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Trade Policy Uncertainty, Market Return, and Expected Return Predictability

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Abstract Using the Trade Policy Uncertainty (*TPU*) index as a proxy for the level of trade policy uncertainty in the U.S. economy, we study the impact of the level of trade policy uncertainty on the conditional mean of market returns. Additionally, we investigate the predictive power of trade policy uncertainty on future market returns. Our findings show that after accounting for business cycle effects, *TPU* does *not* impact contemporaneous market returns. However, *TPU* is a robust predictor of future market returns in both univariate and bivariate regression tests. Specifically, our findings present unequivocal evidence of a positive relation between *TPU* and expected market returns.

Keywords: *Trade Policy Uncertainty*

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1. Introduction

The recent escalation of trade tensions between the U.S. and China; with multiple tariff hikes and their economic and political ramifications, elevates *trade policy uncertainty (TPU)* to a level of significance in current economic policy discussions. Within a six-month period (May, 2019 to October, 2019), the U.S. increased tariffs from 10% to 25% on a wide variety of Chinese agricultural and manufacturing products in multiple bouts, with temporary delays in implementation building up uncertainty. The Chinese government in-turn retaliated with tariff hikes.

Extant empirical research examines the impact of trade policy uncertainty on an economy [1,2]. Particularly, Handley and Limao [1] investigating tariffs, find that uncertainty about future tariffs could affect investors' expectations about the future returns and risk of the stock market. Biaconi, Esposito, and Sammon [3] find that before China was granted Normal Trade Relations [NTR] rates, U.S. manufacturing industries more exposed to trade policy uncertainty had higher stock returns than industries less exposed to trade policy uncertainty and the authors argue the difference in returns is a risk premium for trade policy uncertainty exposure. It is apparent that trade policy uncertainty has economic outcomes and political ramifications.

In this study, we investigate the relationship between the level of trade policy uncertainty [*TPU*] and stock market returns. Additionally, we investigate the predictive power of *TPU* for future stock market returns. The originality of our study is that with the new *TPU* measure; *TPU* Index, we can isolate trade policy uncertainty effects from business cycle effects and study the impact of trade policy uncertainty on market returns and also examine the predictive power of *TPU* on future market returns beyond the impact of the business cycle. Our study is the first study to examine the predictive power of *TPU* on future market retuns. Before the *TPU* measure was constructed, one could not truly separate trade policy uncertainty effects from business cycle effects.

Baker, Bloom, and Davis [4], find that there is a high correlation between economic policy uncertainty index and the business cycle. There are usually more economic policy amendments during recessions and the market seems to react more to economic policy changes during such periods. During a recession, investors expect rapid expansionary actions from government; exercising an inherent put option invested in government. Hence it is logical that economic policy uncertainty during recessions will have higher effects on the market than economic policy uncertainty during expansionary periods. However, economic policy uncertainty may have ramifications distinct from the business cycle effects and may impact affect the business cycle by moderating the speed of recovery from a recession or the general state of the economy and hence the stock market return and risk. With TPU being one of the categories of the economic policy uncertainty index, we conjecture that TPU affects asset prices.

2. Trade policy Uncertainty (*TPU*) and Market Returns

Numerous studies in the existing literature document a theoretical relationship between the level of trade policy uncertainty and stock market performance. Pastor and Veronesi [5] develop a theoretical model for the link between policy uncertainty and stock market risk and propose that the degree of policy uncertainty affects stock market risk. Additionally, Pastor and Veronesi indicate that high policy uncertainty may decrease macroeconomic activity by increasing the cost of capital and also by increasing managerial risk aversion.

Bernanke [6] illustrates the effect of economic policy uncertainty on investment, by theorizing that when prospective corporate ventures are too expensive to abandon, elevated economic uncertainty affords firms a reason to delay such ventures until the uncertainty abates. Next, Caliendo and Parro [7] build a model to investigate the effects of tariff changes on economic outcomes such as production quantities and welfare effects. Caliendo and Parro find that following NAFTA's tariff reductions there were significant increases in trade and welfare effects in the U.S., Mexico, and Canada. Blaum, Lelarge and Peters [8] develop a model on trade in intermediate inputs and theorize that trade in intermediate inputs allows firms to decrease their costs of production by using better-quality, inexpensive, or innovative inputs from abroad. Blaum et al. find that the degree to which companies participate in foreign input markets impacts consumer prices.

Examining the impact of tariffs on stock returns, Huang, Lin, Liu, and Tang [9] evaluate the economic implications of policy shocks, particularly tariff hikes between U.S. and China, on U.S. and Chinese production networks. Huang et al. find that U.S. firms that are more reliant on imports from China have higher default risks and lower stock returns around the tariff hike announcement dates. Unsurprisingly, Chinese firms that are more reliant on imports from the U.S. also suffer higher default risk and lower stock returns around the tariff hike announcement dates. Additionally, Antras, Fort, and Tintelnot [10] develop a new framework to investigate the global import decisions of companies whose production involves multiple inputs. Antras et al. find that a firm's decision to import from one country is paired to its decision to import from other countries. Trade shocks such as tariff hikes in one country may drive a firm to import from another country.

