Do Oil Futures Prices Predict Stock Returns?*

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October 18, 2016

*We thank seminar participants at Sacred Heart University for helpful comments.

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Abstract

This paper explores stock return predictability by exploiting the cross-section of oil *futures* prices. Motivated by the principal component analysis, we find the curvature factor of the oil futures curve predicts monthly stock returns: a 1% per month increase in the curvature factor predicts 0.4% per month decrease in stock market index return. This predictive pattern is prevailing in non-oil industry portfolios, but is absent for oil-related portfolios. The in- and out-of-sample predictive power of the curvature factor for non-oil stocks is robust and outperforms many other predictors, including oil *spot* prices. The predictive power of the curvature factor comes from its ability to forecast supply-side oil shocks, which only affect non-oil stocks and are hedged by oil-related stocks.

JEL: G12; G13; G17

Keywords: Oil; Futures; Predictability; Curvature; Futures Curve.

1 Introduction

This paper studies the stock return predictability by an array of oil futures contracts. We intend to answer three empirical questions: do oil *futures* prices contain information regarding future stock returns? Is the stock return predictability by oil-related factors present in all stocks or limited to certain stocks? Do oil-related predictors outperform other conventional predictors, such as dividend yield, interest rates, among others, in and out of sample?

We extend the existing stock return predictability literature by exploiting the cross section of oil futures prices, and examine whether the shape of futures curve helps predict stock returns. Motivated by principal component analysis results, we identify a new predictor—the curvature factor of the oil futures curve—with strong and robust forecasting power. In the entire 1983–2014 sample of monthly observations, a 1% per month increase in the curvature factor predicts 0.4% per month decrease in stock market index return. Step-ahead forecasts by expanding-window regressions generate a statistically significant out-of-sample R^2 of 2.3%. The predictive power of the new curvature factor is stronger and more robust than conventional predictors, including spot oil prices. This result is prevailing in non-oil stocks but absent in oil-related industry and sub-sectors, and can be attributed to the non-oil stocks' vulnerability to supply-side oil shocks.

Intuitively, the price of crude oil is an important economic variable. Oil is a major global resource and is a significant input for many industrial sectors. While there is a large literature that corroborates its importance to the macroeconomy and documents a strong link between oil prices and economic output,[1] attempts to find a link between oil and the stock market have been less successful. Earlier studies, such as Chen, Roll, and Ross (1986) and Huang, Masulis, and Stoll (1996), find virtually no relation between oil price and U.S. stock market returns. Not until recently do researchers (for example, Jones and Kaul (1996), Sadorsky (1999), Kilian and Park (2009), Chiang, Hughen, and Sagi (2015), and Ready (2016)) find a stronger link between the two markets, and it appears to be non-linear and time-varying.

These new findings suggest time-variation in investment opportunity sets may be captured by variation in oil prices. Indeed, existing studies show that *spot* oil price returns predict stock returns: Driesprong, Jacobsen, and Maat (2008) find that monthly stock returns tend to be lower after monthly oil price increases, and higher after oil price decreases. Hong, Torous, and Valkanov (2007) show that petroleum industry return, among others, forecasts monthly stock returns by up to two months. Fan and Jahan-Parvar (2012) find that while the overall U.S. stock market is predicted by oil price returns, this predictability is concentrated in a relatively small number of industries. Similarly, Narayan and Sharma (2011) find this predictability is confined to 25% of firms. On the other hand, Casassus and Higuera (2012) find that oil price changes strongly predict excess stock returns at quarterly

[1] For example, Hamilton (2003) finds a strong negative relation between oil price increases and U.S. GDP growth.

horizons. These studies find the oil-predictability relation is statistically significant and negative for the U.S. stock market; that is, an increase in oil price this period significantly predicts lower stock returns next period. Driesprong, Jacobsen, and Maat (2008) find this predictive pattern only exists in non-oil stocks and is absent in oil stocks. For this pattern they propose an under-reaction explanation, which argues that investors have difficulty in assessing the impact of oil price information on the value of non-oil stocks, whose prices reflect new oil price information only after some delay.

While the above studies present an interesting and seemingly robust negative relation between lagged *spot* oil price changes and stock returns, they ignore the information content in the oil *futures* contracts with various maturities. As futures prices are forward-looking and reflect potentially informative economic outlooks, we conjecture they matter in predicting stock returns. Intuitively, futures prices contain important information about oil risk, information that may not be contained in the spot price, that could impact firms' future earnings. For example, suppose that a firm is unable to fully hedge against oil shocks and its net earnings are affected by oil prices, perhaps because the firm uses oil in its production and manufacturing processes or because its customers' spending and confidence are sensitive to oil prices. In this case, changes in expected future earnings depend on changes in expected future oil prices. To the extent that oil futures prices move in response to changing expectations about future oil prices, the firm's returns should therefore depend on oil futures price returns. Furthermore, if information in oil price changes is reflected in stock returns only after some delay, then it is likely that the information in changes in oil futures prices is also reflected in stock returns only after some delay. Hence, we conjecture that the stock return predictability by oil futures is more pronounced in non-oil stocks than in oil-related stocks.

The main contribution of this paper is to uncover a new stock return predictor—the oil curvature factor—by exploiting the cross-section of highly liquid oil futures contracts, and identify the channel through which it predicts stock returns. This curvature factor has rich statistical, empirical, and economic implications. Statistically, it is a linear combination of oil futures returns with fixed weights motivated by the third principal component extracted from oil futures contracts, and that linear combination resembles the curvature of the futures curve. As the weights are pre-determined and free of estimation, the curvature factor is not subject to look-ahead bias and hence can be used to forecast stock returns in real time. This estimation-free feature is empirically and practically compelling. Economically, curvature positively predicts supply-side oil shocks which are negatively related with stock returns for non-oil companies. On the other hand, oil-related companies have natural hedge against supply-side oil shocks, and thus their stock returns are less predictable by the curvature factor.

The paper is organized as follows. In Section 2 we discuss the data and describe the basic regression model. In Section 3 we present the results using the principal components constructed from futures price returns. We present our curvature factor and document its ability to forecast stock returns in Section 4, and we explore possible channels through which it predicts returns in Section 5. We conclude in Section 6.

2 Data and Empirical Model

2.1 Data

We obtain daily WTI light crude oil futures prices as reported on NYMEX from Datastream. The first six monthly maturity contracts began trading in March 1983; longer maturity contracts did not trade regularly until later dates, with much lower liquidity and potentially less informative prices. Therefore, we use the first six contracts for the period March 1983 to December 2014 in our analysis.

Following the term structure of interest rates literature (e.g., Litterman and Scheinkman (1991), and Knez, Litterman, and Scheinkman (1994)), we extract the first three principal components for monthly oil futures returns (monthly differences in log futures prices). These three components account for 99.9% of the variation in futures returns and suggest that futures prices have a pronounced factor structure. Figure 1 plots the loadings of the first three principal components. The first principal component ("PC_1") has the familiar level pattern of loadings, the loadings on the second principal component ("PC_2") have a strongly downward tilt, and the loadings of the third principal component ("PC_3") have a pronounced hump shape.

