in testing the risk-return tradeoff, by introducing an exogenous factor: *ambiguity*, into the model GARCH model and testing the risk-return tradeoff. Ambiguity, or Knightian uncertainty is the central concept of decision theory, with studies such as Gilboa and Schmeidler [19], Schmeidler [20], and Klibanoff et al. [21] utilizing a variety of methods to model decision-making given ambiguity. A shared concept in these methods is that, under ambiguity, ambiguity-averse investors tend to overweight the likelihood of negative returns and underweight the likelihood of the positive returns, lowering the perceived expected returns to future investments. Another theory in the Knightian uncertainty family is the Expected Ambiguity with Uncertain Probabilities (EUUP) by Izhakian [22]. This theory models ambiguity as statistically orthogonal or independent of outcomes and differentiates the concepts of ambiguity from risk. Essentially, the EUUP work horse enables us to calculate or measure ambiguity separate from risk. The level of ambiguity can be determined by the volatility of probabilities of returns or outcomes, and this is separate from the level of risk which is traditionally measured by the volatility of returns or outcomes [23]. Importantly, adding ambiguity as a measure, covers variations of the first three statistical moments of the return distribution: mean, variance, and skewness; and can be used in empirical studies. Effects of ambiguity on asset pricing models have been investigated mostly in relation to the equity premium. Izhakian and Benninga [24] and Ui [25], for instance, decompose the equity premium into two parts: ambiguity premium and risk premium. Other studies such as Dow and Werlang [26] and Easley and O'Hara [27] find that ambiguity aversion leads to limited market participation by investors and affects the equity premium. Additionally, the concept of ambiguity being a missing factor in risk-return tradeoff models has been investigated mostly from a theoretical perspective in studies such as Epstein and Schneider [28] and Izhakian and Benninga [24]. Andreou et al. [29] and So et al. [30], using option implied ambiguity, examine the role of ambiguity in the risk-return relation and find that ambiguity is a cardinal determinant, adding to risk to explain expected excess returns.

3. Ambiguity and GARCH-M

In this study, our main hypothesis is that the level of ambiguity influences the conditional mean of market returns. To investigate our hypothesis, we utilize the GARCH-M framework to examine the contemporaneous impact of ambiguity on the conditional mean of returns

after accounting for the conditional risk of returns. The extant literature on the relation between conditional mean and conditional risk models time-varying risk using GARCH models. GARCH models began from autoregressive conditional heteroskedasticity (ARCH) models. The original ARCH model (Engle [31] estimates time varying conditional variance by connecting it to historical levels of identified variables. In its basic form, an ARCH model estimates the time varying conditional variance as a function of past squared innovations. Bollerslev [32] generalized the ARCH model creating the GARCH model. In the elemental framework of GARCH, Bollerslev shows that the best estimator of future variance of returns is a weighted average of the current period squared residual, the long-run average variance, and the current period variance. An extension of the GARCH model is the GARCH-in-Mean (GARCH-M) model by Engle, Lilien and Robins [17]. The GARCH-M model expands the GARCH model to include the hidden connection between risk and time-varying expected return. Chauvet and Potter [33] study the risk-return tradeoff using modifications of the GARCH-M model. The GARCH-M framework incorporates the conditional variance; h_t in the conditional mean equation and estimates the impact of the conditional variance on the conditional mean of the returns, $r_t; r_t = \psi + \delta h_t + \sqrt{h_t} \varepsilon_t$, (1) where $h_t = \omega + \beta h_{t-1} + \alpha u_{t-1}^2$, with $u_t = r_t - \psi - \delta h_t$ and $\omega > 0$, $\beta \geq 0$, and $\alpha > 0$ and $\varepsilon_t \sim \text{IID}(0,1)$. In our study, we examine the effect of the *level of ambiguity* (AMB) on the conditional mean of returns using an extension of the GARCH-M model. Following Nyberg [34], we impregnate the model by including exogenous control variables and the *level of ambiguity* in the GARCH-M model as follows:

$$r_t = \psi + \theta \text{AMB}_t + \Phi X_t + \delta h_t + \sqrt{h_t} \varepsilon_t, \quad (2)$$

where ψ is the intercept term, $\varepsilon_t \sim \text{IID}(0,1)$ and follows the Student's t distribution, θ is the *level of ambiguity* slope coefficient, Φ is a matrix of slope coefficients, X_t is a vector of control variables and $h_t = \omega + \beta h_{t-1} + \alpha u_{t-1}^2$, where $u_t = r_t - \psi - \delta h_t$ and $\omega > 0$, $\beta \geq 0$, and $\alpha > 0$. This framework enables the examination of the effect of ambiguity on the time-varying risk-return relation. **Hypothesis 1: Level of ambiguity is directly related to the contemporaneous stock market returns.**

