Does Oil and Gold Price Uncertainty Matter for the Stock Market?

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Abstract: We proxy the uncertainty in the stock, oil and gold markets with the variance risk premia, extracted from futures and option contracts traded on each of these asset classes. We observe that an independent increase in the stock, oil or gold markets uncertainty coincides with negative returns for a large portion of stocks. However, only the stock market uncertainty is a market-wide priced factor in the cross section of stock expected returns. The oil price uncertainty is a sector-specific factor, and due to the industry segmentation of the market, it is only priced within oil-relevant industries. Finally, the gold price uncertainty is asset-specific and it is neither priced across nor within industries.

***Keywords*:** Uncertainty, Volatility Risk Premium, Stock Market, Oil, Gold, Oil-relevant Industry, Market Segmentation (*JEL* G10, G12, G13)

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1. Introduction

Bernanke (1983) theoretically shows that uncertainty about future returns cuts firms' investment rate and sharply reduces consumer durables production. Return uncertainty originates from different sources. For example, it can be caused by the overall uncertainty in the stock market, the uncertainty about the future price of energy and raw material or inflationary uncertainty. Moreover, different sectors of the economy have various levels of exposure to uncertainty sources; while uncertainty about future price of oil is a crucial factor for firms investing on shale oil extraction, it has a negligible effect for firms in the health care industry. In this paper, we investigate the distinctive effect of the uncertainty originating from the stock, oil and gold markets on the time series and the cross section of stock prices. While the relationship between the stock market and return shocks of the oil and gold markets has been extensively investigated in the literature, we are the first to explore the impact of uncertainty originating from these two major alternative asset classes on stock prices.

Knight (1921) and Ellsberg (1961) theoretically emphasize the importance of differentiating risk from uncertainty: an event is risky, if its outcome is unknown but the distribution of its potential outcomes is known. An event is uncertain, if its outcome and outcomes distribution are both unknown. Consequently, previous studies show that uncertainty plays a unique role in financial markets and economic agents have distinctive aversions towards these two concepts. For example, according to the theoretical model of Bansal and Yaron (2004), Bekaert, Engstrom and Xing (2009) and Boguth and Kuehn (2013), uncertainty in the future consumption is the essential factor in explaining the equity risk premium. Anderson, Ghysels and Juergens (2009), Drechsler and Yaron (2010) and Bali and Zhou (2015) provide strong evidence of a positive relationship between price uncertainty and expected stock returns. Moreover, numerous studies show that the economic impact of uncertainty is not limited to the stock market, but it extends to other asset classes such as the bond market. (See e.g.

Connolly, Stivers and Sun (2005), Baele, Bekaert and Inghelhecht (2010) and Buraschi, Trojani and Vedolin (2013)). The large amount of evidence regarding the impact of uncertainty on financial markets highlights the importance of gaining deeper insight about different sources of uncertainty.

Since oil price uncertainty negatively affects macroeconomic variables such as investment, aggregate output and durables consumption (Elder and Serletis (2010)), we believe that it is also an important factor for stock valuations. Furthermore, due to the negative relation between gold price and stock markets (Chan, Treepongkaruna, Brooks and Gray (2011), Elder, Miao and Ramchander (2012), Baur and McDermott (2010) and Baur and Lucey (2010)) investors use gold to hedge against inflation uncertainty and uncertainty surrounding the fiscal and monetary policies of the central banks. Therefore, escalating uncertainty about the future price of gold can potentially convey decisive information about the monetary situation of the market for stock valuations.

We proxy economic uncertainty originating from the stock, oil and gold markets, with the variance risk premia time series of the S&P 500 index, West Texas Intermediate crude oil and 100-oz gold bar, respectively. Subsequently, we investigate their impact on the time series and the cross section of stock returns. We find that rising uncertainty in any of these markets is accompanied by falling stock prices. Uncertainty makes firm valuations, investment decisions and cash flow forecasts non-transparent, and thereby, uncertainty-averse investors will buy the stocks, exposed to an uncertainty shock, at a discount. Moreover, a comparison of the three uncertainty sources shows that although the uncertainty originating from the stock market has a dominant effect, stock returns are also exposed to oil and gold market uncertainty.

Rational investors require extra compensation for holding assets that are negatively affected by a *systematic* uncertainty shock. Having shown that stocks are exposed to these three alternative uncertainty factors, we further investigate whether these sources of uncertainty are priced risk factors in the cross section of stock expected returns. Our empirical results show that, in contrast to oil and gold price uncertainty which are diversifiable, the stock market uncertainty is a *systematic* factor that is priced within and across industries.

Previous studies find that although the oil shocks affect stock prices negatively (Jones and Kaul (1996), Driesprong and Jacobsen and Maat (2008) and Narayan and Sharma (2011)), oil return is not a priced risk factor and it does not affect the discount rate or the risk premium (Chen, Roll and Ross (1986), Jones and Kaul (1996) and Driesprong, Jacobsen and Maat (2008)). We empirically document the same results for oil price uncertainty and conclude that oil price uncertainty, although relevant for the overall economy, is not a systematic priced factor that affects the expected return of every stock. Our findings also provide support for the interpretation of Driesprong, Jacobsen and Maat (2008) that oil-price-based return predictability is not explained by a time-varying premium.

Moreover, an intra-industry investigation reveals interesting results for oil; while oil uncertainty is not a priced risk factor for all types of stocks and therefore it is diversifiable across different industries, it is priced within oil-relevant industries. In each of these industries, the stocks with the highest exposure to oil uncertainty are compensated with substantially higher returns than the ones with the least exposure. Therefore, oil price uncertainty is not a relevant factor for the equity premium in every industry, but only for stocks in oil-relevant industries. An economic interpretation of this result suggests industry segmentation of the market. In accordance with the interpretation of Pollet (2005) and Hong, Torous and Valkanov (2007), industry-specialized investors, who hold undiversified portfolios, cause the oil uncertainty to be a priced factor within the oil relevant industries, because they cause the oil-relevant news to be more quickly and efficiently reflected in those industries.

Narayan and Sharma (2011) and Scholtens and Yurtsever (2012) find that the impact of oil price on stock returns is not homogeneous but it depend on the sectoral location of the firms. We unravel a similar finding for the impact of oil price uncertainty; while escalating oil price uncertainty prevents cash flow forecasts and stock valuations in oil-relevant industries, it is not a distinctive pricing factor in the rest of the market.

These findings imply that for firm valuations, investors must consider the stock market uncertainty factor, because this is a systematic factor that affects the risk premium and the expected stock returns. The investors in oil-relevant industries, in addition, must consider oil price uncertainty risk because as a sector-specific factor, it affects the risk premium and the expected return of the stocks in those industries.

2. Variance Risk Premium, Measure of Uncertainty

One major challenge is to obtain a robust measure of uncertainty that is comparable across different markets. Anderson, Ghysels and Juergens (2005) point out the limitations of relying on analysts' forecasts dispersion. They conclude that because of analysts' optimism (pessimism) on long-term (short-term) forecasts, agency issues and behavioral biases, beliefs disagreements cannot be a reliable proxy. In addition, they note that similar education, goals and interactions prevent analysts' forecasts dispersion from being a generic survey of disagreement in a heterogeneous market with different participants.

Following previous literature, instead, we proxy uncertainty with the variance risk premium. (See e.g. Carr and Wu (2009), Drechsler and Yaron (2010), Drechsler (2013), Buraschi, Trojani and Vedolin (2014), Bollerslev, Marrone and Zhou (2014), Bekaert and Hoerova (2014), and Bali and Zhou (2015)). The variance risk premium measures the price of a hedge against variance fluctuations, and it is equal to the difference between the expected variance, under the physical and the risk-neutral measures:

$$VRP_t^\tau = E^P\big(Variance(t,\tau)\big) - E^Q\big(Variance(t,\tau)\big) \quad (1)$$

In Eq. 1, $E^P(.)$ and $E^Q(.)$ are the expectation operators under the physical and the risk-neutral measures and τ is the horizon for which we calculate the variance expectations. VRP_t^τ is equivalent to the price of a long position on a variance swap contract with τ years to maturity. The risk-neutral variance expectation exceeds the physical variance expectation. Therefore, by buying a variance swap contract and paying the variance risk premium, investors can protect themselves against future shocks in the realized variance.

Option contracts are hedging vehicles against uncertainty in the price of the underlying asset, and therefore, they reflect investors' expectation about the underlying's future price distribution. When investors are uncertain about the shape of this distribution, the option prices and thereby the risk-neutral variance expectation increase. Therefore, an increase in uncertainty is associated with a decrease (more negative values) in the variance risk premium. Bali and Zhou (2015) take variance risk premium as a market-wide measure of uncertainty, and show that it highly correlates with other uncertainty proxies, such as the conditional variance of CFNAI and the conditional variance of the growth rate of industrial production. Moreover the strong association between volatility risk premia of individual stocks and analysts' forecast disagreements, explained by Buraschi, Trojani and Vedolin (2014), assures us that the variance risk premium is an appropriate measure of uncertainty.