The predictability literature so far has studied the predictive power of spot oil price return ("Spot"), typically proxied by the return on the nearby contract: $\Delta \ln F_1$, where F_n is the n-month oil futures price; see for example, Driesprong, Jacobsen, and Maat (2008). In this paper we uncover the stock return predictability by the curvature factor of the oil futures curve ("Curv"), defined as $(\Delta \ln F_2 - \Delta \ln F_1) - (\Delta \ln F_6 - \Delta \ln F_3)$. We motivate this predictor by a pre-diagnosis using principal components in Section 3. As Figure 1 demonstrates, its composition closely resembles that of the third principal component.[2]

Panel A of Table 1 reports the summary statistics of spot and curvature factors, along with the first three principal components. Panel B of Table 1 reports the correlations between the two predictors and the principal components. The table shows that the monthly oil price return is about 1.9% per annum, its standard deviation is 32.6% per annum, and it features weakly positive autocorrelation. The first principal component has similar positive autocorrelation, and is more volatile than the oil price return. The oil price return is very highly correlated with the first principal component, with correlation over 98%. The curvature factor has mean close to zero (−0.1% per annum), moderate standard deviation (5.6% per annum), very low autocorrelation, and is highly correlated with the third principal component with correlation almost 90%.

[2] The weights of the curvature factor in Figure 1 are halved for illustrative purpose.

Our stock return data consist of monthly observations of the CRSP value-weighted market return, and 49 value-weighted industry-level returns which include an overall oil industry return, from Kenneth French's online library at Dartmouth College; see Kenneth French's website for industry name abbreviations. To further examine oil industries, we also include four Datastream indexes of stocks in oil subsectors: Oil & Gas ("OG"), Oil & Gas Exploration & Production ("OGEP"), Integrated Oil & Gas ("IOG"), and Oil Equipment & Services ("OES"). This sample selection results in a total of 54 test assets: one market index return, 48 non-oil industry returns, and five oil-related industry and subsector returns. Summary statistics of stock returns are available upon request.

2.2 Predictive regression model

We investigate the ability of oil futures prices to forecast stock returns. The basic regression model is

$$R_t = a + b^\top X_{t-1} + \epsilon_t, \tag{1}$$

where R_t is the return of the portfolio under consideration over month t, a is a constant, X_{t-1} represents the predictor variables observed at month $t-1$, and ϵ_t is the usual error term. We test the significance of the slope coefficients, b. Following Driesprong, Jacobsen, and Maat (2008), we use heteroskedasticity consistent

(White) standard errors to test statistical significance;[3] in addition, we use actual return as dependent variable, and we obtain nearly identical results when we use excess return instead (results are available upon request).

3 Pre-diagnosis: Principal Components

To investigate the possibility that futures prices contain forecasting information, we first examine the abilities of the oil futures returns' principal components to forecast the aggregate stock market as a pre-diagnosis. Unlike raw futures prices, the principal components are orthogonal to each other and hence allow for cleaner side-by-side comparison between predictors. Furthermore, as argued in Ludvigson and Ng (2007), principal components allow the information from a large cross-section of predictive variables, in this case futures prices, to be effectively incorporated. We focus on the first three principal components since they explain virtually all (99.9%) of the cross-sectional variation in futures returns, as Section 2 suggests. We estimate the regression (1) using the CRSP value-weighted market return as dependent variable and each of the three components as predictor variables using the entire sample period. The in-sample results are reported in Table 2. The third principal component is the only component that has statistically significant loading, with predictive coefficient -0.713 and t-ratio -2.16. The second component

[3] We obtain essentially identical main results using heteroskedasticity and autocorrelation consistent standard errors (e.g., Newey-West); this is because neither the dependent variable (stock return) nor our key predictor (Curvature) is serially correlated.

has no predictive ability, and while the first explains 0.9% of the variation of stock market returns its loading is not significant at conventional levels.

Note that, with correlation of 98.4%, the first principal component closely resembles spot oil return. Yet, we find no statistically significant relation between stock returns and lagged first principal component. This is somewhat surprising given the findings of previous research. Indeed, when we use the spot oil return to forecast market returns in the entire sample we find the loading is -0.041 (with t-ratio -1.37), a loading less than half the loading documented in Driesprong, Jacobsen, and Maat (2008). Exploring this further, we estimate the regression (1), with spot oil return as the forecasting variable, using expanding windows. The initial window is 120 months, May 1983 to April 1993; the second window is 121 months, May 1983 to May 1993; the third window is 122 months, May 1983 to June 1993; and so on. The t-ratios of the predictive coefficients of these expanding window regressions, depicted in Figure 2, are striking. For windows ending prior to late 2008, the loadings are significantly negative. For example, on the window ending August 2008 the loading is -0.094 with t-ratio -3.62. But for windows ending early 2009 or later the loadings are no longer significant at conventional levels; for example, on the window ending January 2009 the loading is -0.055 with t-ratio -1.38.

In contrast, when the third principal component is used as predictor variable in the expanding window regressions, the loadings become more significant over time, especially so in early 2009, about the time that the spot oil return's forecasting ability deteriorates; see Figure 2. Of course, the principal components are computed ex post and hence are subject to "look-ahead" bias. We address this issue in the following section, where we introduce a fixed linear combination of futures prices, closely related to the third principal component, that significantly predicts stock returns without suffering from look-ahead bias.

4 Stock Return Predictability by the Curvature

4.1 The Curvature Factor

An investor looking to exploit the predictive ability of the principal components would need to recompute the components every period, using only the futures data available at the actual time she makes her forecast. The loadings of the computed principal components, and thus the components' values, on a given date change as more data become available. Furthermore, principal component analysis assumes the covariance matrix of futures returns is constant. Empirical evidence refutes this assumption; for example, it is well documented that futures returns are strongly heteroscedastic (e.g., Duffie, Gray, and Hoang (1995), and Chiang, Hughen, and Sagi (2015)).

We sequentially compute principal components for futures returns using expanding windows (with initial window of 120 months) and examine the loadings for

PC_3 over time. While there is some variability in the loadings, on average they are closely proportional to $\omega \equiv [-1\,1\,1\,0\,0\,-1]^\top$ for the futures contract with maturities from one to six months. Applying ω to the *levels* of log prices of the six futures contracts obtains a measure $(-\ln F_1 + \ln F_2 + \ln F_3 - \ln F_6)$ that has the interpretation of curvature of the futures curve, as it is "short-term slope" $(\ln F_2 - \ln F_1)$ minus "long-term slope" $(\ln F_6 - \ln F_3)$ of the futures term structure. As the principal components are extracted from *changes*, instead of levels, of futures prices, we define our "curvature factor" as $(\Delta \ln F_2 - \Delta \ln F_1) - (\Delta \ln F_6 - \Delta \ln F_3)$, as described previously. The correlation between the sequentially computed third principal component and the curvature factor (Curv) is 84.5%, which is comparable to the full sample estimate (89.6%). Below we assess the predictive power of the curvature factor for stock returns, and we relate it to oil shocks in Section 5.

4.2 In-sample Predictability for the Market Index

We first examine whether the curvature factor predicts overall stock market return. We find that it strongly predicts negative CRSP stock market index return in and out of sample. As shown in Table 3, in the entire 5/1983–12/2014 sample, a 1% increase in the curvature factor leads to 0.405% *decrease* in stock market index return, with t-ratio of -3.08. As the standard deviation of the curvature factor is 5.65% per annum, a one standard deviation increase leads to 2.28% decrease in annual market index return.

We observe similar patterns when we split the sample into two equal-length samples: 5/1983–2/1999 and 3/1999–12/2014. The predictive regression coefficients are -0.318 and -0.553 for the first and second sub-periods, respectively, and both are statistically significant. Interestingly, the predictive power of the curvature factor is stronger in the recent sub-period. Figure 2 depicts the time series of the sequentially computed t-ratios from the expanding window regressions that use the curvature factor as the forecasting variable. The predictive power of the curvature factor has generally increased over time, and its loading is significant (at the 5% level) for all of the expanding windows ending October 2001 or later. In particular, the loadings on the curvature factor become even more significant for windows ending early 2009, about the time the loadings on spot oil return become insignificant.