There is extensive research that attempts to empirically evaluate the effect of policy uncertainty on asset prices. Pastor and Veronesi [11] find empirical evidence consistent with the prediction that political uncertainty necessitates a risk premium whose size is larger in recessionary economic conditions. Pastor and Veronesi also find that political uncertainty lowers the value of the tacit put protection that government offers to the market. Brandt, Van Biesebroeck, Wang, and Zhang [12] study the impacts of trade liberalization in China: following WTO entry; on the progression of productivity and margins of manufacturing firms, and find that cuts in input tariffs raise both gross profit margins and productivity. Second, cuts in output tariffs reduce gross profit margins, but increase productivity.

Coelli [13] finds that tariffs discussions generate varied exposure to uncertainty. Additionally, Coelli finds that a decrease in trade policy uncertainty spurs innovation in industries with higher exposure, with the result mostly driven by increased export revenues. Coelli's findings signify that a decrease in trade policy uncertainty may motivate firms to both export more and increase investment in innovative technologies, ultimately leading to an increase in stock performance. Greenland, Iony, Lopresti, and Schott [14] use average abnormal equity returns to measure firms' sensitivity to variations in trade policy and find that average abnormal equity returns is a good indicator of trade policy exposure.

Handley and Limao [1] using a heterogeneous firms model of exporting, demonstrate that entry and investment in export markets decreases when trade policy is tentative. Additionally, Handley and Limao find that after Portugal joined the European Community (EC) in 1986, the trade policy transformation accounted for a large part of the observed increase in Portuguese exporting firms' revenues. The accession eliminated future EC trade policy uncertainty towards Portugal and accounted for a large portion of the subsequent economic growth in Portugal.

Pierce and Schott [15], employing a difference-in-differences identification approach, uncover that industries with higher exposure to import tariff uncertainty display relative declines in investment following a modification in trade policy. Steinberg [16], using *Brexit;* United Kingdom's departure from the European Union, examines the macroeconomic impact of trade policy uncertainty. Steinberg predicts that Brexit will have a significant impact on the U.K. economy, mostly in the long run, with trade with the European Union decreasing by up to 49 percent, however, uncertainty about Brexit will have minimal macroeconomic impact.

In this study, after accounting for business cycle effects, we investigate the impact of the level of trade policy uncertainty on market returns. Additionally, we investigate the predictive power of trade policy uncertainty on future stock returns. With the *TPU* index, we are able to extend previous studies such as Bernanke [6] and Pastor and Veronesi [5] who document that economic policy changes impact asset prices and risk.

Our primary hypothesis is that higher trade policy uncertainty may lead to lower stock market returns. Specifically, higher trade policy uncertainty may impact households' and businesses' investment in the export market and consequently the stock market [13] by decreasing investor and firm confidence in the market, respectively. Investors may respond by reducing their investment positions leading to a decline in market returns. Bernanke and Kuttner (2005) propose that the channel by which impacts of changes in economic policy are conveyed to the stock market is via changes in private portfolios' values. Firms may respond to trade policy uncertainty by delaying purchase of imported raw materials leading to productivity declines. Huang, Lin, Liu, and Tang (2019) evaluating the economic implications of policy shocks, find that U.S. firms that are more reliant on imports from China have lower stock returns around the tariff hike announcement dates. The *TPU* index presents a prospect to take a holistic approach to investigating the impacts of threats of tariff hikes, actual tariff hikes, changes to import quotas, and other trade restrictions which may cause trade policy uncertainty.

Hypothesis I: Higher trade policy uncertainty is correlated with a decline in contemporaneous stock market returns.

Next, we discuss the components of the *TPU* measure and our primary model for testing our main hypothesis.

3. Trade Policy Uncertainty (*TPU*) and GARCH-M

In this segment, we discuss the trade policy uncertainty measure and present our primary model; the GARCH-M.

3.1. The Trade policy Uncertainty (TPU) Index

The trade policy uncertainty perceived by households and businesses is cultivated from the apparent nebulousness, erratic or unpredictable nature of policymakers' decision-making process [18]. The *TPU* index, our primary measure of trade policy uncertainty, was built by Baker, Bloom, and Davis [18] as a category in the Economic Policy Uncertainty [EPU] index. In developing the *TPU* index, Baker et al. use automated text-searches of 10 leading newspapers: Washington Post, USA Today, Boston Globe, Chicago Tribune, Miami Herald, Los Angeles Times, Dallas Morning News, San Francisco Chronicle, the Wall Street Journal, and New York Times. The search terms are the following: *import tariffs, import duty, import barrier, government subsidies, government subsidy, wto, world trade organization, trade treaty, trade agreement, trade policy, trade act, doha round, uruguay round, gatt, dumping.*

Although the *TPU* index is comparatively new; it has been employed in Caldara et al. [19] to investigate the economic impacts of trade policy uncertainty. We use the *TPU* index, our measure of trade policy uncertainty, as an exogenous variable along with macroeconomic control variables in a conditional mean GARCH-M model. We present our model next.