2.1. Variance Risk Premium Estimation

We proxy the variance risk premium of day t with the ex-post return of a synthetic variance swap contract, written on this day. In other words, to estimate the variance under the physical measure, we rely on the assumption that the ex-post realized variance is an unbiased estimator of the ex-ante variance expectation. This is a common assumption used to compute the volatility risk premium (e.g. Buraschi, Trojani and Vedolin (2014)), and the variance risk premium (e.g. Carr and Wu (2009), Trolle and Schwartz (2010) and Prokopczuk and Wese-Simen (2013)). It holds that:

$$E^P\big(Variance(t,\tau)\big) = \frac{252}{360\times\tau} \times \frac{\sum_{s=t}^{t+360\times\tau}\left(R_s^\tau - \overline{R_t^\tau}\right)^2}{N-1}, \tag{2}$$

In Eq. 2, N is the number of return observations between day t and $t+\tau$, $R_s^\tau = \ln(F_s^\tau) - \ln(F_{s-1}^\tau)$ is the logarithmic return of a futures contract with τ years to maturity on day s,[1] and $\overline{R_t^\tau}$ represents the average of the observed daily returns between day t and $t+\tau$.[2]

We use the model-free methodology of Bakshi, Kapadia and Madan (2003) [BKM] to calculate the variance expectation under the risk-neutral measure.[3] The BKM methodology exploits the risk-neutral variance of each day from the out-of-money [OTM] European options traded on that specific day. Hence, the computed variance is strictly conditional and forward-looking. The BKM methodology calculates the risk-neutral variance as,

$$E^Q\big(Variance(t,\tau)\big) = \frac{e^{r\tau}\,V(t,\tau) - \mu(t,\tau)^2}{\tau}, \tag{3}$$

where,

$$\mu(t,\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V(t,\tau) - \frac{e^{r\tau}}{6}W(t,\tau) - \frac{e^{r\tau}}{24}X(t,\tau), \tag{4}$$

[1] Futures with exactly τ years to maturity are not traded on every day. In order to calculate the realized variance with the constant horizon of τ, on each day, we interpolate between the prices of two futures contracts with shorter and longer maturities than τ.

[2] Some authors (e.g. Bali and Zhou (2015)) proxy the variance with the second moment of log returns, assuming that $\overline{R_t^\tau}$ is zero in long run. However as seasonality might deviate $\overline{R_t^\tau}$ from zero, to have a more accurate estimation, we do not use the second moment.

[3] To obtain the risk-neutral variance time series, one could alternatively use the volatility indexes, computed and released by the Chicago Board Options Exchange (CBOE). Although the time series of the S&P 500 volatility index (VIX) starts 1986 and it covers our entire study period, the time series of oil risk-neutral volatility (OVX) and gold risk-neutral volatility (GVZ) are short and non-applicable for this research.

Moreover VIX, OVX and GVZ are measures of risk-neutral expectation about the volatility of the next 30 days, while we need the risk-neutral volatility for the next 90 days. From the end of 2007, CBOE also reports the 3-month volatility index of the S&P 500 index (VXV). Since the correlation between our measure of risk-neutral volatility for the S&P 500 index and VXV is 0.96, we are certain that our methodology is accurate and robust.

$$V(t,\tau) = \int_{S(t)}^{\infty} \frac{2\left(1 - ln\left[\frac{K}{S(t)}\right]\right)}{K^2} C(t,\tau;K)\, dK + \int_{0}^{S(t)} \frac{2\left(1 + ln\left[\frac{S(t)}{K}\right]\right)}{K^2} P(t,\tau;K)\, dK, \quad (5)$$

$$W(t,\tau) = \int_{S(t)}^{\infty} \frac{6\, ln\left[\frac{K}{S(t)}\right] - 3\left(ln\left[\frac{K}{S(t)}\right]\right)^2}{K^2} C(t,\tau;K)\, dK - \int_{0}^{S(t)} \frac{6\, ln\left[\frac{S(t)}{K}\right] + 3\left(ln\left[\frac{S(t)}{K}\right]\right)^2}{K^2} P(t,\tau;K)\, dK, \quad (6)$$

and,

$$X(t,\tau) = \int_{S(t)}^{\infty} \frac{12\left(ln\left[\frac{K}{S(t)}\right]\right)^2 - 4\left(ln\left[\frac{K}{S(t)}\right]\right)^3}{K^2} C(t,\tau;K)\, dK + \int_{0}^{S(t)} \frac{12\left(ln\left[\frac{S(t)}{K}\right]\right)^2 + 4\left(ln\left[\frac{S(t)}{K}\right]\right)^3}{K^2} P(t,\tau;K)\, dK. \quad (7)$$

In Eq. 3 to 7, r is the risk-free rate, $S(t)$ shows the underlying's price at time t, and $C(t,\tau;K)$ and $P(t,\tau;K)$ respectively represent the price of a European call option and a European put option at time t, with τ years to maturity and strike price of K. Appendix A provides more details on how we calculated the variance under the risk-neutral measure.

We obtain prices of futures and option contracts traded on the S&P 500 index, West Texas Intermediate crude oil and 100-oz gold bar from the Commodity Research Bureau (CRB) database. This database provides us with various information, such as closing price, transaction date and expiration date of futures contracts and the American put and call options, written on these futures contracts. We take the returns on futures contracts as proxies for price changes in each of these three markets. We match each option with its corresponding futures contract on the same day and eliminate those, for which we cannot find the underlying futures contract in the database. Also to avoid illiquidity and microstructural anomalies, following Chang, Christoffersen and Jacobs (2013), we omit all option contracts with less than 6 days to maturity and cheaper than 8/3 dollars. Table 1 provides summary statistics on our data.

***** INSERT TABLE 1 ABOUT HERE*****

Prices of options with shorter time-to-maturity reflect investors' short-term expectations and uncertainty more evidently. Hence, we measure the variance risk premia for a reasonably small time horizon. As Table 1 shows, the futures contracts on the S&P 500 index are written quarterly, which is less frequent compared to West Texas Intermediate crude oil and 100-oz gold bar futures. In order to have a unique and comparable horizon for our analysis, we take the shortest common time-to-maturity i.e. 90 days ($\tau = \frac{1}{4}$) for the variance risk premia computations. The number of observations in our database rises drastically over time, suggesting considerably higher transaction volumes over the past years. Due to insufficiency of the data for measuring the oil variance risk premium with $\tau = \frac{1}{4}$ in the earlier years, we conduct our analysis based on the last 18 years of the data sample, i.e. from 1996 to 2013.

2.2. Descriptive Statistics

Figure 1 plots our proxies for the variance risk premia in the stock, oil and gold markets. Panel A to C, respectively, display the ex-post return time series of the synthetic variance swap contracts, written on the S&P 500 index, oil and gold from 1996 to 2013. The returns are mostly negative for all the three variance swap contracts, indicating that on average, investors are willing to lose money to hedge themselves against the shocks in the variance of the S&P 500 index, oil and gold.

*****INSERT FIGURE 1 ABOUT HERE*****

The remarkable common variations in these three time series reveal that some systematic patterns exist across the markets' uncertainty. As an example in 2008, variance swap sellers experienced dramatic losses in all three markets. The losses were most pronounced on the S&P 500 index and least evident on gold. Moreover due to increasing economic uncertainty right after the 2008 turmoil, the variance risk premia in all three markets reached their all-time low, implying higher costs of hedging against uncertainty.

The three time series also exhibit some divergence movements. For example from 2003 to 2008, while the return on the variance swap contracts of the S&P 500 index was very stable, the returns of the variance swap contracts on both crude oil and gold were volatile. This suggests the existence of asset-specific components in uncertainty, which motivates our investigation about their impact on the stock market. An even more compelling case is the oil uncertainty escalation from January 2001 until June 2003. During this period, oil variance risk premium was 9.46% on average, and even reached a peak of 21.16%. The oil market situation during this period is well summarized by the New York Times on June 25, 2002: *"Yet in such unpredictable times, with one conflict worsening in the Middle East and the rumor of another rising, the 10-member cartel's inaction amounts to a gamble that could send the price of oil rocketing in the coming months."* (Banerjee, 2002)

*****INSERT TABLE 2 ABOUT HERE*****

Table 2 presents descriptive statistics on the return time series of the variance swaps contracts, our proxy for variance risk premia and uncertainty. The average return of long positions in these contracts are significantly negative for all three markets, which shows the hedging costs against variance shocks. In line with the results of Prokopczuk and Wese-Simen (2013), gold has a relatively smaller variance risk premium. Furthermore consistent with the findings of Trolle and Schwartz (2010), the large premium of a hedge against oil variance is caused by the additional exposure of oil price to political uncertainty. Moreover, since the three uncertainty measures correlate highly with their first principal component and this component explains 65.9% of the overall variations, we deduce that these three uncertainty measures follow a common systematic pattern. In addition, as the S&P 500 index uncertainty has the highest correlation with the first principal component, it can be considered to be the best proxy for the systematic uncertainty of the whole economy.

We want to study stocks' reaction to a shock (innovation) in the different uncertainty measures. Thus, we take the residuals of three ARMA(1, 1) processes, fitted to the variance risk premia time series as the innovations in the uncertainty measures.[4] The significantly positive correlation between the residuals time series, shown in Table 2, support our previous conjecture that there is a systematic factor across all three markets' uncertainty. However these correlations remain low, suggesting the existence of asset-specific components.