To check the robustness of this predictability in relation to contemporaneous correlations of stock returns with spot oil returns and the curvature factor, we include the contemporaneous curvature factor and spot oil return as explanatory variables. These variables allow us to check whether movements in spot and curvature factors are reflected in stock returns instantly; Driesprong, Jacobsen, and Maat (2008) conduct similar test using only the spot factor. We also include lagged spot oil return and lagged market return to check whether these variables subsume the predictive ability of the curvature factor. Finally, to determine whether the predictability survives more than one lag we also include the two-month lagged curvature factor as an additional explanatory variable in the regression.[4] The results are reported in Table 4. Loading on lagged curvature is still very significant: -0.486, with t-ratio of -2.53, *over and above* the spot oil return, along with other explanatory variables. Interestingly, the loading on *contemporaneous* curvature is also negative: -0.454, but only statistically significant at the 10% level. This negative yet weak correlation conforms to the under-reaction explanation by Driesprong, Jacobsen, and Maat (2008), but now the relevant information variable is the curvature factor. Furthermore, the loading on two-month lagged curvature is not significant; thus predictability is short-lived.

4.3 Out-of-sample Predictability for the Market Index

To further examine the robustness of the in-sample results, we next conduct an out-of-sample test by using an expanding estimation window to produce step-ahead forecasts of stock returns. The procedure is similar to the one used to generate the results in Figure 2, but now for each window ending in month t, in which $\{R_s\}_{s=2}^{t}$ is regressed on $\{\text{Curv}_s\}_{s=1}^{t-1}$, we use the estimated coefficients $\hat{a}_t$ and $\hat{b}_t$ to construct the step-ahead forecast

$$\hat{R}_{t+1} = \hat{a}_t + \hat{b}_t \text{Curv}_t.$$

[4] We obtain essentially the same results when we include more lags. To conserve space, those results are not tabulated but available upon request.

Following the return predictability literature (Goyal and Welch (2008), Campbell and Thompson (2008), and Casassus and Higuera (2012), among others), we test the null hypothesis that the curvature factor has no predictive power by computing the out-of-sample R^2 statistic, defined by

$$R^2_{OS} = 1 - \frac{\sum_{t=T_1+1}^{T}(R_t - \hat{R}_t)^2}{\sum_{t=T_1+1}^{T}(R_t - \bar{R}_t)^2},$$

where T_1 is the size of the initial window and $\bar{R}_t$ is the historical average forecast:

$$\bar{R}_{t+1} = \frac{1}{t}\sum_{s=1}^{t} R_s.$$

A positive R^2_{OS} indicates the curvature forecast outperforms the historical average forecast, and a negative R^2_{OS} indicates the opposite. McCracken (2007) shows that the R^2_{OS} statistic has non-standard asymptotic distribution and also provides asymptotically valid critical values to test the null hypothesis $R^2_{OS} \leq 0$ against the alternative $R^2_{OS} > 0$.[5]

We choose T_1 to be 190 months so that the size of the initial window is equal to the number of out-of-sample periods, as suggested by Casassus and Higuera

[5] The critical values are for the "OOS-F" statistic defined in Equation (3) of McCracken (2007), which in our analysis is given by

$$\text{OOS-F} = (T - T_1)\frac{\sum_{t=T_1+1}^{T}(R_t - \bar{R}_t)^2}{\sum_{t=T_1+1}^{T}(R_t - \hat{R}_t)^2} R^2_{OS}$$

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(2012), in order to achieve a reasonable level of power without producing excessive forecasting errors for earlier windows. The out-of-sample R^2_{OS} statistic is 2.35% (reported in Table 3), which according to McCracken (2007) is significantly positive at the 1% level.

Based on R^2_{OS}, our curvature factor rather strongly outperforms the historical average benchmark. In contrast, many of the predictor variables that have been examined in previous studies, including those with successful in-sample predictive ability, fail to outperform the historical average benchmark. For example, Goyal and Welch (2008) find that popular predictor variables, despite significant evidence of in-sample predictive ability, often display negative out-of-sample R^2_{OS} statistics. We investigate these variables in Section 4.5.

4.4 Industry Level Predictability

We now take a closer look at the predictability of the 48 non-oil industries, and the results are reported in Table 3. Consistent with the broad market evidence, we find that over the full sample period, 18/27/34 of the 48 predictive coefficients are significant at the 1%/5%/10% level, and *all* of the significant ones are negative. In terms of magnitude of the predictive coefficients, the top three predictable industries by the curvature factor are: textiles ("Txtls"), electronic equipment ("Chips"), and computers ("Hardw"), with predictive coefficients of -0.951, -0.867, and -0.854, respectively, and all of them are significant at the 1% level. In terms of R^2, the top three are retail ("Rtail"), restaurants ("Meals"), and textiles. Only two industries have positive predictive coefficients: precious metals ("Gold"; 0.347) and coal (0.051), and neither is significant. The negative relation between non-oil industry returns and lagged curvature remains largely consistent in the sub-periods, and usually stronger (more negative) in the second sub-sample. For example, the predictive coefficients for the entertainment industry ("Fun") are -0.389 and -1.013 in the first and second sub-samples, respectively.

The above results remain robust when we include contemporaneous curvature and spot oil return, lagged spot oil return, 2-month lagged curvature, and lagged industry return in regression: Table 4 shows the predictive regression coefficients are significant at the 5% level for 23 industries, and only 3 load significantly on 2-month lagged curvature. Among the industries significantly predictable by lagged curvature, all of them are negatively correlated with *contemporaneous* curvature, although only a handful of these correlations are significant at the 5% level. This evidence again conforms to the under-reaction explanation by Driesprong, Jacobsen, and Maat (2008), defined over the information content in the curvature factor. Furthermore, predictability is short-lived for industry portfolios.

Out-of-sample expanding-window regressions generate step-ahead forecasts with out-of-sample R^2_{OS} of 0.97% on average, and are significant at the 5% level for 25–more than half–of the non-oil industries. The results are reported in Table 3. Interestingly, in-sample and out-of-sample predictability concentrates on similar industries: of the 27 industries with significant in-sample loading, 22 have significant out-of-sample R^2_{OS}. More than one-third (17) of the non-oil industries have loadings that display in-sample significance across all sub-periods and display significant R^2_{OS}, with three industries, automobiles ("Autos"), retail ("Rtail"), and restaurants ("Meals"), displaying significance at the 1% level.

Lastly, we investigate the predictability of the oil-related stocks. We find no predictability for any of the 5 oil portfolios (the 4 Datastream portfolios and French's Oil industry portfolio): in-sample loadings are all insignificant, with t-ratios lower than 0.3, and the out-of-sample R^2_{OS}s are all negative.

4.5 Comparison with Other Predictors

Previous research (see Goyal and Welch (2008) for a comprehensive study) has identified several variables that exhibit, with various degrees of success, the ability to forecast stock returns, such as the valuation ratios DP (log dividend-price ratio), DY (log dividend yield), EP (log earnings-price ratio), and BM (book-to-market ratio); and the interest rate variables LTY (long-term Treasury yield), LTR (long-term Treasury return), TMS (Treasury yield spread), TBL (Treasury bill rate), and DFY (default yield spread). Below we compare the abilities of these nine variables to forecast stock returns with the forecasting abilities of the spot and the curvature factors.