3.2. Model 1: GARCH-M

The rudimentary concept in the GARCH-M model is to incorporate the conditional variance; h_t, in the conditional mean equation and examine the impact of the conditional variance upon the conditional mean of return; r_t. This is formally stated as

$$r_t = \psi + \delta h_t + h_t^{1/2} + \varepsilon_t, \qquad (1)$$

where ε_t – IID (0,1). Existing research assumes that the conditional variance follows the GARCH (1,1) model

$$h_t = \omega + \beta h_{t-1} + \alpha u^2_{t-1}, \qquad (2)$$

where $u_t = r_t - \psi - \delta h_t$ and $\beta \geq 0$, $\omega > 0$, and $\alpha > 0$.

The inclusion of the conditional variance; h_t in the mean return equation (1) is known as the volatility feedback effect. In Merton's ICAPM [20], the parameter δ is interpreted as the coefficient of relative risk aversion.

3.3. Model 2: GARCH-M with TPU

In this study, our main hypothesis is that the degree of trade policy uncertainty affects the conditional mean of market returns. To investigate our hypothesis, we use the GARCH-M framework to examine the contemporaneous influence of trade policy uncertainty on the conditional mean of returns by inserting the *TPU* index and other exogenous control variables into the GARCH-M setup as follows:

$$r_t = \psi + \theta TPU_t + \Phi \mathbf{X_t} + \delta h_t + h_t^{1/2}\varepsilon_t, \qquad (3)$$

where r_t is the conditional mean of returns, ψ is the intercept term, θ is the *TPU* index coefficient, Φ is a matrix of slope coefficients, $\boldsymbol{X_t}$ is a vector of macroeconomic control variables, ε_t – IID (0,1), and h_t is conditional variance of returns modeled as;

$$h_t = \omega + \beta h_{t-1} + \alpha u^2_{t-1}, \qquad (4)$$

where $u_t = r_t - \psi - \delta h_t$ and $\omega > 0, \beta \geq 0, and\ \alpha > 0$. We estimate the GARCH-M model using maximum likelihood and assume the error term follows the Student's t distribution [21]. Beyond the immediate impacts of trade policy uncertainty, we examine the long-term impacts of trade policy uncertainty on asset returns. We investigate whether future stock market returns can be predicted by the degree of trade policy uncertainty.

4. Return Predictability of *TPU*

The extant research on asset return predictability has established predictors of expected returns. These predictors are primarily macroeconomic indicators and by association predictors of asset returns. Stambaugh [22] finds that the term structure of interest rates is a gauge of macroeconomic activity as well as a forecaster of future stock returns. Fama and French [23] show that the dividend yield and term spread are predictors of future stock market returns and find that term spread is an indicator of short-term macroeconomic activity, whereas the dividend yield is an indicator of long-term business activity.

Regulatory policy uncertainty can have detrimental impacts on the economy [24,25,26]. Baker, Bloom, and Davis [18], employing the *TPU* index, show that the degree of trade policy uncertainty is an indicator of the macroeconomic activity. Particularly, trade policy uncertainty affects investments in the stock market by households and businesses. Lower trade policy uncertainty, ceteris paribus, may increase investor sentiment in the stock market. The increase in sentiment, may lead to an increase in stock returns [18]. Consistent with the asset return predictability literature and following the preceding discussion and which proposes that macroeconomic indicators may forecast market returns, we hypothesize that the degree of trade policy uncertainty is a predictor of future excess stock returns.

Hypothesis II: Trade policy uncertainty is a predictor of future stock market returns.

4.1. TPU and the Forecasting Model

We study the relationship between *TPU* and future stock market returns using the multi-period forecasting model of Fama and French [23]. With univariate and bivariate regressions using the *TPU* index and one of the return predictors as a control variable [27,28,29]; book-to-market ratio, payout yield, dividend-to-price ratio, and earnings-to-price ratio (the predictors are defined in section 5), we estimate the multi-period forecasting model of Fama and French [23];

$$\sum_{n=1}^{N} \frac{r_{t+N}}{N} = a + b\mathrm{x}X_t + u_{t+N,t} \tag{5}$$

where r_{t+N} is the continuously compounded excess monthly return computed as the continuously compounded monthly return on the value-weighted market return (including dividends) minus the monthly continuously compounded one-month Treasury bill rate, N is the forecasting horizon in months, $\boldsymbol{b}$ is a 1 x m matrix of slope coefficients, $\boldsymbol{X}_t$ is a 1 x m matrix of m independent variables (excluding the intercept but including the *TPU* index), and $u_{t+N,t}$ is the regression residual. We run the univariate and bivariate regressions for different horizons: N = 1, 6, 12, 18, and 24 months.

A potential problem with the use of overlying observations, as in the Fama and French multi-period model, is that it may lead to serial correlation in the regression residuals resulting in a *Type II Error*. Also, the regression residuals could be conditionally heteroskedastic. To address both potential problems; the conditional heteroskedasticity and the induced autocorrelation, we follow Hansen [30] and employ a generalized method of moments (GMM) estimator.