3. Empirical Analysis

In this section, we investigate the impact of uncertainty on the time series and the cross section of stocks. In contrast to Bali and Zhou (2015) who solely focus on stock market uncertainty or Bekaert, Engstrom and Xing (2009) who look at economic uncertainty, we examine the role of the different sources of uncertainty.

3.1. Time Series Evidence

To acknowledge for heterogeneity among firms' exposure to uncertainty, similar to Narayan and Sharma (2011), we investigate the relationships for individual stocks rather than for the aggregated market. Hence, we perform the following time series regressions for each stock with at least 1000 daily observations in the CRSP database, from 1996 to 2013.

Model 1

$$R_{i,t} = \alpha_i + \beta_i^{MRKT} R_{MRKT,t} + \beta_i^{SMB} R_{SMB,t} + \beta_i^{HML} R_{HML,t} + \beta_i^{MOM} R_{MOM,t} + \tag{8}$$

[4] As Table (2) shows, the three autoregressive parameters are extremely close to one, and the moving-average parameters are much smaller. Thus fitting any ARMA(p, q) process, such that $p > 1$ and $q \geq 0$, does not change our results qualitatively and quantitatively. (Not reported, but available from the authors.)

$$\delta_i^{S\&P}\Delta VRP_{S\&P,t} + \gamma_i^{S\&P}R_{S\&P,t} + \varepsilon_{i,t},$$

$$R_{i,t} = \alpha_i + \beta_i^{MRKT}R_{MRKT,t} + \beta_i^{SMB}R_{SMB,t} + \beta_i^{HML}R_{HML,t} + \beta_i^{MOM}R_{MOM,t} + \delta_i^{OIL}\Delta VRP_{OIL,t} + \gamma_i^{OIL}R_{OIL,t} + \varepsilon_{i,t}, \quad (9)$$

$$R_{i,t} = \alpha_i + \beta_i^{MRKT}R_{MRKT,t} + \beta_i^{SMB}R_{SMB,t} + \beta_i^{HML}R_{HML,t} + \beta_i^{MOM}R_{MOM,t} + \delta_i^{GOLD}\Delta VRP_{GOLD,t} + \gamma_i^{GOLD}R_{GOLD,t} + \varepsilon_{i,t}. \quad (10)$$

Model 2

$$R_{i,t} = \alpha_i + \beta_i^{MRKT}R_{MRKT,t} + \beta_i^{SMB}R_{SMB,t} + \beta_i^{HML}R_{HML,t} + \beta_i^{MOM}R_{MOM,t} + \delta_i^{S\&P}\Delta VRP_{S\&P,t} + \delta_i^{OIL}\Delta VRP_{OIL,t} + \delta_i^{GOLD}\Delta VRP_{GOLD,t} + \gamma_i^{S\&P}R_{S\&P,t} + \gamma_i^{OIL}R_{OIL,t} + \gamma_i^{GOLD}R_{GOLD,t} + \varepsilon_{i,t}. \quad (11)$$

To account for the heteroscedasticity, we run these regressions with the feasible generalized least square estimation technique. In Eq. 8 to 11, R_i and R_{MRKT} are the excess return of stock i and the market portfolio, over the risk-free rate. Moreover, R_{SMB}, R_{HML} and R_{MOM}, respectively, represent the Fama-French and the momentum factors. $\Delta VRP_{S\&P}$, ΔVRP_{OIL} and ΔVRP_{GOLD} are the variance risk premia innovations of the S&P 500 index, oil and gold, and $R_{S\&P}$, R_{OIL} and R_{GOLD} represent the daily return on futures contracts with 90 days to maturity.[5] Remarkably, the negative values of $\Delta VRP_{S\&P}$, ΔVRP_{OIL} and ΔVRP_{GOLD} are associated with rising uncertainty in each of the markets. Table 3 reports the proportion of stocks for which $\hat{\delta}_i^{S\&P}$, $\hat{\delta}_i^{OIL}$and $\hat{\delta}_i^{GOLD}$ are positive or negative. We report the statistically significant and insignificant coefficients with $(1-\alpha=)$ 95% confidence levels. These statistics are reported for the entire stock market and individual industries, based on stocks' Standard Classification Code (SIC).[6]

[5] Since the correlation coefficient between R_{MRKT} and $R_{S\&P}$ is 0.95, to avoid multi-co-linearity, we rerun regression 8 and 11, after dropping $R_{S\&P}$ from the regressors. The results (not reported, but available from the authors) are numerically similar and qualitatively the same, and therefore our conclusions remain unchanged.

[6] We obtain stocks' SIC from the US Department of Labor. We omit "Public Administration" sector from our analysis, because the number of stocks in this industry is very small, and therefore our analysis cannot provide a statistically meaningful interpretation for this sector.

*****INSERT TABLE 3 ABOUT HERE*****

We perform one-sided exact binomial tests to see whether the proportion of stocks that are significantly exposed to the uncertainty factor is statistically different from the type I error rate ($\alpha = 5\%$). The significant results at the 95% confidence level are printed in **bold**. Table 3 shows that the distributions of the estimated coefficients are positively skewed. Based on Model 1, the number of significantly positive $\hat{\delta}_i^{S\&P}$, $\hat{\delta}_i^{OIL}$ and $\hat{\delta}_i^{GOLD}$ coefficients for the entire stock market are respectively 10, 24 and 18 times higher than the number of the significantly negative coefficients. Stocks are strongly affected by uncertainty, such that an increase in uncertainty, i.e. a negative innovation in the variance risk premium, is accompanied by falling stock prices. Only a small number of stocks offer a hedge against this unpleasant change in uncertainty.

Furthermore, as Table 3 shows industries are, disproportionately, sensitive to uncertainty. For example based on Model 1, while 49.9%, 42.4% and 34.9% of the firms in the “Mining” sector are significantly negatively exposed to the uncertainty in the S&P 500 index, oil and gold, the corresponding numbers for “Retail Trade” sector are only 16.3%, 14.3% and 16.1%. The disproportion in uncertainty sensitivity of different industries is our motive for preforming intra-industry investigation in section 3.3.

By comparing the results of Model 1 and Model 2, we observe that even after controlling for the effect of different sources of uncertainty (i.e. $\Delta VRP_{S\&P}, \Delta VRP_{OIL}$ and ΔVRP_{GOLD}) still a significant number of stocks are exposed to the oil and gold uncertainty factors. For instance, for the “Mining” sector, where the oil price is an important factor for firm valuation and investment decision making, 23.3% of the stocks are significantly negatively affected by a shock in oil price uncertainty. Stocks returns are not only exposed to stock market uncertainty

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We also repeat our entire study with the Fama-French industry classification, available at Kenneth French personal website. The results (not reported, but available from the authors) are numerically similar and qualitatively the same, and therefore our conclusions remain unchanged.

but also to the uncertainty in the oil and gold markets. In addition to Jones and Kaul (1996), Driesprong, Jacobsen and Maat (2008) and Narayan and Sharma (2011) who document a negative relationship between the oil price and the stock market, we find that the uncertainty in the oil market also negatively affects the stock prices.

Finally, the results of Model 2 show that the stock market uncertainty has a dominant effect in every industry as well as in the entire universe of stocks, as a greater portion of stocks are significantly affected by S&P 500 index uncertainty; while based on Model 2, 18.8% of the stocks in the entire market are exposed to the S&P 500 index uncertainty, only 12.4% and 8.5% of them are exposed to the oil and gold uncertainty. This finding suggests that the stock market uncertainty is related to the overall economic outlook.

3.2. Cross-Sectional Evidence

In the previous section, we showed that a significant number of stocks are exposed to uncertainty originating from the stock, oil and gold markets. The question that now rises is whether stock holders are compensated for their exposure to these factors. Do three sources of uncertainty explain the cross section of expected stock returns? An increase in uncertainty represents an unpleasant outlook for uncertainty-averse agents. Consequently, a premium is expected for the assets that correlate with the *systematic* uncertainty factor.

To see whether stocks with various exposures to uncertainty innovations have different expected returns, we adopt the out-of-sample methodology of Harvey and Siddique (2000), Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013). We measure the relative exposure of a stock to the S&P 500 index, oil and gold uncertainty innovations with the parameter estimates $\hat{\delta}_i^{S\&P}, \hat{\delta}_i^{OIL}$ and $\hat{\delta}_i^{GOLD}$, obtained from regression 12 to 14.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \delta_i^{S\&P} \Delta VRP_{S\&P,t} + \gamma_i^{S\&P} R_{S\&P,t} + \varepsilon_{i,t}, \tag{12}$$

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \delta_i^{OIL} \Delta VRP_{OIL,t} + \gamma_i^{OIL} R_{OIL,t} + \varepsilon_{i,t}, \tag{13}$$

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \delta_i^{GOLD} \Delta VRP_{GOLD,t} + \gamma_i^{GOLD} R_{GOLD,t} + \varepsilon_{i,t}. \tag{14}$$

We estimate $\hat{\delta}_i^{S\&P}$, $\hat{\delta}_i^{OIL}$ and $\hat{\delta}_i^{GOLD}$ for each stock in each month using 1-month non-overlapping rolling-windows on the daily time series of stock returns. Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013) also use 1-month rolling-windows, as it creates a good balance between the precision and the conditionality of the estimated factor loadings.