We first estimate the regression equation (1) for each of these variables. The

t-ratios are reported in Table 5. Compared with Table 3, the oil curvature factor outperforms all of these variables both in terms of R^2 and number of significant predictive loadings. None of these variables has more than five, out of 54, predictive loadings that are significantly different than zero at the 5% level. None displays significant loading for the broad market portfolio. At the 10% significance level, the variable with the greatest number of significant loadings is DY with 12, followed by DP with 9, and then EP and LTR with 6 each. These variables, along with BM, also have the highest average R^2 across the 54 portfolios, with R^2 ranging from 0.3% for EP and BM to 0.5% for DP. The oil curvature factor, for comparison, has average R^2 equal to 1.5% and 10%-level significant loadings for 35 of the 54 portfolios.

We next examine the robustness of the oil curvature factor to the inclusion of these alternative predictive variables. For brevity, we consider the five variables with the highest average R^2: DY, DP, EP, LTR, and BM. The results are reported in Table 6. The forecasting performance of the oil curvature factor remains largely unscathed: 15/25/31 of the 54 curvature coefficients are significant at the 1%/5%/10% level. In contrast, the next best performing predictive variable, DY, displays 3/8/10 significant coefficients at the respective levels. In addition, none of the other variables displays significant coefficients at even the 10% level for the broad market portfolio, while the oil curvature factor coefficient does so at the 1% level.

Finally, we compute the Diebold and Mariano (1995) statistic to formally compare the return forecasts generated by the oil curvature factor with those generated by the alternative predictor variables. The Diebold-Mariano statistic dm is the ratio of the sample mean to the standard error of the loss differential–the difference between the squared forecast errors generated by an alternative predictor variable and the squared forecast errors generated by the oil curvature factor. A positive dm statistic indicates greater forecast error for the alternative variable. We compute the "in-sample" dm statistic for each of the nine alternative predictor variables and for the spot oil return, where the forecasts are generated using coefficients estimated on the entire sample period.[6]

The results are reported in Table 7. For the broad market portfolio, the dm statistic is positive for all ten alternative predictor variables and is significantly positive at the 10% level for the term structure variables TMS, TBL, and DFY. The results are similar for the 48 non-oil industry portfolios: overall, 76% (366 out of 480) of the dm statistics are positive, and for every alternative predictor variable $dm > 0$ for at least 75% of the industries. These results indicate that the forecasts of most of the non-oil industry returns generated by the curvature factor have lower squared forecast error than those generated by any of the alternative variables.

[6] Much of the literature computes an "out-of-sample" dm statistic, in which the forecasts are generated using coefficients sequentially estimated on expanding windows. However, in a recent paper, Diebold (2015) argues that tests based on the out-of-sample statistic are largely inferior to the test based on the in-sample dm statistic. For completeness, we repeat our analysis using the out-of-sample dm statistic with initial window size of 190 months; results are similar to the in-sample dm statistic and are available upon request.

The forecasts generated by the curvature factor especially outperform the forecasts generated by the alternative variables for the construction ("Cnstr"), fabricated products ("FabPr"), automobiles ("Autos"), computers ("Hardw"), computer software ("Chips"), retail ("Rtail"), restaurants ("Meals"), and real estate ("RlEst") industries. On the other hand, for the oil-related portfolios, the curvature factor generates forecasts with greater error than do the alternative variables, providing further evidence that the curvature factor does not forecast returns of oil-related portfolios.

5 Channels of Predictability

Oil futures prices reflect the risk-adjusted forecasts of oil prices and therefore move in response to changing expectations about future oil prices. Because oil futures returns are not all perfectly correlated, we conjecture that the shape of the oil futures return term structure, and in particular, the curvature factor, gives information about future spot oil returns. We examine this conjecture by estimating the regression equation (1) using spot oil return as dependent variable and the oil curvature factor as the independent variable. The estimated predictive coefficient is 0.878 with t-ratio 2.25 and the R^2 is 2.3%. Thus the curvature factor positively predicts spot oil return: an increase (decrease) in this month's curvature factor is followed by an increase (decrease) in next month's spot oil return.

A puzzling feature of oil prices is that they move largely independently of the stock market; for example, the correlation of spot oil return and the broad stock market return is 7.8% over the full sample period March 1983 to December 2014. Recent research, most notably Killian and Park (2009) and Ready (2016), suggests that this feature is due to the offsetting effects of two types of oil price shocks, those driven by demand concerns and those driven by supply concerns. Demand driven shocks represent oil price changes caused by changes in demand concerns; for example, during an economic boom oil prices typically increase as demand increases with overall production. Supply driven shocks, on the other hand, represent oil price changes caused by changes in supply concerns–such as concerns about future supply disruptions. Thus demand driven shocks should be positively related, while supply driven shocks should be negatively related, to stock market returns.

Ready (2016) develops a method for classifying oil price changes as supply or demand driven. The basic idea is that oil producers have a natural hedge against supply shocks. For example, when Iraq invaded Kuwait in August 1990, oil prices spiked but returns of oil producers in aggregate were little affected. This allows demand driven shocks to be constructed from an index of oil producing firms; demand shocks are defined to be the portion of the index returns that are orthogonal to innovations in the VIX index (included to control for aggregate changes in discount rates). Supply shocks are then defined as the portion of oil price changes that are orthogonal to both demand shocks and VIX innovations.

We follow this technique and decompose oil price shocks into supply and demand driven components. Consistent with Ready (2016), we find that about 78% of the variance in oil prices is classified as supply shocks and 21% is classified as demand shocks, with VIX innovations explaining the remaining 1% of the variance. More importantly, stock returns are related to the two types of shocks with the expected signs. The supply shocks have a strongly significant negative relation with the overall stock market return (with loading -0.107 and corresponding t-ratio -4.42), while the demand shocks have a strongly significant positive relation (with loading 0.434 and corresponding t-ratio 9.64). Moreover, with the exception of gold and coal, *all* non-oil industries are negatively related to supply shocks. Counter to intuition, those industries that are most sensitive are not those that heavily rely on oil as input to production but are instead those related to consumer expenditure, such as apparel, textiles, and retail. This suggests that non-oil firms are vulnerable to supply shocks primarily because of reduced consumer demand rather than higher production costs.

We then investigate whether the ability of the curvature factor to forecast oil price returns is concentrated in the supply component or the demand component. We estimate the predictive regression equation (1) with the curvature factor as independent variable and either supply shocks or demand shocks as dependent variable. We find that the curvature factor has little predictive power for demand shocks ($b = 0.090$ with t-ratio 0.69), but does significantly predict supply shocks

($b = 0.827$ with t-ratio 2.22, and R^2 2.6%).

Thus it appears the curvature factor contains information about future supply driven oil price shocks: increases in the curvature factor are typically followed by increases in supply driven shocks. Because these shocks are bad news for non-oil industries, the curvature factor negatively forecasts stock returns for all non-oil industries except gold and coal. This also explains why the predictive power of the curvature factor is greater for the retail and textiles industries, and, since by construction supply shocks are orthogonal to oil industry returns, why the curvature factor does not predict oil industries.

6 Conclusion

This paper studies the stock return predictability by an array of oil futures contracts, and examines three empirical questions: Do oil *futures* prices contain information regarding future stock returns? Is the stock return predictability by oil-related factors present in all stocks or limited to certain stocks? Do oil-related predictors outperform other conventional predictors, such as dividend yield, interest rates, among others, in and out of sample?