4. Ambiguity and Return Predictability

To develop a model of market return predictability, we must review the theoretical relations among exogenous variables and expected market returns. Most of the variables recognized by the extant research as estimators of expected returns are macroeconomic indicators and by extension predictors of market returns. Fama and French [8] find that dividend yield and the term spread are predictors of future market returns. Hassett and Metcalf [35] show that economic policy uncertainty could adversely affect the performance of the economy. Following studies such as Dow and Werlang [26] and Easley and O'Hara [27] which find that ambiguity aversion leads to reduced market participation by investors and impacts the equity premium, we examine the

predictive power of ambiguity for future market returns. Arguably, ambiguity aversion may be correlated with a decline in market sentiment. According to Baker and Wurgler [36], a decline in market sentiment may lead to a decline in market returns. Consistent with the above discussion and extant research on asset return predictability, we hypothesize that the level of ambiguity is a predictor of future excess market returns. **Hypothesis II: The level of ambiguity is a predictor of future market returns.** We examine the relation between the *level of ambiguity* and future market returns, in univariate and in bivariate regressions using the *level of ambiguity* and one of the following traditional return predictors as a control variable; dividend-to-price ratio, earnings-to-price ratio, term spread, and default spread (see Cochrane [37] and Li, Ng, and Swaminathan [38]).

We use the multiperiod prediction model of Fama and French [8]:

$$\sum_{n=1}^N \frac{r_{t+N}}{N} = a + bX_t + u_{t+N,t} \quad (3)$$

where r_{t+N} is the continuously compounded monthly excess return calculated as the continuously compounded monthly return on the market return minus the continuously compounded one-month Treasury bill rate. X_t is a $1 \times m$ matrix of m independent variables: the *level of ambiguity* and one traditional of the return predictors; dividend-to-price ratio, earnings-to-price ratio, term spread, or default spread, b is a $1 \times m$ matrix of slope coefficients, N is the prediction horizon in months; we estimate monthly regressions for different time horizons: $N = 1, 6, 12, 18$, and 24 months, and $u_{t+N,t}$ is the regression residual. The Fama and French multiperiod prediction model uses overlapping observations in the regressions which may result in conditional heteroskedasticity in the residuals. We address this problem by employing a generalized method of moments (GMM) estimator (see Hansen (1982)). Using the GMM, the estimator $\theta = (a, b)$ has an asymptotic distribution $\sqrt{T}(\hat{\theta} - \theta) \sim N(0, \Omega)$, where $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t')$, with $x_t = (1, X_t')$. S_0 is the spectral density calculated at frequency zero. Under the null hypothesis that expected market returns cannot be forecasted,

$S_0 = \sum_{j=-N+1}^{N-1} E(w_{t+N} w'_{t+N-j})$ and S_0 is estimated with a Newey-West correction; $N-1$ moving average lags, and $w_{t+N} = u_{t+N,t} x_t$. The resulting test

statistic is the asymptotic Z-statistic. Another issue with our multiperiod regressions is that we use the same data for different time horizons, and this could result in correlation in regression coefficients and undermine inferences for any given horizon. To resolve the regression coefficients correlation hitch, we use the Richardson and Stock [39] joint slopes test. The first step in the test is to estimate the GMM estimator by a set of multiple horizons regressions in which the coefficient estimates are restricted to be the same across horizons rendering the GMM estimator a special form of the single-equation GMM. We setup as follows:

$$\sum_{n=1}^{N=1} \frac{r_{t+1}}{1} = a + b_1 \times X_t + u_{t+1,t} \quad (4)$$

$$\sum_{n=1}^{N=6} \frac{r_{t+1}}{6} = a + b_1 \times X_t + u_{t+1,t} \quad (5)$$

$$\sum_{n=1}^{N=12} \frac{r_{t+12}}{12} = a + b_{12} \times X_t + u_{t+12,t} \quad (6)$$

$$\sum_{n=1}^{N=18} \frac{r_{t+18}}{18} = a + b_{18} \times X_t + u_{t+18,t} \quad (7)$$

$$\sum_{n=1}^{N=24} \frac{r_{t+24}}{24} = a + b_{24} \times X_t + u_{t+N,t}, \quad (8)$$

where r_{t+N} is the continuously compounded monthly excess market return calculated as the continuously compounded monthly return on the market minus the continuously compounded one-month Treasury bill rate, X_t is a $1 \times m$ matrix of m independent variables: *the level of ambiguity* and one of the traditional return predictors; dividend-to-price ratio, earnings-to-price ratio, term spread, or default spread, b is a $1 \times m$ matrix of slope coefficients, N is the prediction horizon in months; we estimate monthly regressions for different time horizons, $N = 1, 6, 12, 18$, and 24 months, and $u_{t+N,t}$ is the regression residual. For the Richardson and Stock [39] joint slopes test, $b = b_1 = b_6 = b_{12} = b_{18} = b_{24}$ and S_0 cannot be estimated with the Newey-West correction in this case due to the restrictions on the coefficient estimates.