The GMM estimator $\theta = (a, \boldsymbol{b})$ follows an asymptotic distribution $\sqrt{T}(\hat{\theta} - \theta) \sim N\,(0, \Omega)$, with $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t')$, $x_t = (1\ X_t')'$, and S_0 is the spectral density. With the null hypothesis that future stock market returns cannot be predicted

$$S_0 = \sum_{j=-N+1}^{N-1} E\left(w_{t+N} w'_{t+N-j}\right), \tag{6}$$

with S_0 estimated at frequency of zero with $w_{t+N} = u_{t+N,t}\, x_t$ and with Newey-West correction with N-1 moving average lags. The resultant statistic from the GMM estimation is the asymptotic Z statistic.

Another issue with prediction regressions which utilize the same data from different time horizons is that the regression coefficients may be correlated, invalidating the results from any one regression. To mitigate the potential regression slopes correlation problem, we utilize the Richardson and Stock [31] joint slopes test. The test is predicated on the averaging of slope coefficients. Specifically, we re-estimate the GMM estimator with a set of multiple equations in which the coefficients are restricted to be the same across all equations in the set (following [31]), reverting the GMM estimator into a special case of the single-equation GMM. We continue as follows

$$\sum_{n=1}^{N=1} \frac{r_{t+1}}{1} = a + b_1 \mathrm{x}X_t + u_{t+1,t} \tag{7}$$

$$\sum_{n=1}^{N=6} \frac{r_{t+1}}{6} = a + b_1 \mathrm{x}X_t + u_{t+1,t} \tag{8}$$

$$\sum_{n=1}^{N=12} \frac{r_{t+12}}{12} = a + b_{12} \mathrm{x}X_t + u_{t+12,t} \tag{9}$$

$$\sum_{n=1}^{N=18} \frac{r_{t+18}}{18} = a + b_{18} \mathrm{x}X_t + u_{t+18,t} \tag{10}$$

$$\sum_{n=1}^{N=24} \frac{r_{t+24}}{24} = a + b_{24} \mathrm{x}X_t + u_{t+N,t}, \tag{11}$$

where r_{t+N} is the continuously compounded excess monthly return computed as the continuously compounded monthly return on the value-weighted market return (including dividends) minus the monthly continuously compounded one-month Treasury bill rate, N is the forecasting horizon in months, b is a slope coefficient, $\boldsymbol{X}_t$ is a 1 x m matrix of m independent variables (excluding the intercept but including the *TPU*), and $u_{t+N,t}$ is the regression residual. Note that $b = b_1 = b_6 = b_{12} = b_{18} = b_{24}$ and S_0 cannot be estimated with the Newey-West correction in this case due to the simultaneous use of multiple time horizons.

5. Data and Descriptive Statistics

The sample period is January 2000 to October 2019, resulting in a sample size of 235 after adjusting for missing data. The *TPU* index was built and is maintained by Baker, Bloom, and Davis [4] with the data available on their website: https://www.policyuncertainty.com/index.html. We extract data on value-weighted portfolio monthly returns (*VWR*) from CRSP database. To analyze excess returns, we also obtain data on the risk-free rate: the three-month Treasury bill rate; from the Federal Reserve Economic Data database.

We follow Santa-Clara and Valkanov [32] in selecting the macroeconomic control variables for the GARCH-M model. We use the *inflation rate*, the *relative interest rate* computed as the deviation of the three-month Treasury bill rate from its one-year moving average, the *default spread* which is the difference between yields of BAA-rated bonds and AAA-rated bonds, *term spread* which is the difference between the yield to maturity of a 10-year Treasury note and the three-month Treasury bill, and the annualized *log dividend-price ratio*. Data on the macroeconomic variables are extracted from the Federal Reserve Economic Data database, and the dividend-price ratio data are obtained from the CRSP database.

For monthly prediction control variables, book-to-market ratio is the value-weighted average of firm-level book value to market value ratio for the S&P 500 firms, with the firm-level book-to-market ratio calculated as the total book value of equity from the end of the latest fiscal year divided by market capitalization at the end of the month. Dividend-to-price-ratio is the value-weighted average of the firm-level dividend-to-price ratios for the S&P 500 firms, with the firm-level dividend-to-price-ratio calculated as the total dividends from the end of the latest fiscal year divided by market capitalization at the end of the month. Earnings-to-price ratio is the value-weighted average of firm-level earnings-to-price ratios for the S&P 500 firms, with the firm-level earnings-to-price ratio calculated as earnings from the end of the latest fiscal year divided by market capitalization at the end of the month.

Table 1 depicts the descriptive statistics of the variables used in the study. Panel A presents that the *TPU* index (scaled by dividing by 100) is higher during the expansion months; with a median of 0.485, than in the recession months; with a median of 0.449. However, the difference is not statistically significant.

The mean of excess monthly returns for the full sample period is 0.450 percent and the standard deviation is 4.376 percent. As expected, excess market returns are higher during the expansion months than during recession months.