To answer the first question, we examine the stock return predictability by the principal components extracted from returns of six highly liquid oil futures contracts. The pre-diagnosis motivates the key predictor of this paper—the curvature factor, which strongly predicts the market index return, *over and above* the spot factor. A 1% increase in curvature predicts 0.4% decrease in stock market return at monthly frequency. The stock return predictability by the curvature factor is prevailing in and out of sample, and over and above contemporaneous or stale (lagged two or more months) oil information.

To answer the second question, we replicate the above analysis using industry level data. We find the predictability is concentrated on non-oil industries, and we uncover very little predictability in the oil industry and its sub-sectors. The industries that appear to be most strongly predicted are those that have high sensitivities to supply driven oil shocks.

The answer to the third question is yes, at least with respect to the conventional predictors. We compare the forecasting ability of the curvature factor with that of nine conventional predictors using out-of-sample R-squared and Diebold-Mariano statistics. Our results show that curvature indeed outperforms other predictors in the majority of instances, concentrating in non-oil industries.

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Table 1: Summary Statistics

Panel A reports the numbers of monthly observations (obs), means (in percentages), standard deviations (in percentages), and first-order autocorrelations of five variables: spot oil return (Spot $\equiv \Delta \ln F_1$), the first three principal components (PC_1, PC_2, and PC_3) constructed from all oil futures returns, and in the curvature (Curv$\equiv \Delta \ln F_2 + \Delta \ln F_3 - \Delta \ln F_1 - \Delta \ln F_6$). Panel B reports the correlations between these variables.

Panel A: Summary Statistics

Variable	Obs	Mean (%)	StDev (%)	AR(1)
Spot	381	1.88	32.56	0.187
PC_1	381	4.85	70.06	0.210
PC_2	381	0.57	8.16	−0.091
PC_3	381	−0.13	2.57	−0.176
Curv	381	−0.08	5.62	−0.143

Panel B: Correlations

	Spot	PC_1	PC_2	PC_3	Curv
Spot	1	0.984	−0.175	−0.040	0.398
Curv	0.398	0.440	−0.004	0.896	1

Table 2: Aggregate Stock Market Returns and Lagged Principal Components

Estimation results of the predictive regression $R_t = a + bX_{t-1} + \epsilon_t$ for the CRSP value-weighted market return using each of the principal components (PC_1, PC_2, and PC_3) as predictor variable. t-ratios are based on White standard errors.

Predictor	b	t-ratio	R^2 (%)
PC_1	-0.021	-1.52	0.9
PC_2	-0.042	-0.35	0.0
PC_3	-0.713	-2.16	1.4

Table 3: Stock Returns and Lagged Curvature

Estimation results of the predictive regression $R_t = a + b\,\mathrm{Curv}_{t-1} + \epsilon_t$ for the different stock portfolios with the curvature factor $\mathrm{Curv} \equiv \Delta \ln F_2 + \Delta \ln F_3 - \Delta \ln F_1 - \Delta \ln F_6$ as predictor variable. Columns 2–7 report in-sample results and the final column reports the out-of-sample R^2_{OS}. "*" denotes significance at 10% level, "**" denotes significance at the 5% level, and "***" denotes significance at the 1% level. Significance of the predictive loading b is determined using White standard errors. Significance of R^2_{OS} is determined using the critical values reported in McCracken (2007).

	May 1983—Dec 2014		May 1983—Feb 1999		Mar 1999—Dec 2014		OOS
	b	R^2 (%)	b	R^2 (%)	b	R^2 (%)	R^2_{OS} (%)
Market	-0.405***	2.2	-0.318**	1.9	-0.553**	2.8	2.3***
Agric	-0.247	0.4	-0.397*	1.6	0.012	0.0	-0.5
Food	-0.227	0.7	-0.382	2.0	0.044	0.0	-1.4
Soda	-0.475**	1.3	-0.411*	1.2	-0.581	1.4	1.2*
Beer	-0.236	0.6	-0.219	0.5	-0.260	0.7	0.4
Smoke	-0.177	0.2	-0.235	0.4	-0.077	0.0	-0.3
Toys	-0.658***	2.5	-0.494*	1.7	-0.939**	4.1	3.1***
Fun	-0.619***	1.8	-0.389*	1.2	-1.013**	2.8	1.8**
Books	-0.331*	0.9	-0.418*	2.2	-0.176	0.2	-0.2
Hshld	-0.190	0.5	-0.206	0.6	-0.160	0.3	0.1
Clths	-0.670**	2.8	-0.627*	3.1	-0.744*	2.5	2.1***
Hlth	-0.113	0.1	-0.597**	2.5	0.717*	2.5	-3.2
MedEq	-0.324**	1.0	-0.451**	2.0	-0.104	0.1	-0.6
Drugs	-0.249	0.7	-0.254	0.8	-0.233	0.6	0.3
Chems	-0.258	0.5	-0.191	0.5	-0.372	0.7	0.2
Rubr	-0.570***	2.4	-0.405*	1.8	-0.852**	3.4	2.4***
Txtls	-0.951***	3.8	-0.542*	2.6	-1.657***	6.1	4.1***
BldMt	-0.477**	1.5	-0.425*	1.9	-0.564	1.3	1.1**
Cnstr	-0.751***	3.1	-0.728***	4.2	-0.792*	2.2	2.0***
Steel	-0.570**	1.3	-0.315	0.9	-1.009*	2.1	1.1**
FabPr	-0.653***	2.3	-0.619***	3.9	-0.710	1.5	1.3**
Mach	-0.567***	2.0	-0.382*	1.5	-0.886**	2.8	1.9***
ElcEq	-0.457**	1.3	-0.399*	1.5	-0.553	1.3	0.9**
Autos	-0.832***	3.2	-0.555***	2.8	-1.305***	4.3	3.2***
Aero	-0.414*	1.2	-0.335*	1.1	-0.549	1.4	0.7*
Ships	-0.428*	0.8	-0.574**	2.3	-0.183	0.1	-0.6
Guns	-0.146	0.1	-0.118	0.1	-0.194	0.2	-0.2
Gold	0.347	0.3	0.336	0.3	0.364	0.2	0.0
Mines	-0.542**	1.2	-0.560**	2.4	-0.512	0.6	0.4
Coal	0.051	0.0	-0.155	0.2	0.401	0.2	-0.4
Util	-0.049	0.0	-0.124	0.4	0.081	0.1	-0.6