5. Data and Descriptive Statistics

We obtain ambiguity data from Yehuda Izhakian Brenner and Yehuda Izhakian [4]. The ambiguity measure calculates variability in probabilities of market returns only and hence does not depend on the magnitude of the return, making the measure orthogonal to measures of risk. The study is based on monthly data from February 1993 to December 2022 consistent with the Ambiguity data availability. We obtain monthly market returns and risk-free rate data from the Kenneth R. French Library. For macroeconomic control variables for the GARCH-M model, we follow Santa-Clara and Valkanov [40] and use the *default spread* between yields of BAA-rated bonds and AAA-rated bonds, the *term spread* between the yield to maturity of a 10-year Treasury note and the three-month Treasury bill, the *inflation rate*, the *relative interest rate* computed as the deviation of the Treasury bill (three-month) rate from the one-year moving average, and the *dividend-to-price ratio*. Data for the macroeconomic control variables are obtained from the Federal Reserve Economic Data (FRED). Next, we discuss the prediction control variables. We follow Li, Ng, and Swaminathan [38] for the monthly prediction control variables and obtain the data from the New York University's public data on S&P 500 with computations based on data from *Bloomberg* database [https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/spearn.html]. Earnings-to-price ratio, an inverse of the P/E ratio, is the value-weighted average of firm-level earnings-to-price ratios for the S&P 500 firms. Dividend-to-price-ratio is the value-weighted average of the firm-level dividend-to-price ratios for the S&P 500 firms.

Table 1. Summary Statistics

Panel A: Descriptive Statistics of Main Variables										
	Full Sample [N=324]			Expansion [N=264]			Recession [N=60]			T-test Diff of Means (p-val)
Variable	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD	
Returns	-0.243	-0.020	4.407	0.261	-0.020	4.168	-2.579	0.020	4.741	2.840 (0.000)
AMB	0.205	0.213	0.071	0.212	0.217	0.064	0.169	0.130	0.091	0.043 (0.000)
E/P[%]	2.987	3.000	1.554	3.273	3.073	1.502	1.667	0.959	1.021	1.606 (0.000)
D/P[%]	1.854	1.820	0.384	1.822	1.820	0.258	2.000	1.510	0.709	-0.178 (0.000)
Term Spread [%]	1.637	1.726	1.345	1.758	1.881	1.209	0.987	0.023	1.798	0.770 (0.006)
Relative Rate[%]	0.003	0.003	0.044	0.005	0.003	0.022	-0.006	0.000	0.098	0.011 (0.106)
Inflation[%]	2.976	2.884	1.146	2.887	2.762	1.212	3.387	3.739	0.626	-0.501 (0.000)
Default Spread [%]	1.041	0.940	0.498	0.951	0.940	0.945	1.459	0.860	0.945	-0.508 (0.000)

Table 1 Panel B: Pairwise Correlation of Main Variables

	Returns	Ambiguity	E/P	Dividend Yield	Term Spread	Relative Rate	Inflation	Default Spread
Returns	1.000							
Ambiguity	0.138 (0.013)	1.000						
E/P	0.071 (0.213)	0.278 (0.000)	1.000					
D/P	-0.059 (0.296)	0.169 (0.003)	-0.173 (0.002)	1.000				
Term Spread	-0.422 (0.000)	-0.150 (0.009)	0.176 (0.002)	0.1432 (0.012)	1.000			
Relative Rate	-0.017 (0.766)	0.022 (0.705)	0.046 (0.424)	0.018 (0.753)	-0.043 (0.451)	1.000		
Inflation	-0.020 (0.734)	-0.038 (0.511)	0.219 (0.000)	-0.010 (0.860)	-0.138 (0.016)	0.012 (0.828)	1.000	
Default Spread	-0.340 (0.000)	-0.412 (0.000)	-0.323 (0.000)	0.302 (0.000)	0.324 (0.000)	0.022 (0.704)	-0.276 (0.000)	1.000