For each month, we run regression 12 to 14 and sort stocks three times based on their loadings on the uncertainty innovations (i.e. $\hat{\delta}_i^{S\&P}$, $\hat{\delta}_i^{OIL}$ or $\hat{\delta}_i^{GOLD}$). For each of the uncertainty measure, we form five independent value-weighted exposure portfolios, such that the first exposure portfolio (P1) contains of one fifth of stocks with the smallest loadings, and the fifth exposure portfolio (P5) holds one fifth of stocks with the largest loadings. We record the return of these portfolios over the subsequent month. Therefore, we can compare the performance of five portfolios with different levels of exposure to the uncertainty innovations. We roll the window one month ahead and repeat the same procedure. This process results in a total of 15 portfolios; five portfolios sorted on $\hat{\delta}_i^{S\&P}$, five portfolios sorted on $\hat{\delta}_i^{OIL}$ and five portfolios sorted on $\hat{\delta}_i^{GOLD}$.

In order to obtain sufficient cross-sectional dispersion in exposures, we include all the ordinary common shares in the CRSP database, from January 1996 to December 2013. Stocks with missing observations in a particular month are excluded from the analysis of that month. Table 4 reports the performance measure of the exposure portfolios in terms of the average monthly return and different alpha values. In this table, P5-P1 is a self-financing long-short portfolio that invests in P5 and short-sells P1.

*****INSERT TABLE 4 ABOUT HERE*****

In this table, Panel A shows the performance of the uncertainty exposure portfolios of the S&P 500 index, and Panel B and C are dedicated to the oil and gold markets uncertainty. The performance measures of exposure portfolios in Panel B and C do not display an increasing pattern from P1 to P5. In other words, there is no significant relationship between the exposure to oil or gold price uncertainty and the expected stock returns. Moreover, the P5-P1 portfolio does not yield any significant return or alpha, implying that the uncertainty in the oil or gold market is not a market-wide priced risk factors.

These results contrast with the clear pattern obtained for the S&P 500 index uncertainty, in Panel A. The portfolios sorted on $\hat{\delta}_{S\&P}$ display monotonically increasing average monthly returns. The P5-P1 portfolio yields 0.52% on a monthly basis, which translates into an economically significant value of 6.24% per year. This excess return of P5 over P1 is statistically significant, based on the t-statistics adjusted with the Newey-West (1987) technique, and it remains economically and statistically significant even when we orthogonalize it to the Fama-French and momentum factors. Therefore, S&P 500 index uncertainty is a market-wide priced risk factor.

According to Narayan and Sharma (2011) oil return shocks affect firms with different sizes, distinctively. To examine the robustness of our results with respect to firm sizes, we implement a double sorting procedure; in each month, first, we sort and categorize the stock universe in three size terciles and then within each tercile, we form five portfolios sorted on stocks' conditional uncertainty loadings, obtained from regression equations 12 to 14. The performance measures of the double-sorted portfolios are presented in Table 5.

*****INSERT TABLE 5 ABOUT HERE*****

The return on the P5-P1 portfolio of the S&P 500 index uncertainty is always positive, and it is rather stronger for large capitalization firms. In the smallest size tercile, the premium for the S&P 500 index uncertainty appears insignificant but still positive. This insignificance of the premium can be explained by the lower reliability of the estimated loadings for small firm. In conclusion, the stock market uncertainty remains as a market-wide priced risk factor, even after controlling for firm sizes.

However, the return or the alpha of P5-P1 portfolios is never significantly positive for any of the size terciles, reported in Panel B and C of Table 5. Hence for no size tercile, the exposure to oil or gold uncertainty yields a significantly positive return, confirming that uncertainty in the oil and gold markets are not priced factors. Remarkably, the oil uncertainty premium is found to be negative for the small firms segment, which is against economic intuition and can be caused by less reliable loading estimations for the small capitalization stocks.

We find strong evidence that innovations in variance risk premium or uncertainty of the S&P 500 index is a priced risk factor and explains the cross section of expected stock returns. This finding is consistent with theory and economic intuition. A stock that yields a negative return, when systematic uncertainty increases, is not a good hedge for uncertainty-averse investors. Therefore based on the intertemporal CAPM of Merton (1973), this stock must be compensated with higher expected returns. On the other hands, although oil and gold price uncertainty contemporaneously negatively covary with a large portion of stocks, these linkages across markets do not exist at the expected return level, because oil and gold price uncertainty are not systematic factors. These results confirm the findings of Bali and Zhou (2015) that the S&P 500 index uncertainty is a market-wide priced risk factor, and in addition, show that the nature of uncertainty matters.[7] Oil and gold uncertainty factors are asset-specific, idiosyncratic and diversifiable. Stock market uncertainty, however, represents

[7] Our methodology diverges from Bali and Zhou (2015) in several ways. First to find the uncertainty premia in stocks cross section, we use the whole CRSP universe, rather than portfolios of stocks, sorted on size and book-to-market ratio. Second to obtain the conditional exposures and form the portfolios, we rely on past realized correlations, while Bali and Zhou (2015) adopt a seemingly unrelated regression method together with a dynamic conditional covariance estimation. Thirdly, unlike them who use monthly observations, we run all our analysis with daily time series. Finally, we use the 3-month option-implied information instead of the 1-month VIX. Despite the differences in our approach, we obtain similar results.

a systematic uncertainty factor that affects the whole economy, and is relevant for the cross section of expected stock returns.

3.3. Market Segmentation and Industry Effect

Another important avenue to study is whether oil and gold uncertainty are sector-specific priced risk factors. The time series regressions of section 3.1 showed that oil and gold uncertainty news are more relevant for certain industries. Because of this heterogeneity across different industries, we investigate the three uncertainty risk premia within each industry in Table 6. The "Agriculture, Forestry and Fishing" industry is excluded as it has less than 20 stocks, and therefore, its cross-sectional dispersion cannot provide meaningful and interpretable results. The conditional uncertainty loadings are computed using regression equations 12 to 14. Since there are fewer stocks in each industry, we split the cross section of the industries into three value-weighted exposure portfolios.

*****INSERT TABLE 6 ABOUT HERE*****

This more granular analysis shows that in every industry the exposure to the S&P 500 index uncertainty is compensated with a positive return. Moreover, although our previous analysis showed that oil price uncertainty is not a priced risk factor in the whole cross section of stock expected returns, Table 6 reveals that there is a significantly positive compensation for bearing oil price uncertainty risk within three of the industries. In comparison with oil price uncertainty, gold price uncertainty is never priced in any industry.

The three industries where oil uncertainty is priced are "Construction", "Transportation, Communications, Electric, Gas and Sanitary Service", and "Finance, Insurance and Real Estate". For the first two sectors oil price is a key input for the core of the economic activity and for the latter oil has become an importance investment vehicle. This relevance was also highlighted by the time series regressions that showed, in these industries, higher proportions of stocks are significantly exposed to the oil uncertainty risk. Therefore, oil uncertainty is priced within oil dependent industries.

There are two explanations, why the premium for oil uncertainty is only identifiable in certain industries. The first explanation is related to econometric factors. In a cross-sectional test, in order to be able to detect a significant risk premium a sufficient dispersion among different observations, in our case exposure to uncertainty, is necessary. If all assets are virtually equally exposed to a risk factor, this factor can be priced but not be statistically identifiable.[8] This interpretation suggests that in non-oil-relevant industries even if there is an oil-specific uncertainty premium, stocks are so homogeneously exposed to it that it is hard to detect such a premium.

This line of reasoning also explains the absence of a gold price uncertainty premium. Although certain sectors are relatively more exposed to gold price uncertainty, no gold uncertainty premium is detected in any industry. Stocks are exposed to gold uncertainty because it captures some variations in the macro-economic environment. However apart from the firms involved in the actual trading of gold, firms' exposure to gold price uncertainty is negligible.

The second and more economic reason relates to the segmentation of markets. Cavaglia, Brightman and Aked (2000) find that over years, while the market has become more integrated and global diversification has declined, industry diversification has increased. Hong, Torous and Valkanov (2007) and Hong and Stein (2007) argue that a considerable portion of investors are industry specialized, who pay no attention or are unable to interpret the information from the markets that they do not specialize in. These investors only slowly become aware of events in related industries. Menzy and Ozbas (2010) and Cohen and

[8] For instance as Borgers, Derwall, Koedijk and Ter Horst (2015) show, the sin stock premium can only be detected for sin stock funds and not standard mutual funds. Because the latter funds are homogeneous with respect to their "sin exposure". Also Ben-Rephael, Kadan and Wohl (2008) cannot identify the liquidity premium among large stocks, which are all fairly liquid.

Frazzini (2008) show that news are reflected with different speed and accuracy in different industries.

Similarly, investors specialized and concentrated in an oil-relevant industry are more aware of the impact of oil on their investment. These investors do not diversify oil uncertainty in their portfolio, and therefore, it directly affects their marginal utility. This is also in line with Driesprong, Jacobsen and Maat (2008) and Narayan and Sharma (2011), who find that oil price information is incorporated faster in stock prices of oil-relevant industries. Also, Pollet (2005) shows that the impact of oil price predictability is misevaluated or incorporated slowly for non-oil-relevant industries. Hence, the impact of oil price uncertainty is only evaluated properly for oil-relevant industries but not in the expected return of the stocks in other industries.