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	May 1983—Dec 2014		May 1983—Feb 1999		Mar 1999—Dec 2014		OOS
	b	R^2 (%)	b	R^2 (%)	b	R^2 (%)	R^2_{OS} (%)
Telcm	-0.343*	1.2	-0.171	0.5	-0.633	2.6	1.3**
PerSv	-0.342**	0.8	-0.529**	2.4	-0.019	0.0	-0.8
BusSv	-0.550***	2.8	-0.537**	3.6	-0.571*	2.1	2.0***
Hardw	-0.854***	3.1	-0.493*	1.8	-1.473**	5.4	3.5***
Softw	-0.773***	2.5	-0.766**	2.7	-0.779	2.1	1.8**
Chips	-0.867***	3.2	-0.560**	2.2	-1.393**	4.8	3.3***
LabEq	-0.551**	1.6	-0.583**	2.8	-0.496	0.8	0.4
Paper	-0.159	0.2	-0.205	0.5	-0.080	0.0	-0.4
Boxes	-0.351	0.9	-0.251	0.6	-0.524	1.4	0.8**
Trans	-0.539***	2.7	-0.407*	1.9	-0.765**	4.0	3.1***
Whlsl	-0.264*	0.7	-0.367*	1.8	-0.086	0.1	-0.5
Rtail	-0.704***	4.5	-0.668***	4.4	-0.763***	4.6	4.5***
Meals	-0.642***	4.2	-0.532**	3.3	-0.831***	5.8	4.8***
Banks	-0.451*	1.4	-0.368	1.3	-0.589	1.7	1.3**
Insu	-0.335*	1.0	-0.374*	1.9	-0.265	0.4	0.0
RlEst	-0.676***	2.5	-0.682***	5.0	-0.670*	1.3	1.2**
Fin	-0.596***	2.2	-0.443**	2.2	-0.856*	2.5	1.8**
Other	-0.690***	2.9	-0.581**	2.5	-0.876*	3.4	2.8***
OG	0.014	0.0	0.037	0.0	-0.025	0.0	-0.2
OGEP	0.014	0.0	-0.021	0.0	0.071	0.0	-0.3
IOG	0.020	0.0	0.011	0.0	0.037	0.0	-0.2
OES	0.065	0.0	0.242	0.3	-0.243	0.1	-0.5
Oil	0.025	0.0	0.018	0.0	0.038	0.0	-0.2

Table 4: Robustness Checks

Estimation results of the predictive regression $R_t = a + b^\top X_{t-1} + \epsilon_t$ for the different stock portfolios using one-month lagged curvature Curv_{t-1} and spot oil return Spot_{t-1}, contemporaneous curvature Curv_t and spot oil return Spot_t, two-month lagged in curvature Curv_{t-2}, and lagged portfolio return R_{t-1} as independent variables. "*" denotes significance at 10% level, "**" denotes significance at the 5% level, and "***" denotes significance at the 1% level. Significance is determined using White standard errors.

	Curv_{t-1}	Spot_{t-1}	Curv_t	Spot_t	Curv_{t-2}	R_{t-1}
Market	-0.486***	-0.025	-0.454*	0.084**	-0.080	0.071
Agric	-0.373*	-0.005	-0.436	0.048	-0.187	-0.033
Food	-0.255	0.005	-0.096	-0.039	-0.253	0.010
Soda	-0.534*	0.036	0.055	-0.034	-0.042	0.031
Beer	-0.361**	0.042	-0.234	-0.054	-0.207	-0.023
Smoke	-0.192	-0.028	-0.088	0.017	-0.299	0.038
Toys	-0.805***	0.017	-0.411	0.022	-0.340	0.049
Fun	-0.754**	0.012	-0.368	0.066	-0.122	0.155**
Books	-0.463*	0.005	-0.660*	0.043	-0.186	0.086
Hshld	-0.259	0.007	-0.222	-0.020	-0.253	0.031
Clths	-0.690**	-0.009	-0.569	-0.001	-0.104	0.114*
Hlth	-0.272	0.022	-0.554*	0.020	-0.369	0.100*
MedEq	-0.357*	-0.029	-0.252	0.051	-0.133	0.059
Drugs	-0.254	-0.023	-0.299	-0.013	-0.097	-0.027
Chems	-0.431*	0.019	-0.408	0.073	-0.097	0.018
Rubr	-0.638**	0.003	-0.250	0.014	-0.152	0.026
Txtls	-1.107**	0.027	-0.524	0.021	-0.256	0.130
BldMt	-0.643**	0.003	-0.512	0.047	-0.370	0.037
Cnstr	-0.843***	-0.072	-0.690*	0.133**	-0.419*	0.065
Steel	-0.907***	-0.014	-0.838**	0.252***	-0.276	0.011
FabPr	-0.896***	0.030	-0.344	0.117*	-0.164	0.063
Mach	-0.665***	-0.047	-0.515	0.166***	0.047	0.065
ElcEq	-0.590 **	-0.025	-0.601**	0.079	-0.226	-0.034
Autos	-0.966***	-0.018	-0.625**	0.072	-0.275	0.090
Aero	-0.425*	-0.028	-0.189	0.030	-0.155	0.083
Ships	-0.499*	-0.028	0.123	0.076	-0.401	0.075
Guns	-0.279	0.045	0.139	-0.011	-0.384	0.051
Gold	0.289	-0.054	0.118	0.254***	-0.552**	-0.114*
Mines	-0.816***	-0.029	-0.516	0.268***	-0.355	-0.030
Coal	-0.381	-0.014	-0.817**	0.385***	-0.157	0.013
Util	-0.149	0.018	-0.074	0.019	-0.222	0.043
Telcm	-0.350*	-0.039	-0.381*	0.065*	0.036	0.072
PerSv	-0.246	-0.079**	-0.363	0.007	-0.145	-0.003

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	Curv_{t-1}	Spot_{t-1}	Curv_t	Spot_t	Curv_{t-2}	R_{t-1}
BusSv	-0.574***	-0.047	-0.416	0.083*	-0.074	0.065
Hardw	-0.885***	-0.057	-0.703*	0.140**	0.339	0.048
Softw	-0.708**	-0.089*	-0.704	0.129**	0.424	0.012
Chips	-0.900***	-0.073	-0.800**	0.154***	0.229	0.027
LabEq	-0.618**	-0.053	-0.669*	0.134**	-0.042	0.069
Paper	-0.300	0.025	-0.351	0.013	-0.183	-0.001
Boxes	-0.321	-0.049	-0.395	0.054	0.076	0.047
Trans	-0.620***	0.007	-0.448*	0.013	-0.107	0.069
Whlsl	-0.348**	-0.020	-0.441*	0.057	-0.233	0.075
Rtail	-0.668***	-0.024	-0.483*	-0.026	-0.026	0.072
Meals	-0.643***	-0.040	-0.328	0.005	-0.378**	0.079
Banks	-0.576*	0.016	-0.529	-0.003	-0.306	0.076
Insu	-0.383	0.003	-0.293	-0.033	-0.301	0.072
RlEst	-0.873***	0.007	-0.373	0.066	-0.584*	0.184**
Fin	-0.694***	-0.015	-0.701**	0.079	-0.103	0.128*
Other	-0.883***	-0.002	-0.859***	0.082*	-0.128	0.016
OG	-0.268	-0.004	-0.256	0.280***	-0.293*	-0.079
OGEP	-0.346	0.017	-0.177	0.373***	-0.308	-0.099
IOG	-0.165	-0.010	-0.145	0.205***	-0.283*	-0.10*
OES	-0.423	-0.015	-0.663	0.449***	-0.253	0.006
Oil	-0.252	-0.001	-0.239	0.274***	-0.280	-0.074

Table 5: Predictive Results with Commonly Used Predictive Variables

This table reports the t-ratios (based on White standard errors) corresponding to the loading b of the regression $R_t = a + bX_{t-1} + \epsilon_t$ using conventional predictive variables. The predictive variables used are i) log dividend-price ratio (DP), ii) log dividend yield (DY), iii) log earnings-price ratio (EP), iv) book-market ratio (BM), v) long-term Treasury yield (LTY), vi) Treasury yield spread (TMS), vii) Treasury bill rate (TBL), viii) default yield spread (DFY), ix) long-term Treasury return (LTR), and x) spot oil price return (Spot).