Table 1 reports the summary statistics of the variables used in the study. We obtain data on *level of ambiguity (AMB)* in the market from Yehuda Izhakian Brenner and Yehuda Izhakian [4]; monthly data from February 1993 to December 2022 consistent with the Ambiguity data availability. We obtain monthly market returns and risk-free rate data from the Kenneth R. French Library. For macroeconomic control variables (data obtained from the Federal Reserve Economic Data (FRED)), we use the *default spread* between yields of BAA-rated bonds and AAA-rated bonds, the *term spread* between the yield to maturity of a 10-year Treasury note and the three-month Treasury bill, the *inflation rate*, the *relative interest rate* computed as the deviation of the Treasury bill (three-month) rate from the one-year moving average. For prediction control variables, earnings-to-price ratio is the value-weighted average of firm-level earnings-to-price ratios (E/P) for the S&P 500 firms. Dividend-to-price-ratio (D/P) is the value-weighted average of the firm-level dividend-to-price ratios for the S&P 500 firms. E/P and D/P data is obtained from the New York University's public data on S&P 500 with computations based on data from *Bloomberg* database. Panel A reports the mean, median, and standard deviations of the variables for the full sample period, expansion and recession periods, and *t*-test results of the difference of means between the expansion and recess periods. Panel B presents the

pairwise correlations between the variables with *p*-values in parentheses

Table 1 delineates the summary statistics of the main variables used in the study. The mean of monthly excess market returns for the full sample period is -0.243 percent and the standard deviation is 4.4 percent. As expected, there is significantly higher excess market return during the expansion periods than during the recession periods. Panel A shows that the *level of ambiguity* is higher during periods of economic expansion; with a median of 0.213, than in the recession months; with a median of 0.130. A *t*-test of the difference of means of the *level of ambiguity* for the expansion versus the recession periods is significant at the 1% level. This initial finding is curious, since it is contrary to extant research [41], which suggests that there is higher market uncertainty and volatility during recessionary periods. Panel B of Table 1 depicts the pairwise correlations between the variables. We find that the *level of ambiguity* is positively correlated with excess market returns and earnings-to-price ratio.

6. a. Empirical Results of Estimations of the GARCH-M Model

We review the findings of the estimations of the GARCH-M model in this section.

Table 2. Estimation results of GARCH-M models

Variable	GARCH-M (Model 1- full sample)	GARCH-M (Model2-full sample)	GARCH-M (Model2-expansion periods)	GARCH-M (Model 2-recession periods)
ψ	0.009 (0.019)	-0.027 (0.002)	-0.036 (0.000)	-0.029 (0.415)
<i>AMB</i>		0.129 (0.000)	0.159 (0.000)	-0.372 (0.011)
<i>E/P</i>		-0.001 (0.902)	-0.002 (0.156)	0.041 (0.000)
<i>Term Spread</i>		0.001 (0.752)	0.001 (0.559)	0.021 (0.018)
<i>Default Spread</i>		-0.002 (0.575)	0.001 (0.798)	-0.007 (0.462)
δ	1.602 (0.396)	4.740 (0.003)	9.088 (0.008)	-9.887 (0.864)
ω	0.001 (0.035)	0.001 (0.025)	0.001 (0.014)	0.001 (0.060)
α	0.325 (0.002)	0.319 (0.000)	0.327 (0.000)	0.638 (0.208)
β	0.603 (0.000)	0.632 (0.000)	0.563 (0.000)	-
TDFI	0.044 (0.509)	0.080 (0.116)	0.001 (0.000)	0.001 (0.000)
Log-L	561.110	577.617	515.382	88.735
N	324	324	264	60

NOTE: Significance of TDFI parameter from zero indicates differences in ML estimates under the assumption of normality and under the assumption of the t-distribution

Table 2 presents the estimation results of the GARCH-M models.

The original GARCH-M framework incorporates the conditional variance; h_t , in the conditional mean equation and estimates the impact of the conditional variance on the conditional mean of the returns, r_t :

$$r_t = \psi + \delta h_t + \sqrt{h_t} \varepsilon_t, \quad (1)$$

In our study, we examine the effect of the *level of ambiguity* (*AMB*) on the conditional mean of returns using an extension of the GARCH-M model. Following Nyberg [34], we impregnate the model by including exogenous control variables and *ambiguity* in the GARCH-M model as follows: $r_t = \psi + \theta AMB_t + \Phi X_t + \delta h_t + \sqrt{h_t} \varepsilon_t$, (3) where ψ is the intercept term, ε_t -IID (0,1) and follows the Student's t distribution, θ is the *ambiguity* slope coefficient, Φ is a matrix of slope coefficients, X_t is a vector of control variables and $h_t = \omega + \beta h_{t-1} + \alpha u_t^2$, where $u_t = r_t - \psi - \delta h_t$ and $\omega > 0$, $\beta \geq 0$, and $\alpha > 0$. P-values are presented in parentheses.