4. Concluding Remarks

Escalating uncertainty is generally accompanied with declining stock prices, because, when uncertainty escalates stock valuation and investment decision making becomes more difficult. Uncertainty-averse investors require a premium for investing on the stocks that are exposed to *systematic* uncertainty risk. We identify stock market uncertainty, as a systematic factor that is priced in the entire cross section of stock expected returns, and therefore, it is an important factor for investment in any stock. Oil price uncertainty, however, is a sector-specific factor that must be considered for investment in the oil-relevant industries. Finally, gold price uncertainty is neither priced across nor within any particular industry.

Appendix A

Theoretically, the BKM methodology is only applicable to European options. However Bakshi, Kapadia and Madan (2003) argue that, due to the ignorable early-exercise premium of OTM options, using American options does not change the results notably. Still to be on the safe side, we convert all the American options of our database to their European counterparts. To do so, following Trolle and Schwartz (2009), we adjust the prices by deducting the early-exercise premia, measured by the Barone-Adesi and Whaley (1987) procedure.

To implement the BKM methodology, for each day we need a fine continuum of OTM European options with different strike prices. We consider the put options whose underlying price is more than 97% of their strike price, and the call options whose underlying price is less than 103% of their strike price, as OTM options. Also due to illiquidity concerns, we eliminate put options with moneyness $\left(\frac{S(t)}{K}\right)$ values more than 1.5 and call options with moneyness $\left(\frac{S(t)}{K}\right)$ values less than 0.5. The last two rows in Table 1 show the number of the OTM option contracts that we used for calculating the 90-day risk-neutral variance expectation.

On each day, only a few OTM call and put options are traded. Hence to be able to compute the integrals more accurately, we fit a natural cubic spline to the Black-Scholes implied volatility of the available options. Therefore we can compute implied volatilities and options prices, for every moneyness value $\left(\frac{S(t)}{K}\right)$ from 0.01 to 2.01. Price of OTM options with moneyness values outside these boundaries are negligible. In line with Chang, Christoffersen and Jacobs (2013), for moneyness values above the highest available moneyness and below the lowest available moneyness, we assume that the implied volatility is constant and equal to the implied volatility of the highest moneyness and the lowest moneyness, respectively.

Option contracts with exactly 90 days to maturity are not traded on every day. Therefore to calculate each day's risk-neutral variance with a constant horizon of 90 days, we calculate the risk-neutral variances of the two closest maturities shorter and longer than 90 days, and then interpolate between these two variance values. More details about the implementation are available upon request.

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Table 1 –Data Summary Statistics

This table provides some information about the futures contracts and the options, written on the future contracts of the S&P 500 index, West Texas Intermediate crude oil and 100-oz gold bar. We obtain this data from the Commodity Research Bureau database.

Panel A: Futures Contracts

	S&P 500 index	Oil	Gold
Exchange	CME	NYMEX	COMEX
First Date	21/04/1982	30/03/1988	31/12/1974
Last Date	31/12/2013	31/12/2013	31/12/2013
Trading Months	March, June, September, December	Every Month	February, April, June, August, October, December

Panel B: Option Contracts

		S&P 500 index			Oil			Gold		
First Date			28/01/1983			16/01/1989			01/09/1988	
Last Date			31/12/2013			31/12/2013			31/12/2013	
Observations Before Cleaning			4,355,473			6,505,303			10,162,803	
	Year	Total	Calls	Puts	Total	Calls	Puts	Total	Calls	Puts
Observations After Cleaning	1983	6,440	3,405	3,035	0	0	0	0	0	0
	1984	6,985	3,728	3,257	0	0	0	0	0	0
	1985	8,621	4,388	4,233	0	0	0	0	0	0
	1986	12,067	6,002	6,065	0	0	0	0	0	0
	1987	19,165	9,696	9,469	0	0	0	0	0	0
	1988	16,480	7,755	8,725	40	20	20	443	219	224
	1989	17,771	8,905	8,866	11,552	5,595	5,957	19,156	10,601	8,555
	1990	19,470	9,111	10,359	32,712	16,356	16,356	38,644	19,354	19,290
	1991	20,845	9,483	11,362	38,766	21,004	17,762	37,787	18,961	18,826
	1992	21,145	9,658	11,487	28,268	14,729	13,539	37,158	18,574	18,584
	1993	22,549	10,274	12,275	32,775	17,824	14,951	56,946	28,478	28,468
	1994	21,343	9,912	11,431	38,727	22,136	16,591	52,933	26,560	26,373
	1995	36,409	18,155	18,254	46,492	28,088	18,404	55,221	27,613	27,608
	1996	44,792	21,831	22,961	58,489	33,165	25,324	67,730	33,869	33,861
	1997	40,240	19,245	20,995	45,681	25,750	19,931	54,270	28,019	26,251
	1998	40,657	20,230	20,427	43,172	24,499	18,673	51,938	26,806	25,132
	1999	41,950	20,416	21,534	79,222	43,836	35,386	78,405	39,209	39,196
	2000	72,786	33,720	39,066	141,773	71,291	70,482	100,119	50,033	50,086
	2001	73,334	32,803	40,531	131,174	72,382	58,792	97,898	48,920	48,978
	2002	77,613	36,832	40,781	140,740	77,902	62,838	114,001	57,011	56,990
	2003	65,815	31,562	34,253	144,307	74,257	70,050	140,526	70,267	70,259
	2004	68486	33,318	35,168	207,566	101,443	106,123	164,952	82,461	82,491
	2005	76,055	36,020	40,035	352,751	171,342	181,409	186,782	93,403	93,379
	2006	111,375	45,476	65,899	387,624	193,751	193,873	304,068	152,012	152,056
	2007	150,453	55,582	94,871	419,028	216,838	202,190	291,847	145,954	145,893
	2008	197,637	87,644	109,993	813,726	416,054	397,672	378,149	189,043	189,106
	2009	174,061	80,224	93,837	783,286	406,853	376,433	458,061	229,073	228,988
	2010	183,706	89,522	94,184	642,025	340,485	301,540	925,373	464,596	460,777
	2011	309,518	155,511	154,007	675,634	354,199	321,435	1,386,915	693,676	693,239
	2012	337,200	168,511	168,689	700,938	371,861	329,077	1,657,902	828,837	829,065
	2013	363,152	181,649	181,503	507,227	270,695	236,532	1,692,184	846,092	846,092
	Total	2,658,120	1,260,568	1,397,552	6,503,695	3,392,355	3,111,340	8,449,408	4,229,641	4,219,767
OTM Options Used for Calculating 90-Day Risk-Neutral Volatility (1996 -2013)	Total	409,977	229,431	180,546	314,152	208,467	105,685	420,993	285,715	135,278
	Average Per Day	90.46	50.62	39.84	69.61	46.19	23.42	93.35	63.35	30.00

Figure 1 – Variance Risk Premia Time Series

We proxy the variance risk premium (VRP) as the ex-post return of a synthetic variance swap contract, written on the S&P 500 index, West Texas Intermediate crude oil and 100-oz gold bar. We exploit the return of the variance swap contracts from the futures contracts and the option contracts, written on each of these assets. The time to maturity of the synthetic variance swap contracts is 90 days. The Y-axes show the return on the variance swap contracts and have quadratic dimensions.