	DP	DY	EP	BM	LTY	TMS	TBL	DFY	LTR	Spot
Market	1.73	1.91	0.98	1.24	0.24	-0.40	0.39	-0.25	0.80	-1.39
Agric	0.42	0.57	1.63	0.53	-0.27	-1.63	0.50	-0.52	0.51	-0.65
Food	2.70	2.72	2.47	2.68	2.22	-0.53	2.25	0.11	1.05	-0.89
Soda	1.09	1.25	0.06	0.85	0.38	0.35	0.11	0.54	0.99	-0.20
Beer	2.18	2.25	1.74	1.57	1.61	-0.87	1.82	-0.16	-0.74	0.10
Smoke	0.72	0.79	1.60	1.10	0.77	-1.92	1.65	-0.03	1.10	-1.06
Toys	1.94	2.18	0.41	1.38	0.09	0.80	-0.25	0.65	1.53	-0.88
Fun	1.24	1.64	-0.04	1.12	0.14	0.55	-0.11	0.13	0.55	-0.48
Books	1.21	1.44	-0.09	0.99	0.50	0.62	0.20	-0.02	0.75	-0.59
Hshld	1.24	1.42	0.66	0.66	0.39	0.12	0.30	-0.68	0.15	-0.77
Clths	0.98	1.21	0.20	0.85	-0.82	0.10	-0.77	0.48	0.95	-1.48
Hlth	0.17	0.47	0.44	-0.19	-0.61	-0.95	-0.12	-0.38	1.36	-0.07
MedEq	0.65	0.92	0.68	0.00	-0.34	-1.71	0.37	-0.47	2.01	-1.17
Drugs	1.83	1.77	2.22	1.29	0.68	-2.18	1.66	-0.57	0.86	-1.35
Chems	1.75	1.85	0.42	1.42	-0.20	0.08	-0.20	0.40	0.66	0.07
Rubr	1.43	1.63	0.08	1.03	-0.23	0.06	-0.22	0.20	1.35	-1.00
Txtls	1.54	1.98	-0.21	1.51	-0.61	0.89	-0.83	0.45	1.10	-0.88
BldMt	1.59	1.86	0.29	1.12	-0.25	0.62	-0.46	0.25	1.27	-1.03
Cnstr	-0.23	0.01	0.16	-0.32	-0.90	-1.03	-0.36	0.06	1.83	-2.38
Steel	0.44	0.61	0.16	0.14	-0.36	-0.45	-0.10	-0.08	0.79	-0.57
FabPr	1.17	1.54	0.42	0.58	-0.34	0.47	-0.50	0.22	0.87	-0.14
Mach	0.57	0.73	-0.02	0.17	-0.77	0.00	-0.67	0.10	0.77	-1.23
ElcEq	1.04	1.13	0.42	0.43	0.09	-0.28	0.19	-0.19	0.47	-1.52
Autos	1.58	1.87	-0.39	1.13	-0.29	0.74	-0.54	0.59	1.01	-1.57
Aero	0.69	1.00	0.62	0.42	-0.14	-0.06	-0.10	-0.43	0.98	-1.36
Ships	-0.83	-0.53	-0.22	-0.41	-1.45	0.34	-1.39	0.01	1.13	-1.05
Guns	0.22	0.39	0.98	0.31	-0.36	-0.71	0.02	-0.55	1.68	0.38
Gold	-0.09	-0.30	-1.22	-0.53	-0.36	0.32	-0.49	1.24	1.65	-0.47
Mines	0.25	0.49	-0.98	-0.18	-0.99	-0.85	-0.57	1.01	0.54	-0.97
Coal	-1.63	-1.47	-1.45	-1.78	-0.55	-1.70	0.42	-0.11	-0.63	0.49
Util	0.86	0.98	1.98	1.58	1.18	-1.03	1.51	-1.14	0.76	0.26
Telcm	2.32	2.42	1.93	2.11	0.87	-0.20	0.82	-0.39	0.44	-1.48
PerSv	1.17	1.25	0.85	0.75	0.00	0.79	-0.32	0.08	1.00	-2.80

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	DP	DY	EP	BM	LTY	TMS	TBL	DFY	LTR	Spot
BusSv	1.39	1.59	1.06	0.94	-0.33	-0.26	-0.19	-0.14	0.60	-2.18
Hardw	0.20	0.29	-0.35	-0.34	-1.15	-0.19	-0.86	-0.19	1.22	-1.79
Softw	0.77	0.78	0.06	-0.24	-0.78	-0.48	-0.51	-0.42	0.19	-2.06
Chips	0.77	0.83	-0.04	0.01	-0.50	0.50	-0.70	-0.42	0.37	-1.97
LabEq	0.55	0.71	0.41	0.13	-0.90	-0.13	-0.74	-0.19	0.24	-1.43
Paper	1.65	1.77	0.19	1.51	0.38	0.22	0.25	0.32	0.68	0.07
Boxes	1.91	1.96	0.74	1.42	0.20	0.24	0.05	1.23	0.11	-1.62
Trans	1.42	1.61	0.95	1.22	-0.35	0.21	-0.40	-0.36	1.01	-1.11
Whlsl	1.44	1.62	0.81	1.32	-0.10	0.05	-0.12	0.30	1.74	-1.11
Rtail	1.34	1.53	0.85	1.05	-0.08	-0.48	0.14	0.18	0.93	-2.38
Meals	1.28	1.55	0.99	1.15	-0.44	0.42	-0.58	0.28	1.42	-2.94
Banks	1.30	1.54	0.54	0.94	0.80	-0.10	0.72	-0.61	0.39	-0.73
Insu	1.11	1.29	0.84	0.99	0.64	-0.41	0.71	-0.46	1.68	-1.11
RlEst	0.04	0.70	-0.76	-0.50	-1.61	1.70	-1.92	0.32	1.53	-0.85
Fin	0.82	1.05	-0.07	0.51	0.04	-0.62	0.36	0.01	0.83	-1.05
Other	1.39	1.53	1.24	1.46	0.26	-1.02	0.67	-0.47	-0.02	-1.05
OG	0.33	0.39	1.02	0.28	-0.06	-1.25	0.47	-0.61	-0.43	0.07
OGEP	-0.15	-0.20	0.11	-0.10	-0.42	-0.72	-0.04	-0.22	-0.10	0.51
IOG	0.43	0.42	1.98	0.55	0.29	-1.39	0.84	-0.97	-0.40	-0.36
OES	-0.09	0.04	0.00	-0.56	-0.54	-1.56	0.23	-0.37	-0.75	0.78
Oil	0.28	0.31	1.14	0.36	0.17	-1.17	0.66	-0.68	-0.46	0.24

Table 6: Robustness Check Against Commonly Used Predictive Variables

Estimation results for the loading b of the regression equation $R_t = a + b^\top X_{t-1} + \epsilon_t$ for the different stock portfolios using the curvature factor and log dividend-price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), book-market ratio (BM), and long-term Treasury return (LTR) as independent variables. "*" denotes significance at 10% level, "**" denotes significance at the 5% level, and "***" denotes significance at the 1% level. Significance is determined using White standard errors.