Table 2 presents the results of the estimation of the GARCH-M models [with conditional variance following a GARCH(1,1) model and error term of Student's t distribution]. Model 1 is the traditional GARCH-M model, estimated with an intercept. First, the coefficient for β is statistically significant at the 1% level, indicating the presence of GARCH effects. Next, congruent with Nyberg [34], the coefficient estimate for δ is positive and statistically significant, an indication of a risk-return tradeoff. Next, we examine the impact of the *level of ambiguity* or Knightian uncertainty on market returns by embedding the GARCH-M model with the *level of ambiguity* and other exogenous control variables (model2). The results of model 2 estimation (full sample) are

presented in Table 2 and demonstrate that the coefficient for *the level of ambiguity* is positive and statistically significant, indicating that the level of Knightian uncertainty has an idiosyncratic impact on the market returns, an effect distinct from the effects of the business cycle. This finding is consistent with Andreou et al. [29] and So et al. [30] who find that ambiguity is an essential determinant, adding to risk to explain expected excess returns. As a robustness check, we split the sample period into expansion and recession periods and re-estimate model 2. We find that the coefficient for *the level of ambiguity* is negative during economic recessions, indicating that the level of ambiguity is inversely related to the concurrent excess returns of the market. This finding is congruent with the concept that ambiguity-averse investors tend to overweight the likelihood of negative returns and underweight the likelihood of positive returns, lowering the perceived expected returns to future investments. Additionally, with the higher economic policy uncertainty during recessions, the contemporaneous level of ambiguity will be high and may explain the strong link between ambiguity and excess returns. This result is presented graphically in Figure 1. Typically, a risk-averse investor will exercise the inherent put option afforded by the federal government during a recession. Hence any uncertainty in policy makers' actions to stimulate the economy may push the investor to exercise cautionary measures: usually leaving the market, resulting in a decrease in market returns.

In expansion periods, however, we find that the coefficient for *the level of ambiguity* is positive. This finding is consistent with the correlation findings in Table 1 panel B.

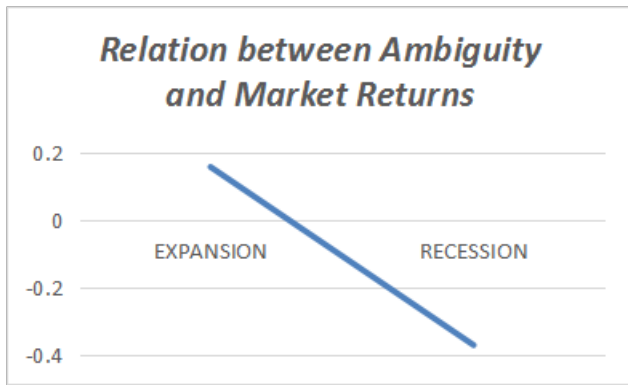


Figure 1. We bifurcate the sample period into expansion and recession periods and re-estimate model 2. We find that the relation between the level of ambiguity and market returns is negative during economic recessions and positive during expansions

6. b. Robustness Check Using GJR-GARCH (1,1) Model

Given that business cycle fluctuations are the result of exogenous as well as endogenous interactions between real and financial variables, significant challenges arise when modeled in a linear fashion. Additionally, the differential impacts of positive and negative news in the market may not be captured in a traditional GARCH

model. Skott (2012) demonstrates that some aggregate investment decisions include lags, their impact in the economy could have lagged and/or indirect effects and so the use of nonlinear models in estimation may be necessary. Hence, we adopt the Glosten-Jagannathan-Runkle (GJR-GARCH) model to reexamine the relationship between the level of ambiguity and excess market returns, for an additional robustness check. We employ the GJR-GARCH(1,1) model as follows: $r_t = \psi + \theta AMB_t + \Phi X_t + \delta h_t + \sqrt{h_t} \varepsilon_t$, (9) where ψ is the intercept term, $\varepsilon_t \sim \text{IID}(0,1)$, θ is the level of ambiguity slope coefficient, Φ is a matrix of slope coefficients, X_t is a vector of control variables and $h_t = \omega + \beta h_{t-1} + \alpha u_{t-1}^2 + \gamma_1 u_{t-1}^2 \hat{a}_{t-1}$ where $u_t = r_t - \psi - \delta h_t$ and $\omega > 0$, $\beta \geq 0$, and $\alpha > 0$. The difference between a GARCH model and a GJR-GARCH model is the last term: $\gamma_1 u_{t-1}^2 \hat{a}_{t-1}$, capturing the differential impacts of positive and negative news in the market. $\hat{a}_t$ is a binary variable which takes the value of 1 for $u_t < 0$ (negative news), and 0 otherwise. γ is the asymmetry term, $\gamma > 0$ indicates asymmetry in volatility, while $\gamma = 0$ indicates symmetry in the volatility responses to the news. This framework enables the examination of the effect of ambiguity on the time-varying risk-return relation and accounts for potential asymmetry in volatility. Table 3 presents the results of the estimation of the GJR-GARCH models.