Panel B of Table 1 shows the pairwise correlations between the main variables with p-values in parentheses. The *TPU* Index is inversely correlated with excess returns, earnings-to-price ratio, *term spread*, *relative interest rate*, and *default spread*.

Table 1. Descriptive Statistics

Panel A: Descriptive Statistics of Main Variables

	Full Sample			Expansion N=165			Recession N=70			T-test (p-val)
Variable	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD	
r_t	0.450	1.090	4.376	0.684	1.090	3.827	-0.846	0.575	6.570	1.94 (0.053)
TPU	0.752	0.484	0.863	0.790	0.485	0.923	0.540	0.449	0.334	1.61 (0.109)
B/M	0.552	0.557	0.086	0.533	0.530	0.061	0.613	0.557	0.118	-5.28 (0.000)
E/P	0.044	0.047	0.018	0.048	0.0523	0.016	0.028	0.029	0.013	6.88 (0.000)
Log[D/P]	-3.754	-3.882	0.384	-3.762	-3.891	0.374	-3.719	-3.654	0.425	-0.043 (0.479)
TS	1.840	1.960	1.112	0.684	1.880	1.119	2.346	2.390	0.933	-3.02 (0.003)
RR	0.004	0.003	0.389	0.790	-0.003	0.272	0.001	0.025	0.771	0.07 (0.943)
INFL	2.178	2.300	1.068	0.533	2.100	0.873	2.067	2.800	1.817	0.68 (0.498)
DEF	1.048	0.930	0.430	0.048	0.920	0.221	1.554	1.305	0.805	-8.86 (0.000)

Panel B: Correlation of Main Variables

	r_t	TPU	B/M	E/P	Log[D/P]	TS	RR	INFL	DEF
r_t	1.000								
TPU	-0.119 (0.15)	1.000							
B/M	0.126 (0.13)	0.06 (0.46)	1.000						
E/P	0.067 (0.42)	-0.052 (0.53)	-0.624 (0.00)	1.000					
Log[D/P]	0.09 (0.09)	0.196 (0.00)	0.696 (0.00)	0.670 (0.00)	1.000				
TS	0.073 (0.38)	-0.042 (0.61)	0.463 (0.00)	-0.272 (0.00)	0.249 (0.00)	1.000			
RR	-0.026 (0.76)	-0.126 (0.13)	-0.077 (0.35)	0.149 (0.07)	0.484 (0.00)	-0.300 (0.00)	1.000		
INFL	-0.190 (0.02)	0.178 (0.03)	-0.764 (0.00)	0.478 (0.00)	0.335 (0.00)	-0.509 (0.00)	0.001 (0.99)	1.000	
DEF	-0.070 (0.40)	-0.103 (0.21)	0.542 (0.00)	-0.475 (0.00)	0.185 (0.00)	-0.509 (0.00)	-0.173 (0.04)	-0.419 (0.00)	1.000

Table 1 reports the descriptive statistics of the main variables used in the study. The data is monthly from January 2000 to October 2019, resulting in a 235 month study period. We analyze excess stock market returns; r_t using the monthly returns of the value-weighted (*VWR*) portfolios from CRSP. We use the *inflation rate [INFL]*, the *relative interest rate [RR]* computed as the deviation of the three-month Treasury bill rate from its one-year moving average, the *default spread [DEF]* which is the difference between yields of BAA-rated bonds and AAA-rated bonds, *term spread [TS]* which is the difference between the yield to maturity of a 10-year Treasury note and the three-month Treasury bill, and the annualized *log dividend-price ratio*. Data on the macroeconomic variables are extracted from the Federal Reserve Economic Data database, and the dividend-price ratio data are obtained from the CRSP database. The *TPU* Index is scaled by dividing by 100. For monthly prediction control variables, dividend-to-price-ratio [D/P] is the value-weighted mean of the firm-level dividend-to-price ratios for the S&P 500 firms, with the firm-level dividend-to-price-ratio computed as the total dividends from the latest fiscal year-end divided by market capitalization at month-end. Earnings-to-price ratio[E/P] is the value-weighted mean of firm-level earnings-to-price ratios for the S&P 500 firms, with the firm-level earnings-to-price ratio computed as earnings from the latest fiscal year-end divided by market capitalization at month-end. Book-to-market ratio is the value-weighted mean of firm-level book value to market value ratio for the S&P 500 firms, with the firm-level book-to-market ratio [B/M] computed as the total book value of equity from the latest fiscal year-end divided by market capitalization at month-end. 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.

6. Empirical Results

6.1. Results of the GARCH-M Model Estimations

In this section, we report and discuss the results of the GARCH-M model estimations.