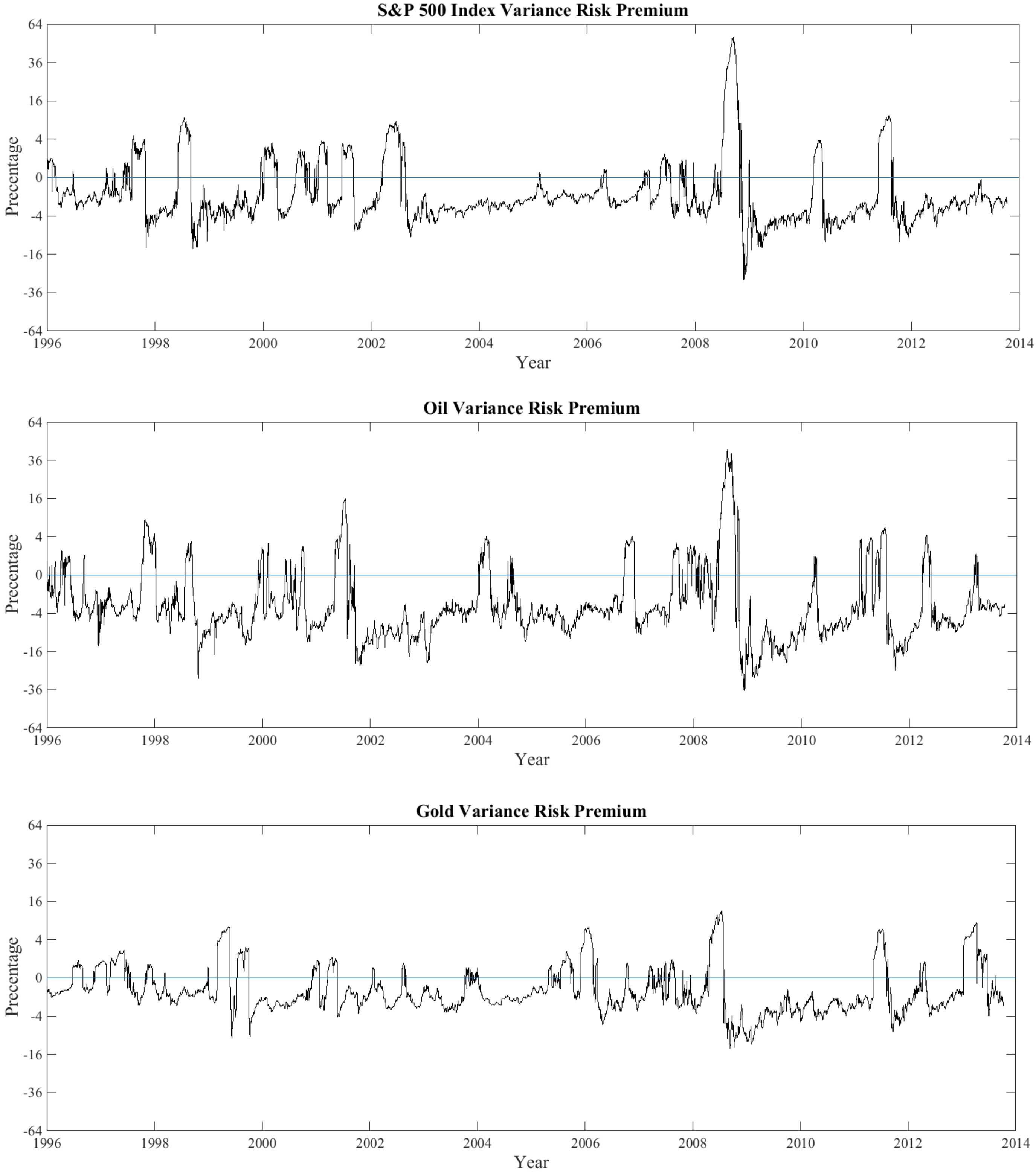


Table 2 – Descriptive Statistics on Variance Risk Premia

We proxy the variance risk premium (VRP) as the ex-post return of a synthetic variance swap contract, written on the S&P 500 index, West Texas Intermediate crude oil and 100-oz gold bar. We exploit the return of the variance swap contracts from the futures contracts and the option contracts, written on each of these assets. The time to maturity of the synthetic variance swap contracts is 90 days. We take the residuals of three ARMA(1, 1) processes, fitted to the VRP time series, as the VRP innovations. The t-statistics are shown in parentheses.

Statistics			**Variance Risk Premium**		
			S&P 500	**Oil**	**Gold**
Number of Observations			4099	4393	4338
Mean (%)			-1.25	-4.37	-0.95
			(-13.70)	(-42.56)	(-23.68)
Standard Deviation (%)			5.82	6.81	2.64
Percentiles					
5^{th} Percentile (%)			-6.60	-15.11	-4.75
25^{th} Percentile (%)			-3.18	-7.19	-2.00
Median (%)			-1.71	-3.87	-0.95
75^{th} Percentile (%)			-0.50	-1.56	-0.12
95^{th} Percentile (%)			5.17	3.14	4.19
Fitted ARMA(1,1) Parameters					
Autoregressive			0.988	0.981	0.979
			(411.71)	(338.38)	(305.84)
Moving-average			-0.112	0.010	0.169
			(-7.30)	(0.67)	(10.70)
Correlations					
Oil			0.60		
Gold			0.48	0.37	
Principal Component Decomposition					
	Standard Deviation	Proportion of Variance (%)		Correlation	
PC1	1.41	65.9%	0.87	0.82	0.74
PC2	0.80	21.4%	0.15	0.44	0.65
PC3	0.62	12.7%	0.47	0.37	0.14
Innovations Correlations					
Oil			0.23		
Gold			0.18	0.16	

Table 3 – Contemporaneous Effect of Uncertainty Innovation on Stock Prices

This table reports the number of stocks which have significantly or insignificantly (at 95% confidence level), positive or negative exposure to the VRP innovations of the three different asset classes, namely the S&P 500 index, oil and gold. Eq. 8 to 11 describe these models.

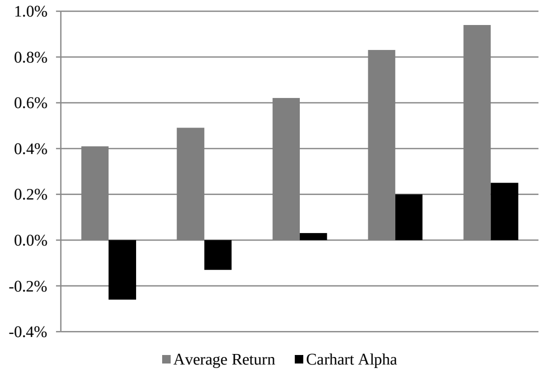
Industry	**Model 1**						**Model 2**					
	S&P 500 Index		**Oil**		**Gold**		**S&P 500 index**		**Oil**		**Gold**	
Entire Stock Market							Number of Stocks = 8330					
Significantly Positive	**1942**	**23.3%**	**1873**	**22.5%**	**1489**	**17.9%**	**1562**	**18.8%**	**1032**	**12.4%**	**705**	**8.5%**
Insignificantly Positive	3803	45.7%	4960	59.5%	4770	57.3%	4010	48.1%	5730	68.8%	5203	62.5%
Insignificantly Negative	2380	28.6%	1419	17.0%	1987	23.9%	2557	30.7%	1501	18.0%	2344	28.1%
Significantly Negative	205	2.5%	78	0.9%	84	1.0%	201	2.4%	67	0.8%	78	0.9%
Agriculture, Forestry and Fishing							Number of Stocks = 17					
Significantly Positive	**4**	**23.5%**	2	11.8%	0	0.0%	**3**	**17.60%**	2	11.80%	0	0.00%
Insignificantly Positive	7	41.2%	11	64.7%	15	88.2%	7	41.20%	11	64.70%	12	70.60%
Insignificantly Negative	5	29.4%	4	23.5%	2	11.8%	6	35.30%	4	23.50%	5	29.40%
Significantly Negative	1	5.9%	0	0.0%	0	0.0%	1	5.90%	0	0.00%	0	0.00%
Mining							Number of Stocks = 387					
Significantly Positive	**193**	**49.9%**	**164**	**42.4%**	**135**	**34.9%**	**180**	**46.5%**	**90**	**23.3%**	**28**	**7.2%**
Insignificantly Positive	136	35.1%	169	43.7%	178	46.0%	144	37.2%	243	62.8%	241	62.3%
Insignificantly Negative	57	14.7%	53	13.7%	70	18.1%	62	16.0%	53	13.7%	113	29.2%
Significantly Negative	1	0.3%	1	0.3%	4	1.0%	1	0.3%	1	0.3%	5	1.3%
Construction							Number of Stocks = 86					
Significantly Positive	**24**	**27.9%**	**20**	**23.3%**	**17**	**19.8%**	**21**	**24.4%**	**15**	**17.4%**	**8**	**9.3%**
Insignificantly Positive	41	47.7%	50	58.1%	42	48.8%	37	43.0%	50	58.1%	49	57.0%
Insignificantly Negative	18	20.9%	15	17.4%	27	31.4%	25	29.1%	20	23.3%	29	33.7%
Significantly Negative	3	3.5%	1	1.2%	0	0.0%	3	3.5%	1	1.2%	0	0.0%
Manufacturing							Number of Stocks = 2893					
Significantly Positive	**687**	**23.7%**	**622**	**21.5%**	**430**	**14.9%**	**537**	**18.60%**	**325**	**11.20%**	**204**	**7.10%**
Insignificantly Positive	1360	47.0%	1841	63.6%	1710	59.1%	1466	50.70%	2111	73.00%	1789	61.80%
Insignificantly Negative	788	27.2%	409	14.1%	729	25.2%	830	28.70%	440	15.20%	877	30.30%
Significantly Negative	58	2.0%	21	0.7%	24	0.8%	60	2.10%	17	0.60%	23	0.80%
Transportation, Communications, Electric, Gas and Sanitary Service							Number of Stocks = 619					
Significantly Positive	**177**	**28.6%**	**173**	**27.9%**	**120**	**19.4%**	**152**	**24.60%**	**100**	**16.20%**	33	5.30%
Insignificantly Positive	283	45.7%	357	57.7%	371	59.9%	305	49.30%	430	69.50%	417	67.40%
Insignificantly Negative	151	24.4%	86	13.9%	121	19.5%	153	24.70%	86	13.90%	165	26.70%
Significantly Negative	8	1.3%	3	0.5%	7	1.1%	9	1.50%	3	0.50%	4	0.60%
Wholesale Trade							Number of Stocks = 296					
Significantly Positive	**61**	**20.6%**	**64**	**21.6%**	**33**	**11.1%**	**51**	**17.20%**	**34**	**11.50%**	17	5.70%
Insignificantly Positive	141	47.6%	173	58.4%	195	65.9%	149	50.30%	201	67.90%	207	69.90%
Insignificantly Negative	90	30.4%	59	19.9%	62	20.9%	94	31.80%	61	20.60%	66	22.30%
Significantly Negative	4	1.4%	0	0.0%	6	2.0%	2	0.70%	0	0.00%	6	2.00%
Retail Trade							Number of Stocks = 442					
Significantly Positive	**72**	**16.3%**	**63**	**14.3%**	**71**	**16.1%**	**52**	**11.80%**	22	5.00%	**35**	**7.90%**
Insignificantly Positive	215	48.6%	288	65.2%	286	64.7%	223	50.50%	323	73.10%	320	72.40%
Insignificantly Negative	144	32.6%	86	19.5%	82	18.6%	157	35.50%	94	21.30%	84	19.00%
Significantly Negative	11	2.5%	5	1.1%	3	0.7%	10	2.30%	3	0.70%	3	0.70%
Finance, Insurance and Real Estate							Number of Stocks = 2126					
Significantly Positive	**430**	**20.2%**	**500**	**23.5%**	**512**	**24.1%**	**326**	**15.30%**	**309**	**14.50%**	**310**	**14.60%**
Insignificantly Positive	895	42.1%	1077	50.7%	1138	53.5%	916	43.10%	1261	59.30%	1292	60.80%
Insignificantly Negative	703	33.1%	512	24.1%	455	21.4%	786	37.00%	521	24.50%	501	23.60%
Significantly Negative	98	4.6%	37	1.7%	21	1.0%	98	4.60%	35	1.60%	23	1.10%
Services							Number of Stocks = 1464					
Significantly Positive	**294**	**20.1%**	**265**	**18.1%**	**171**	**11.7%**	**240**	**16.40%**	**135**	**9.20%**	70	4.80%
Insignificantly Positive	725	49.5%	994	67.9%	835	57.0%	763	52.10%	1100	75.10%	876	59.80%
Insignificantly Negative	424	29.0%	195	13.3%	439	30.0%	444	30.30%	222	15.20%	504	34.40%
Significantly Negative	21	1.4%	10	0.7%	19	1.3%	17	1.20%	7	0.50%	14	1.00%