Table 3. Estimation results of GJR-GARCH models

Variable	GJR-GARCH (Model 1)	GJR-GARCH (Model 2)
ψ	0.014 (0.072)	-0.021 (0.083)
AMB		0.125 (0.000)
E/P		-0.002 (0.195)
Term Spread		0.001 (0.923)
Default Spread		0.002 (0.603)
ω	0.001 (0.009)	0.001 (0.000)
β	-0.007 (0.821)	0.463 (0.024)
α	0.358 (0.001)	0.381 (0.175)
γ	0.750 (0.000)	0.249 (0.005)
TDFI	0.001 (0.000)	0.001 (0.116)
Log-L	755.233	758.519
N	324	324

NOTE: Significance of TDFI parameter from zero indicates differences in ML estimates under the assumption of normality and under the assumption of the t-distribution

Table 3 presents the estimation results of the GJR-GARCH models.

GJR-GARCH(1,1) model as follows:

$$r_t = \psi + \theta AMB_t + \Phi X_t + \delta h_t + \sqrt{h_t} \varepsilon_t, \quad (9)$$

where ψ is the intercept term, $\varepsilon_t \sim \text{IID}(0,1)$, θ is the level of ambiguity slope coefficient, Φ is a matrix of slope coefficients, X_t is a vector of control variables and $h_t = \omega$

$+ \beta h_{t-1} + \alpha u_{t-1}^2 + \gamma_1 u_{t-1}^2 \hat{a}_{t-1}$ where $u_t = r_t - \psi - \delta h_t$ and $\omega > 0$, $\beta \geq 0$, and $\alpha > 0$. P-values are presented in parentheses.

Model 1 is the traditional GJR-GARCH model, estimated with an intercept. Notably, the coefficient for γ is statistically significant at the 1% level, signifying the leverage effect; negative market returns have a stronger influence on increasing market volatility than positive

market returns of the same magnitude, consistent with extant literature. The remaining results of model 1 are consistent with the GARCH model estimated earlier. Next, we reexamine the impact of the *level of ambiguity* on market returns by embedding the GJR-GARCH model with the *level of ambiguity* and other exogenous control variables (model 2). The results of model 2 estimation are presented in Table 2 and show that the coefficient for the *level of ambiguity* is positive and statistically significant, presenting further evidence that the level of Knightian uncertainty has an idiosyncratic effect on market returns, an effect separate from the effects of the business cycle. Beyond the concurrent effects of ambiguity, we investigate the predictive power of the *level of ambiguity* for future market returns.

6. c. Empirical Results of Estimations of the Forecasting Models

We discuss the findings of our forecasting model in this section. The existing literature depicts that the valuation ratios are correlated with expected stock returns.

6. c. 1. Univariate Predictability Results

We examine the forecasting power of the *level of ambiguity* as well as other frequently used valuation ratios in univariate regressions and present the findings in Table 4.

Table 4. Univariate Forecasting Regressions

Panel A: Level of ambiguity						Panel B: Term Spread				
N	β	adj. R ²	RMSE	Z(β)	p-value	β	adj. R ²	RMSE	Z(β)	p-value
1	0.080	0.020	0.048	0.028	0.019	0.001	0.001	0.049	0.002	0.187
6	0.016	0.001	0.023	0.0126	0.102	0.001	0.001	0.023	0.002	0.033
12	0.031	0.023	0.018	0.016	0.029	0.002	0.013	0.018	0.002	0.003
18	0.023	0.015	0.015	0.015	0.054	0.003	0.041	0.015	0.003	0.000
24	0.014	0.001	0.005	0.014	0.083	0.003	0.064	0.014	0.003	0.002
Avg.				0.016	0.028				0.003	0.000
Panel C: E/P						Panel D: Default Spread				
N	β	adj. R ²	RMSE	Z(β)	p-value	β	adj. R ²	RMSE	Z(β)	p-value
1	0.001	0.002	0.049	-0.001	0.079	-0.001	0.001	0.049	0.005	0.092
6	0.001	0.001	0.023	-0.002	0.002	0.003	0.001	0.023	0.004	0.036
12	-0.001	0.001	0.018	-0.002	0.000	0.004	0.013	0.018	0.004	0.019
18	-0.001	0.019	0.005	-0.002	0.000	0.004	0.021	0.015	0.004	0.013
24	-0.002	0.051	0.014	-0.002	0.000	0.004	0.020	0.014	0.004	0.014
Avg.				-0.002	0.000				0.004	0.012
Panel E: D/P										
N	β	adj. R ²	RMSE	Z(β)	p-value					
1	-0.016	0.013	0.048	0.040	0.002					
6	-0.014	0.047	0.023	0.040	0.002					
12	-0.005	0.010	0.018	0.040	0.001					
18	0.002	0.001	0.015	0.040	0.001					
24	0.005	0.013	0.014	0.040	0.001					
Avg.				0.005	0.033					