Table 2. Results of GARCH-M Estimations

Variable	GARCH-M Model 1 With Intercept	GARCH-M Model 2
ψ	0.751 (0.095)	1.429 (0.127)
TPU		0.223 (0.417)
Φ		
TS		0.164 (0.499)
DS		-1.4812 (0.157)
RR		0.0984 (0.854)
Δ	0.003 (0.914)	0.0255 (0.474)
Ω	1.074 (0.162)	0.950 (0.221)
A	0.225 (0.002)	0.213 (0.008)
β	0.731 (0.000)	0.748 (0.000)
TDFI	0.001 (0.001)	0.033 (0.727)
Log-L	-657.630	-655.889
N	235	235

Table 2 presents the results of the estimations of the GARCH-M models.
Model 1: GARCH-M Model: The GARCH-M model including the conditional variance; h_t, using the conditional mean of the return; r_t. This is formally stated as:

$$r_t = \psi + \delta h_t + h_t^{1/2} + \varepsilon_t, \quad (1)$$

$$h_t = \omega + \beta h_{t-1} + \alpha u^2_{t-1}, \quad (2)$$

where $u_t = r_t - \psi - \delta h_t$ and $\omega > 0, \beta \geq 0, and\ \alpha > 0.$
Model 2: *GARCH-M with TPU*
We investigate the impact of trade policy uncertainty; *TPU*, on the conditional mean of returns by inserting the *TPU* index and other exogenous control variables into the GARCH-M setup as follows:

$$r_t = \psi + \theta TPU_t + \Phi \boldsymbol{X_t} + \delta h_t + h_t^{1/2}\varepsilon_t, \quad (3)$$

where r_t is the conditional mean of the returns, ψ is the intercept term, θ is the *TPU* index coefficient, Φ is a matrix of slope coefficients, $\boldsymbol{X_t}$ is a vector of macroeconomic control variables, ε_t – IID (0,1), and h_t is conditional variance of returns modeled as;

$$h_t = \omega + \beta h_{t-1} + \alpha u^2_{t-1}, \quad (4)$$

where $u_t = r_t - \psi - \delta h_t$ and $\omega > 0, \beta \geq 0, and\ \alpha > 0.$ We estimate the GARCH-M model using maximum likelihood and assuming the error term follows the Student's t distribution. Standard errors are presented in parentheses.

All models in Table 2 are GARCH-M models with the conditional variance; a GARCH (1, 1) model, and an error term following the Student's *t* distribution. Model 1 is the fundamental GARCH-M model with no exogenous variable impregnation and run with an intercept. The coefficient for β is statistically significant (1% level), indicating the presence of GARCH effects in model 1. Additionally, the results indicate a positive risk-return tradeoff, however, the coefficient: δ, is not statistically significant (5% level), but is consistent with Nyberg [21].

As discussed previously, this study, accounting for business cycle effects, examines the impact of the level of trade policy uncertainty on excess market returns by inserting exogenous variables and the *TPU* index in the GARCH-M model (eq. 3). Table 2 model 2 indicates that after accounting for business cycle effects, the coefficient for *TPU* is *not* statistically significant, and suggests that trade policy uncertainty has no contemporaneous impact on market returns.

6.2. TPU and Return Predictability Results

This section presents and discusses the results of our forecasting regressions. The existing research shows that the valuation ratios are correlated with future stock returns. Particularly, Boudoukh, Michaely, Richardson, and Roberts [33] show that payout yield has better predictive power than dividend yield in predicting future returns. We examine the forecasting power of the *TPU* index in a set of univariate regressions. Additionally, controlling for other commonly used valuation ratios and macroeconomic predictors, we examine the forecasting power of the *TPU* index in a set of bivariate regressions.

6.2.1. Univariate Predictability Results

We examine the forecasting power of the *TPU* index in univariate regressions and present the results in Table 3.

Table 3. Univariate Forecasting Regressions for *TPU*

		TPU		
N	*B*	adj. R^2	$Z(\beta)$	p-value
1	-0.0175	0.0094	-0.01086	0.1265
6	-0.00242	0.0049	-0.00777	0.0304
12	0.01151	0.0444	-0.01069	0.0013
18	-0.00799	0.0278	-0.00858	0.0042
24	-0.00436	0.0067	-0.00654	0.0244
Avg.			-0.00536	0.0840

This table presents the univariate forecasting regression results in equation (3).

$$\sum_{n=1}^{N} \frac{r_{t+N}}{N} = a + \boldsymbol{b} \times \boldsymbol{X}_t + u_{t+N,t} \quad (5)$$