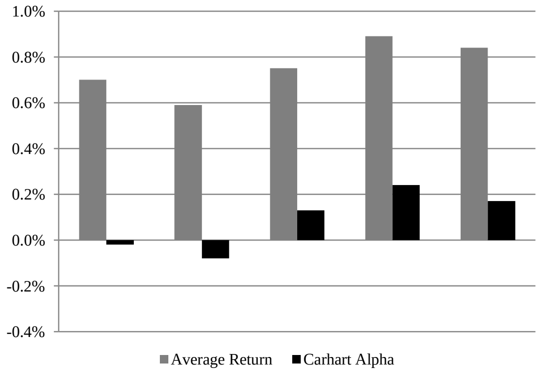
Table 4 – Expected Return of Uncertainty Exposure Portfolios

At the end of each month, we sort the stocks based on their exposers to uncertainty innovations (obtained from regression equations 12 to 14), and form five value-weighted portfolios. We refer to these portfolios as exposure portfolios, and record the daily returns of these portfolios over the month after. By repeating the same algorithm over the whole data sample, we achieve fifteen portfolio return time series. We report the portfolios' average exposers to uncertainty innovations, the average monthly expected returns and the different alpha values of these VRP innovation exposure portfolios. In order to obtain the monthly estimations for the returns and alpha values, the daily returns are multiplied by 21. The t-statistics, shown in parentheses, are adjusted with the Newey-West technique that controls for auto-correlation in the time series.

	Panel (A): S&P 500 Index					**Panel (B): Oil**					**Panel (C): Gold**				
Exposure Portfolios	Average $\delta_i^{S\&P}$	Expected Return: Average Return	Alpha: CAPM	Alpha: Fama-French	Alpha: Carhart	Average δ_i^{OIL}	Expected Return: Average Return	Alpha: CAPM	Alpha: Fama-French	Alpha: Carhart	Average δ_i^{GOLD}	Expected Return: Average Return	Alpha: CAPM	Alpha: Fama-French	Alpha: Carhart
P1	-3.90	0.41	-0.34	-0.35	-0.26	-1.35	0.70	-0.05	-0.14	-0.02	-5.20	0.86	0.15	0.08	0.11
		(0.83)	(-1.78)	(-2.04)	(-1.46)		(1.44)	(-0.28)	(-0.78)	(-0.13)		(1.84)	(0.86)	(0.47)	(0.70)
P2	-1.28	0.49	-0.11	-0.12	-0.13	-0.44	0.59	-0.05	-0.07	-0.08	-1.68	0.82	0.23	0.21	0.18
		(1.36)	(-1.34)	(-1.39)	(-1.52)		(1.60)	(-0.51)	(-0.81)	(-0.88)		(2.28)	(2.48)	(2.28)	(1.95)
P3	-0.01	0.62	0.07	0.06	0.03	0.00	0.75	0.17	0.16	0.13	0.05	0.65	0.10	0.10	0.07
		(1.88)	(0.95)	(0.82)	(0.36)		(2.18)	(2.17)	(2.16)	(1.82)		(1.96)	(1.41)	(1.38)	(0.97)
P4	1.25	0.83	0.25	0.22	0.20	0.46	0.89	0.27	0.25	0.24	1.81	0.67	0.07	0.06	0.07
		(2.36)	(2.76)	(2.52)	(2.24)		(2.48)	(2.84)	(2.76)	(2.59)		(1.80)	(0.71)	(0.67)	(0.75)
P5	3.82	0.94	0.24	0.14	0.25	1.37	0.84	0.11	0.10	0.17	5.42	0.54	-0.21	-0.26	-0.13
		(2.06)	(1.28)	(0.77)	(1.35)		(1.83)	(0.59)	(0.56)	(0.90)		(1.05)	(-1.03)	(-1.29)	(-0.63)
P5-P1	7.72	**0.52**	**0.58**	**0.49**	**0.51**	2.72	0.14	0.16	0.24	0.19	10.62	-0.32	-0.36	-0.33	-0.24
		(1.85)	**(2.08)**	**(1.76)**	**(1.74)**		(0.48)	(0.57)	(0.83)	(0.65)		(-1.07)	(-1.24)	(-1.15)	(-0.82)

Graph





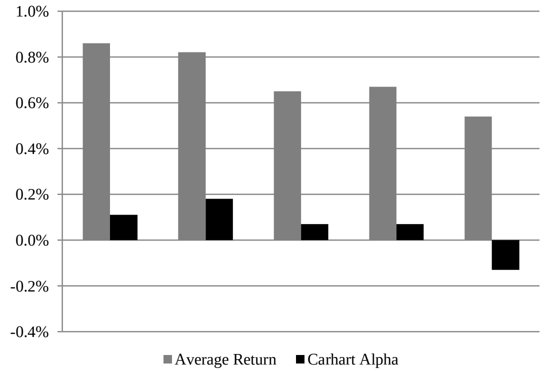


Table 5 – Expected Return of Uncertainty Exposure Portfolios for Small, Medium and Large Firms

Using the same methodology as we used for Table 4, we report the average of δ_i, the average monthly expected return and various alpha values of the exposure portfolios, segregated for small, medium and large firms. In order to obtain the monthly estimations for the returns and alpha values, the daily returns are multiplied by 21. The t-statistics, shown in parentheses, are adjusted with the Newey-West technique that controls for auto-correlation in the time series.