We use the multiperiod prediction model of Fama and French (1989):

$$\sum_{n=1}^N \frac{r_{t+N}}{N} = a + bX_t + u_{t+N,t}$$

where r_{t+N} is the continuously compounded monthly excess return calculated as the continuously compounded monthly return on the market return minus the continuously compounded one-month Treasury bill rate, X_t is one of the following independent variables: the *level of ambiguity*, dividend-to-price ratio, earnings-to-price ratio, term spread, or default spread, b is a slope coefficient, N is the prediction horizon in months; we estimate monthly regressions for different time horizons: $N = 1, 6, 12, 18$, and 24 months, and $u_{t+N,t}$ is the regression residual. To minimize conditional heteroskedasticity, using the GMM, the estimator $\theta = (a, b)$

has an asymptotic distribution $\sqrt{T}(\hat{\theta} - \theta) \sim N(0, \Omega)$, where $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t')$, with $x_t = (1 \ X_t')$. S_0 is the spectral density calculated at frequency zero. Under the null hypothesis that expected asset returns cannot be forecasted,

$$S_0 = \sum_{j=-N+1}^{N-1} E(w_{t+N} w'_{t+N-j}),$$

and S_0 is estimated with a Newey-West correction; $N-1$ moving average lags, and $w_{t+N} = u_{t+N,t} x_t$. The resulting test statistic is the asymptotic Z-statistic. Table 4 panels A-E present univariate regression results for *level of ambiguity*, term spread, earnings-to-price ratio, default spread, and dividend yield, respectively. For *level of ambiguity*, the coefficient is positive at the one-month horizon and positive for all other horizons and with

adjusted R-squared increasing up to the 12-month horizon and RMSE decreasing as the horizon increases. The existing literature on Knightian uncertainty suggests that the *level of ambiguity* is a cardinal factor in market returns and our finding is congruent with that fact and consistent with Andreou et al. [29]. Furthermore, the p-values of the z-statistics for all horizons indicate the *level of ambiguity* is correlated with future market returns. For robustness, we employ the GMM estimator to test the null hypothesis that the slopes at all horizons are jointly equal to zero. Congruent with our earlier findings, we uncover that *level of ambiguity* slopes at different horizons have a mean that is statistically different from zero, with a p-value of 0.028, confirming that the *level of ambiguity* is a predictor of future market returns.

As expected, we find that the traditional prediction variables used are correlated with expected market returns with statistically significant slope coefficients. Additionally, using the GMM estimator, we assess the valuation variables using the joint slopes test. Congruent with our earlier results, all the valuation variables have

joint slope coefficients significantly different from zero. For the economic cycle predictors, as expected, *term spread* has strong predictive power at different horizons and this result is similar to the finding of Fama [39] that *term spread* exhibits strong predictive power for the economic cycle. *Default spread* exhibits similar results as *term spread* and the result is consistent with Chen [42] which indicates that *default spread* is inversely related to future excess market returns.

6. c. 2. Bivariate Predictability Results

As a robustness check, we assess the forecasting power of the *level of ambiguity* paired with one of the other commonly used economic cycle predictors or valuation ratios using bivariate regressions, and present the results in Table 5 panels A-D. Since the economic cycle predictors and valuation ratios are highly correlated, we estimate regressions, with the independent variables being *level of ambiguity* and only one predictor at a time to mitigate multicollinearity.

Table 5. Bivariate Forecasting Regressions

Panel A: Bivariate Regression with <i>Level of Ambiguity</i> and Term Spread								
	<i>Level of Ambiguity</i>			Term Spread				
N	β	$Z(\beta)$	p-value	β	$Z(\beta)$	p-value	adj. R ²	RMSE
1	0.081	0.050	0.000	0.001	-0.002	0.389	0.017	0.048
6	0.017	0.021	0.001	0.001	0.000	0.779	0.000	0.023
12	0.034	0.019	0.000	0.002	0.001	0.090	0.040	0.017
18	0.026	0.012	0.001	0.003	0.002	0.000	0.062	0.015
24	0.018	0.008	0.058	0.003	0.002	0.000	0.074	0.014
Avg.		0.011	0.000		0.002	0.000	0.000	
Panel B: Bivariate Regression with <i>Level of Ambiguity</i> and Default Spread								
	<i>Level of Ambiguity</i>			Default Spread				
N	β	$Z(\beta)$	p-value	β	$Z(\beta)$	p-value	adj. R ²	RMSE
1	0.080	0.052	0.005	0.001	-0.004	0.413	0.017	0.048
6	0.018	0.014	0.103	0.003	0.002	0.394	0.003	0.023
12	0.036	0.015	0.009	0.005	0.002	0.207	0.044	0.017
18	0.027	0.011	0.021	0.005	0.002	0.042	0.044	0.015
24	0.018	0.009	0.072	0.005	0.003	0.019	0.031	0.014
Avg.		0.010	0.023		0.003	0.010		
Table 4 Panel C: Bivariate Regression with <i>Level of Ambiguity</i> and E/P								
	<i>Level of Ambiguity</i>			E/P				
N	β	$Z(\beta)$	p-value	β	$Z(\beta)$	p-value	adj. R ²	RMSE
1	0.078	0.043	0.121	0.001	-0.001	0.602	0.017	0.048
6	0.015	0.017	0.133	0.001	-0.001	0.881	0.000	0.023
12	0.034	0.037	0.000	-0.001	-0.001	0.034	0.026	0.018
18	0.028	0.039	0.000	-0.002	-0.001	0.007	0.043	0.015
24	0.021	0.040	0.000	-0.002	-0.001	0.003	0.066	0.014
Avg.		0.041	0.000		-0.001	0.003		
Table 4 Panel D: Bivariate Regression with <i>Level of Ambiguity</i> and D/P								
	<i>Level of Ambiguity</i>			D/P				
N	β	$Z(\beta)$	p-value	β	$Z(\beta)$	p-value	adj. R ²	RMSE
1	0.084	0.107	0.000	-0.018	-0.009	0.012	0.035	0.048
6	0.019	0.018	0.231	-0.014	0.001	0.483	0.050	0.023
12	0.033	0.023	0.013	-0.006	0.001	0.689	0.035	0.017
18	0.022	0.008	0.245	0.002	0.002	0.021	0.015	0.015
24	0.013	-0.001	0.830	0.005	0.004	0.000	0.017	0.014
Avg.		0.020	0.001		0.001	0.325		