where r_{t+N} is the monthly continuously compounded excess return which is computed as the monthly continuously compounded return on the value-weighted market return including dividends from CRSP less the monthly continuously compounded one-month Treasury bill rate. $\boldsymbol{X}_t$ is the explanatory variable, N is the forecasting horizon in months, $\boldsymbol{b}$ is the slope coefficient, and $u_{t+N,t}$ is the regression residual. We estimate monthly regressions for different time horizons: N = 1, 6, 12, 18, and 24 months. The following are the prediction variables; *TPU* index is rescaled by dividing by 100. Book-to-market ratio is the value-weighted mean of firm-level book value to market value ratio for the S&P 500 firms, with the firm-level book-to-market ratio computed as the total book value of equity from the latest fiscal year-end divided by market capitalization at month-end. Earnings-to-price ratio is the value-weighted mean of firm-level earnings-to-price ratios for the S&P 500 firms, with the firm-level earnings-to-price ratio computed as earnings from the latest fiscal year-end divided by market capitalization at month-end. Also, results of the generalized method of moments (GMM) estimation (correcting for conditional heteroskedasticity and induced autocorrelation) are presented. The GMM estimator $\theta = (a, \boldsymbol{b})$ has an asymptotic distribution $\sqrt{T}(\hat{\theta} - \theta) \sim N\ (0,\ \Omega)$, with $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t')$, and $x_t = (1\ X_t')'$. S_0 is the spectral density estimated at frequency zero of $w_{t+N} = u_{t+N,t}\, x_t$. S_0 is estimated with the Newey-West correction with *N*-1 moving average lags and the resulting statistic from the test is the asymptotic Z-statistic. Also, results of the joint slopes test: the re-estimation of the GMM estimator with a system of multiple equations in which the coefficients are constrained to be the same across equations making the GMM estimator a special case of the single-equation GMM; are also presented. Obviously, S_0 cannot be estimated with the Newey-West correction in this case due to the simultaneous use of multiple time horizons. *B* is the slope coefficient from the OLS forecasting regressions and p-value is reported also. The adj. $R^2$is acquired from the OLS regression. $Z(\beta)$ is the asymptotic Z-statistic. Avg. is the joint slope coefficient.

Table 3 shows univariate regression results for the *TPU* Index. The coefficient is negative at 1, 6, 18, and 24 month horizons consistent with Baker, Bloom, and Davis [4]. The adjusted R^2 indicates that *TPU* explains 0.94% of future market returns in the 1-month horizon and 0.67% of future market returns in the 24-month horizon. Additionally, with the exception of 1-month horizon, the p-values of the z-statistics indicate *TPU* is statistically significantly correlated with future returns. Furthermore, with the GMM estimator, we evaluate the null hypothesis that slopes at different horizons are jointly equal to zero. Consistent with the earlier findings, we uncover that the *TPU* slopes for different time horizons are jointly different from zero.

6.2.2. Bivariate Predictability Results

Table 4. Bivariate Forecasting Regressions for *TPU* and Valuation Ratios

Panel A: Bivariate Regression with *TPU* and *Term Spread [TS]*							
		TPU			TS		
N	*B*	Z(*β*)	p-value	*B*	Z(*β*)	p-value	adj. R^2
1	-0.0167	-0.0164	0.058	0.0035	0.0041	0.082	0.0114
6	-0.0019	-0.0069	0.046	0.0036	0.0027	0.025	0.0227
12	-0.0108	-0.0140	0.001	0.0053	0.0046	0.001	0.1709
18	-0.0071	-0.0123	0.001	0.0066	0.0049	0.001	0.3082
24	-0.0034	-0.0096	0.001	0.0073	0.0048	0.001	0.4387
Avg.		-0.0140	0.001		0.0059	0.001	
Panel B: Bivariate Regression with *TPU* and *Default Spread [DEF]*							
		TPU			*DEF*		
N	*B*	Z(*β*)	p-value	*B*	Z(*β*)	p-value	adj. R^2
1	-0.0182	-0.0119	0.2668	-0.0088	0.0057	0.3059	0.0110
6	-0.0016	-0.0041	0.3048	0.0059	0.0026	0.2966	0.0036
12	-0.0103	-0.0125	0.001	0.0097	0.0074	0.001	0.1063
18	-0.0067	-0.0113	0.001	0.0108	0.0082	0.001	0.1394
24	-0.0029	-0.0087	0.001	0.0113	0.0079	0.001	0.1636
Avg.		-0.0089	0.001		0.0080	0.001	
Panel C: Bivariate Regression with *TPU* and *E/P*							
		TPU			*E/P*		
N	*B*	Z(*β*)	p-value	*B*	Z(*β*)	p-value	adj. R^2
1	--0.0170	-0.0147	0.1285	0.1074	0.1857	0.0644	0.0048
6	-0.0023	-0.0046	0.1873	0.0748	0.0898	0.0324	-0.0079
12	-0.0115	-0.0113	0.0001	0.0450	0.1417	0.0001	0.0405
18	-0.0080	-0.0059	0.0319	-0.0198	0.0863	0.0177	0.0224
24	-0.0044	-0.0015	0.6017	-0.0608	0.0505	0.1739	0.0070
Avg.		-0.0040	0.1377		0.1005	0.0026	
Panel D: Bivariate Regression with *TPU* and *B/M*							
		TPU			*B/M*		
N	*B*	Z(*β*)	p-value	*B*	Z(*β*)	p-value	adj. R^2
1	-0.0186	-0.0187	0.1127	0.0805	0.0132	0.2819	0.0222
6	-0.0030	-0.0035	0.4667	0.1080	-0.0023	0.7145	0.1359
12	-0.0121	-0.0136	0.0003	0.0836	0.0100	0.0103	0.2039
18	-0.0084	-0.0110	0.0001	0.0792	0.0105	0.0005	0.2372
24	-0.0046	-0.0073	0.0066	-0.0733	0.0077	0.0062	0.2419
Avg.		-0.0112	0.000		0.0129	0.000	
Panel E: Bivariate Regression with *TPU* and *Relative Interest Rate [RR]*							
		TPU			*RR*		
N	*B*	Z(*β*)	p-value	*B*	Z(*β*)	p-value	adj. R^2
1	-0.0180	0.0006	0.9300	-0.0050	-0.0026	0.7882	0.0055
6	-0.0032	0.0010	0.6889	-0.0051	-0.0041	0.2225	-0.0015
12	-0.0121	-0.0018	0.4513	-0.0036	0.0017	0.6309	0.0467
18	-0.0087	0.0005	0.8064	-0.0041	-0.0006	0.8252	0.0366
24	-0.0055	0.0025	0.1789	-0.0068	-0.0047	0.0303	0.0524
Avg.		0.0036	0.0520		-0.0074	0.000	