Size	Exposure Portfolios	**Panel (A): S&P 500 Index**					**Panel (B): Oil**					**Panel (C): Gold**				
		Average $\delta_i^{S\&P}$	Expected Return				Average δ_i^{OIL}	Expected Return				Average δ_i^{Gold}	Expected Return			
			Average Return	Alpha				Average Return	Alpha				Average Return	Alpha		
				CAPM	Fama-French	Carhart			CAPM	Fama-French	Carhart			CAPM	Fama-French	Carhart
Small	**P1**	-6.57	1.26	0.84	0.60	0.72	-2.29	1.52	1.08	0.82	0.95	-9.09	1.47	1.06	0.80	0.90
			(2.40)	(2.27)	(2.07)	(2.54)		(2.97)	(3.04)	(2.99)	(3.62)		(2.95)	(3.07)	(2.92)	(3.46)
	P2	-1.66	1.25	0.94	0.75	0.81	-0.58	1.25	0.93	0.74	0.79	-2.33	1.30	1.00	0.80	0.86
			(3.33)	(3.64)	(3.62)	(4.05)		(3.44)	(3.72)	(3.80)	(4.19)		(3.56)	(3.98)	(4.02)	(4.46)
	P3	0.06	1.16	0.91	0.76	0.80	0.03	1.33	1.06	0.89	0.94	0.12	1.18	0.93	0.75	0.79
			(3.80)	(4.29)	(4.43)	(4.77)		(4.31)	(4.99)	(5.25)	(5.62)		(3.79)	(4.29)	(4.35)	(4.64)
	P4	1.81	1.29	0.98	0.80	0.87	0.66	1.30	0.98	0.80	0.86	2.63	1.27	0.96	0.76	0.82
			(3.54)	(3.93)	(4.04)	(4.43)		(3.46)	(3.72)	(3.72)	(4.08)		(3.26)	(3.54)	(3.49)	(3.81)
	P5	6.73	1.34	0.95	0.74	0.84	2.41	1.12	0.71	0.50	0.59	9.50	1.38	0.98	0.74	0.84
			(2.72)	(2.72)	(2.66)	(3.10)		(2.22)	(1.96)	(1.71)	(2.04)		(2.67)	(2.66)	(2.51)	(2.92)
	P5-P1	13.29	0.08	0.11	0.14	0.12	4.70	**-0.41**	**-0.37**	**-0.32**	**-0.36**	18.59	-0.09	-0.08	-0.06	-0.06
			(0.47)	(0.65)	(0.83)	(0.72)		**(-2.38)**	**(-2.15)**	**(-1.90)**	**(-2.11)**		(-0.59)	(-0.50)	(-0.35)	(-0.38)
Medium	**P1**	-4.93	0.64	-0.04	-0.35	-0.22	-1.71	1.01	0.29	-0.05	0.07	-6.53	0.98	0.30	-0.07	0.06
			(1.14)	(-0.15)	(-2.11)	(-1.47)		(1.81)	(1.01)	(-0.32)	(0.51)		(1.77)	(1.07)	(-0.43)	(0.41)
	P2	-1.40	0.86	0.31	0.00	0.08	-0.47	1.04	0.46	0.14	0.21	-1.72	0.94	0.40	0.06	0.13
			(2.03)	(1.51)	(0.01)	(0.76)		(2.48)	(2.29)	(1.31)	(2.06)		(2.24)	(1.97)	(0.50)	(1.27)
	P3	-0.06	0.84	0.37	0.09	0.13	-0.01	0.88	0.37	0.08	0.14	0.06	0.79	0.31	0.00	0.05
			(2.31)	(2.07)	(0.92)	(1.42)		(2.35)	(2.01)	(0.79)	(1.35)		(2.14)	(1.70)	(0.03)	(0.51)
	P4	1.27	1.03	0.49	0.20	0.27	0.46	0.89	0.33	0.04	0.10	1.86	0.94	0.40	0.09	0.15
			(2.45)	(2.42)	(1.84)	(2.63)		(2.15)	(1.66)	(0.35)	(0.98)		(2.19)	(1.91)	(0.79)	(1.41)
	P5	4.76	1.03	0.37	0.07	0.19	1.71	0.82	0.12	-0.18	-0.05	6.74	1.02	0.33	-0.01	0.11
			(1.91)	(1.34)	(0.43)	(1.21)		(1.47)	(0.41)	(-0.96)	(-0.27)		(1.79)	(1.13)	(-0.06)	(0.64)
	P5-P1	9.69	**0.39**	**0.42**	**0.42**	**0.40**	3.42	-0.19	-0.17	-0.13	-0.12	13.27	0.04	0.03	0.06	0.05
			(2.39)	**(2.60)**	**(2.62)**	**(2.43)**		(-1.12)	(-1.01)	(-0.76)	(-0.69)		(0.24)	(0.18)	(0.34)	(0.27)
Large	**P1**	-3.18	0.31	-0.41	-0.39	-0.34	-1.10	0.60	-0.13	-0.18	-0.09	-4.23	0.74	0.04	0.00	0.01
			(0.67)	(-2.50)	(-2.46)	(-2.08)		(1.31)	(-0.76)	(-1.09)	(-0.57)		(1.65)	(0.26)	(0.00)	(0.07)
	P2	-1.04	0.54	-0.06	-0.05	-0.08	-0.36	0.59	-0.03	-0.03	-0.05	-1.35	0.85	0.28	0.27	0.24
			(1.48)	(-0.65)	(-0.55)	(-0.83)		(1.64)	(-0.35)	(-0.38)	(-0.58)		(2.43)	(2.92)	(2.91)	(2.50)
	P3	-0.02	0.65	0.11	0.10	0.07	0.00	0.71	0.12	0.12	0.09	0.02	0.64	0.10	0.10	0.07
			(1.97)	(1.29)	(1.32)	(0.89)		(2.06)	(1.48)	(1.55)	(1.12)		(1.91)	(1.21)	(1.25)	(0.83)
	P4	0.99	0.77	0.20	0.19	0.16	0.36	0.87	0.26	0.26	0.24	1.41	0.57	-0.01	0.00	-0.00
			(2.17)	(2.08)	(2.01)	(1.73)		(2.46)	(2.67)	(2.83)	(2.61)		(1.62)	(-0.08)	(0.05)	(-0.03)
	P5	3.06	0.89	0.22	0.16	0.23	1.10	0.86	0.15	0.16	0.21	4.31	0.61	-0.11	-0.11	-0.00
			(2.08)	(1.45)	(1.03)	(1.51)		(2.00)	(0.95)	(1.07)	(1.29)		(1.28)	(-0.67)	(-0.66)	(-0.02)
	P5-P1	6.25	**0.58**	**0.64**	**0.55**	**0.57**	2.21	0.25	0.28	0.34	0.30	8.54	-0.12	-0.16	-0.11	-0.01
			(2.23)	**(2.46)**	**(2.14)**	**(2.15)**		(0.94)	(1.04)	(1.29)	(1.09)		(-0.45)	(-0.58)	(-0.42)	(-0.05)

Table 6 – Expected Return of Uncertainty Exposure Portfolios for Different Industries

Using the same methodology as we used for Table 4, we split the cross section of each industry into three different exposure portfolios. Then we report the average monthly expected return and various alpha values of the high minus low exposure portfolios. In order to obtain the monthly estimations for the returns and alpha values, the daily returns are multiplied by 21. The t-statistics, shown in parentheses, are adjusted with the Newey-West technique that controls for auto-correlation in the time series.

Industry	**Performance Measure**	**Panel (A): S&P 500 Index**		**Panel (B): Oil**		**Panel (C): Gold**	
Mining	Average Return	0.44	(1.05)	0.24	(0.75)	-0.01	(-0.02)
	CAPM Alpha	0.43	(1.05)	0.24	(0.74)	-0.09	(-0.27)
	Fama-French Alpha	0.41	(0.98)	0.26	(0.81)	-0.10	(-0.29)
	Carhart Alpha	0.43	(1.01)	0.23	(0.72)	-0.09	(-0.29)
Construction	Average Return	**0.86**	**(2.23)**	**1.53**	**(2.91)**	0.66	(1.33)
	CAPM Alpha	**0.92**	**(2.40)**	**1.57**	**(2.94)**	0.72	(1.42)
	Fama-French Alpha	**0.88**	**(2.38)**	**1.52**	**(2.96)**	0.70	(1.43)
	Carhart Alpha	**0.80**	**(2.14)**	**1.55**	**(2.95)**	0.76	(1.45)
Manufacturing	Average Return	0.43	(1.53)	0.28	(0.84)	-0.24	(-0.87)
	CAPM Alpha	**0.51**	**(1.84)**	0.29	(0.86)	-0.27	(-0.96)
	Fama-French Alpha	0.45	(1.51)	0.33	(0.94)	-0.23	(-0.80)
	Carhart Alpha	0.42	(1.27)	0.28	(0.75)	-0.15	(-0.50)
Transportation, Communications, Electric, Gas and Sanitary Service	Average Return	0.38	(1.48)	**0.72**	**(2.03)**	-0.15	(-0.52)
	CAPM Alpha	0.40	(1.55)	**0.71**	**(2.00)**	-0.18	(-0.63)
	Fama-French Alpha	0.37	(1.38)	**0.74**	**(2.00)**	-0.16	(-0.58)
	Carhart Alpha	0.42	(1.56)	**0.73**	**(1.90)**	-0.15	(-0.51)
Wholesale Trade	Average Return	**0.48**	**(1.65)**	-0.16	(-0.43)	0.14	(0.35)
	CAPM Alpha	**0.53**	**(1.70)**	-0.13	(-0.37)	0.14	(0.38)
	Fama-French Alpha	**0.55**	**(1.72)**	-0.10	(-0.27)	0.15	(0.40)
	Carhart Alpha	**0.57**	**(1.71)**	-0.09	(-0.23)	0.20	(0.52)
Retail Trade	Average Return	0.10	(0.38)	0.03	(0.12)	-0.12	(-0.46)
	CAPM Alpha	0.14	(0.54)	0.03	(0.12)	-0.11	(-0.44)
	Fama-French Alpha	0.15	(0.58)	0.04	(0.17)	-0.10	(-0.38)
	Carhart Alpha	0.14	(0.52)	0.01	(0.05)	-0.12	(-0.46)
Finance, Insurance and Real Estate	Average Return	**0.31**	**(1.74)**	**0.34**	**(1.67)**	-0.27	(-1.10)
	CAPM Alpha	**0.34**	**(2.04)**	**0.36**	**(1.72)**	-0.31	(-1.31)
	Fama-French Alpha	**0.32**	**(2.00)**	**0.41**	**(1.83)**	-0.31	(-1.36)
	Carhart Alpha	**0.31**	**(1.83)**	**0.41**	**(1.85)**	-0.24	(-1.01)
Services	Average Return	0.12	(0.41)	-0.05	(-0.19)	-0.18	(-0.64)
	CAPM Alpha	0.16	(0.56)	-0.05	(-0.17)	-0.20	(-0.69)
	Fama-French Alpha	0.11	(0.36)	0.01	(0.05)	-0.19	(-0.68)
	Carhart Alpha	0.13	(0.43)	0.02	(0.07)	-0.12	(-0.43)