We use the multiperiod prediction model of Fama and French [8]:

$$\sum_{n=1}^N \frac{r_{t+N}}{N} = a + b \times X_t + u_{t+N,t}$$

where r_{t+N} is the continuously compounded monthly excess return calculated as the continuously compounded monthly return on the market return minus the continuously compounded one-month Treasury bill rate, X_t is a 1 x 2 matrix of two independent variables: the level of ambiguity, and one of the following variables: dividend-to-price ratio, earnings-to-price ratio, term spread, or default spread, b is a 1 x 2 matrix of slope coefficients, N is the prediction horizon in months; we estimate monthly regressions for different time horizons: $N = 1, 6, 12, 18$, and 24 months, and $u_{t+N,t}$ is the regression residual.

The results show regression coefficients as well as the joint or average slope coefficients for level of ambiguity are positive and statistically significant for all horizons even after controlling for another predictor. The results display strong evidence that the level of ambiguity is a useful predictor of future market returns.

6. d. Practical Implications for Investors and Policymakers

In this study, we investigate the impact of the level of ambiguity in the stock market and find that the level of ambiguity is correlated with contemporaneous market returns and predicts future returns. For investors, a sage advice will be to be ambiguity-averse during recessions given the inverse correlation between the level of ambiguity and market returns during recessions. During expansion periods, the market seems to compensate investors for ambiguity. For policymakers, ambiguity presents a significant challenge to investors and so there must be an increase in education about ambiguity. Additionally, policymakers should account for ambiguity in decision making, particularly during recessions.

7. Conclusion

We study the effect of the level of ambiguity on the conditional mean of market returns, by using a GARCH-M model. Additionally, we investigate the predictive power of the level of ambiguity on future market returns, controlling for other traditional prediction variables. First, the results of the original GARCH-M estimation indicate the presence of GARCH effects and additionally show a positive risk-return tradeoff, presenting additional support for Merton's [1] Intertemporal Capital Assets Pricing Model.

Second, we find that the level of ambiguity, although orthogonal to risk, is correlated with market returns. This finding suggests that the level of ambiguity is an important factor, augmenting risk in explaining market returns. Additionally, on dividing our study period into expansion and recession subperiods, we find that there is an inverse relationship between the level of ambiguity and

contemporaneous market returns only during recessions. Our conclusion from this finding is that ambiguity-averse investors tend to overweight the likelihood of negative returns during recessions, lowering the perceived expected returns to investments. Third, the results of the forecast models indicate that the level of ambiguity is a strong predictor of future market returns in univariate as well as bivariate tests. Specifically, our findings offer the first definite evidence of a positive relationship between the level of ambiguity and future market returns. This study extends the return predictability literature by confirming the utility of the level of ambiguity as a return predictor. Given the complexity of ambiguity, slight changes in the level of ambiguity can cause additional stress on the decision-process and increase risk in policymaker choices. Additionally, measures which mitigate ambiguity, either by decreasing the absolute value of the worst-case return considered by market participants or by decreasing the likelihood of ambiguity, can improve conditions in the stock market. Ambiguity can also be decreased ex post when the state with ambiguity is recognized. Taming the worst-case outcome anticipated by ambiguity averse investors will encourage market participation. With the new measures of ambiguity, traders and portfolio managers can gauge the level of ambiguity in new investments and so should seriously consider it as a factor along with risk in making investment decisions. Future research could examine the level of ambiguity as an additional factor in Fama-French 3-factor models.

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