This table presents the bivariate forecasting regression results in equation (3).

$$\sum_{n=1}^{N} \frac{r_{t+N}}{N} = a + \boldsymbol{b} \text{ x } \boldsymbol{X}_t + u_{t+N,t} \tag{5}$$

where r_{t+N} is the monthly continuously compounded excess return which is computed as the monthly continuously compounded return on the value-weighted market return including dividends from CRSP less the monthly continuously compounded one-month Treasury bill rate. $\boldsymbol{b}$ is a 1 x 2 matrix of slope coefficients, $\boldsymbol{X}_t$is a 1 x 2 matrix of two independent variables, N is the forecasting horizon in months, and $u_{t+N,t}$ is the regression residual. We estimate monthly regressions for different time horizons: N = 1, 6, 12, 18, and 24 months. The following are the prediction variables; *TPU* index is rescaled by dividing by 100. Book-to-market ratio is the value-weighted mean of firm-level book value to market value ratio for the S&P 500 firms, with the firm-level book-to-market ratio computed as the total book value of equity from the latest fiscal year-end divided by market capitalization at month-end. Earnings-to-price ratio is the value-weighted mean of firm-level earnings-to-price ratios for the S&P 500 firms, with the firm-level earnings-to-price ratio computed as earnings from the latest fiscal year-end divided by market capitalization at month-end. Also, results of the generalized method of moments (GMM) estimation (correcting for conditional heteroskedasticity and induced autocorrelation) are presented. The GMM estimator $\theta = (a, \boldsymbol{b})$ has an asymptotic distribution $\sqrt{T}(\hat{\theta} - \theta) \sim N(0, \Omega)$, with $\Omega = Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t')$, and $x_t = (1\ X_t')'$. S_0 is the spectral density estimated at frequency zero of $w_{t+N} = u_{t+N,t}\, x_t$. S_0 is estimated with the Newey-West correction with *N*-1 moving average lags and the resulting statistic from the test is the asymptotic Z-statistic. Also, results of the joint slopes test: the re-estimation of the GMM estimator with a system of multiple equations in which the coefficients are constrained to be the same across equations making the GMM estimator a special case of the single-equation GMM; are also presented. Obviously, S_0 cannot be estimated with the Newey-West correction in this case due to the simultaneous use of multiple time horizons. *B* is the slope coefficient from the OLS forecasting regressions and p-value is reported also. The adj. $R^2$is acquired from the OLS regression. Z(*β*)is the asymptotic Z-statistic. Avg. is the joint slope coefficient.

We investigate the predictive power of the *TPU* index in tandem with other valuation ratios in bivariate regressions, and present the findings in Table 4 panels A - D. Extant research indicates that the valuation ratios are highly correlated [27,28,29]. Hence, we run regressions with the independent variables being *TPU* index and a predictor at a time to mitigate the multicollinearity problems.

The individual and joint slope coefficients for *TPU* index are significant for most horizons. The joint slope coefficients for *TPU* index range from -0.0040 to -0.0140. Evidently, accounting for other predictors, *TPU* index has predictive power to forecast future returns. The findings depict strong evidence that *TPU* index is a valuable predictor of future returns.

7. Conclusion

We study the impact of the level of trade policy uncertainty on the conditional mean of market returns, by using a GARCH-M model, and also we investigate the predictive power of trade policy uncertainty on future market returns.

First, the results of the GARCH-M estimation indicate a positive risk-return tradeoff and present more support for the capital assets pricing model. Additionally, findings from the conditional variance estimation indicate the presence of GARCH effects.

Second, after accounting for business cycle impacts, we find that trade policy uncertainty does *not* impact contemporaneous market returns. These results add to the burgeoning empirical research on the relation between the level of trade policy uncertainty and market returns.

Third, from both the univariate and bivariate tests, our findings indicate that *TPU* is a strong predictor of future market returns. Particularly, our findings offer the first unambiguous evidence of a negative relation between *TPU* and future market returns. These findings expand the *TPU* literature by establishing the utility of the *TPU Index* as a robust predictor.

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