	Curv	DP	DY	EP	BM	LTR
Market	-0.387 ***	-0.042	0.063	0.006	-0.038	0.050
Agric	-0.228	-0.074	0.080	0.020 *	-0.036	0.048
Food	-0.220	0.011	0.007	0.012	-0.019	0.064
Soda	-0.446 **	-0.075	0.093	-0.005	-0.012	0.108
Beer	-0.233	0.000	0.036	0.012	-0.066 *	-0.087
Smoke	-0.161	-0.050	0.049	0.012	0.005	0.107
Toys	-0.615 ***	-0.101	0.131	-0.003	-0.030	0.174
Fun	-0.559 **	-0.265 **	0.277 **	-0.011	0.021	0.059
Books	-0.299	-0.119	0.129	-0.008	0.011	0.070
Hshld	-0.171	-0.062	0.084	0.005	-0.044	0.001
Clths	-0.634 **	-0.132	0.143	-0.003	-0.001	0.091
Hlth	-0.057	-0.194 **	0.212 ***	0.009	-0.059	0.144
MedEq	-0.282 *	-0.101	0.125	0.009	-0.068	0.184 **
Drugs	-0.246	0.059	-0.030	0.018 **	-0.072 **	0.064
Chems	-0.244	-0.020	0.040	-0.001	-0.014	0.057
Rubr	-0.532 **	-0.092	0.114	-0.004	-0.021	0.161
Txtls	-0.873 ***	-0.302 **	0.318 **	-0.020	0.032	0.181
BldMt	-0.430 **	-0.136	0.161 *	0.000	-0.032	0.160
Cnstr	-0.704 ***	-0.140	0.143	0.005	-0.023	0.228 *
Steel	-0.533 *	-0.112	0.130	0.003	-0.040	0.112
FabPr	-0.594 ***	-0.209 **	0.242 ***	0.006	-0.069	0.084
Mach	-0.540 **	-0.075	0.092	0.000	-0.031	0.083
ElcEq	-0.440 **	-0.017	0.048	0.007	-0.067	0.044
Autos	-0.776 ***	-0.194 *	0.219 **	-0.018	0.001	0.127
Aero	-0.365 *	-0.179 **	0.195 **	0.008	-0.038	0.101
Ships	-0.377 *	-0.227 **	0.204 *	-0.004	0.045	0.176
Guns	-0.109	-0.108	0.111	0.013	-0.023	0.183
Gold	0.332	0.257	-0.239	-0.019	-0.032	0.355 *
Mines	-0.504 **	-0.137	0.150	-0.016	-0.004	0.077
Coal	0.069	-0.159	0.134	-0.018	0.029	-0.101
Util	-0.037	-0.060	0.053	0.010	0.018	0.043
Telcm	-0.330	-0.029	0.052	0.013	-0.033	0.011
PerSv	-0.327 *	-0.006	0.028	0.008	-0.044	0.098

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	Curv	DP	DY	EP	BM	LTR
BusSv	-0.527 ***	-0.070	0.092	0.009	-0.043	0.034
Hardw	-0.828 ***	-0.030	0.055	-0.001	-0.062	0.128
Softw	-0.764 ***	0.069	-0.006	0.011	-0.158 **	0.005
Chips	-0.852 ***	0.011	0.033	0.004	-0.098 *	0.025
LabEq	-0.523 **	-0.096	0.121	0.007	-0.061	0.009
Paper	-0.141	-0.052	0.064	-0.007	0.012	0.065
Boxes	-0.340	-0.014	0.044	0.003	-0.041	-0.009
Trans	-0.516 ***	-0.063	0.078	0.006	-0.020	0.087
Whlsl	-0.234	-0.089	0.097	0.001	0.002	0.144
Rtail	-0.683 ***	-0.058	0.074	0.004	-0.020	0.066
Meals	-0.608 ***	-0.116 *	0.127 **	0.004	-0.011	0.110
Banks	-0.420 *	-0.111	0.134	0.005	-0.038	0.030
Insu	-0.302	-0.078	0.090	0.007	-0.021	0.182
RlEst	-0.577 ***	-0.388 ***	0.397 ***	-0.020	0.007	0.239
Fin	-0.559 **	-0.130	0.148	-0.004	-0.020	0.075
Other	-0.681 ***	-0.048	0.061	0.014	-0.017	-0.037
OG	0.016	-0.023	0.030	0.011	-0.028	-0.053
OGEP	0.004	0.043	-0.045	0.003	-0.003	-0.013
IOG	0.015	0.011	-0.007	0.017 **	-0.027	-0.047
OES	0.082	-0.089	0.114	0.009	-0.084	-0.126
Oil	-0.164	-0.015	0.031	0.011	-0.038	0.011

Table 7: Comparison with Commonly Used Predictive Variables

This table reports the Diebold-Mariano statistic *dm* for comparing the predictive performance of the curvature factor against other predictive variables. The predictive variables used for comparison are i) log dividend-price ratio (DP), ii) log dividend yield (DY), iii) log earnings-price ratio (EP), iv) book-market ratio (BM), v) long-term Treasury yield (LTY), vi) Treasury yield spread (TMS), vii) Treasury bill rate (TBL), viii) default yield spread (DFY), ix) long-term Treasury return (LTR), and x) spot oil price return (Spot). A positive *dm* statistic indicates greater forecast error for the alternative variable than the curvature factor. "*" denotes significance at 10% level, "**" denotes significance at the 5% level, and "***" denotes significance at the 1% level.

	DP	DY	EP	BM	LTY	TMS	TBL	DFY	LTR	Spot
Market	0.75	0.65	1.01	1.09	1.41	1.38*	1.38*	1.39*	1.17	0.98
Agric	0.58	0.50	-0.37	0.54	0.64	-0.30	0.49	0.49	0.45	0.48
Food	-0.86	-0.88	-0.81	-0.77	-0.40	0.57	-0.39	0.65	0.26	0.44
Soda	0.72	0.62	1.15	0.94	1.12	1.17	1.15	0.90	0.76	1.24
Beer	-0.63	-0.68	-0.25	-0.10	0.07	0.40	-0.11	0.73	0.51	0.70
Smoke	0.03	-0.03	-0.56	-0.17	0.16	-0.73	-0.48	0.42	-0.18	-0.31
Toys	0.67	0.54	1.30*	1.00	1.36*	1.27	1.36*	1.09	0.78	1.32*
Fun	0.96	0.73	1.32	1.04	1.29	1.24	1.31	1.30	1.17	1.30*
Books	0.43	0.27	0.86	0.56	0.73	0.78	0.83	0.85	0.60	0.74
Hshld	0.00	-0.13	0.39	0.43	0.59	0.66	0.62	0.26	0.64	0.34
Clths	1.08	1.01	1.20	1.13	1.13	1.22	1.15	1.14	1.06	0.82
Hlth	0.20	0.01	0.04	0.20	-0.05	-0.27	0.23	0.05	-0.52	0.25
MedEq	0.82	0.69	0.80	0.98	0.93	0.28	0.92	0.78	-0.17	0.28
Drugs	-0.21	-0.17	-0.49	0.21	0.61	-0.38	0.06	0.59	0.39	-0.06
Chems	-0.25	-0.30	0.47	0.07	0.68	0.69	0.68	0.48	0.42	0.66
Rubr	0.92	0.81	1.34	1.17	1.35*	1.35*	1.35*	1.27	0.72	1.18
Txtls	1.32*	1.13	1.61*	1.40*	1.58*	1.53*	1.53*	1.22	1.22	1.35*
BldMt	0.57	0.39	1.00	0.87	1.12	1.07	1.08	1.01	0.42	0.82
Cnstr	1.63*	1.66**	1.65**	1.62*	1.48*	1.44*	1.63*	1.66**	0.88	0.45
Steel	1.00	0.96	1.01	1.02	0.99	0.93	1.02	1.01	0.76	0.97
FabPr	1.28*	1.08	1.40*	1.49*	1.51*	1.49*	1.48*	1.53*	1.38*	1.58*
Mach	1.27	1.22	1.32*	1.32*	1.18	1.32*	1.22	1.32*	1.11	1.03
ElcEq	0.72	0.68	0.93	0.99	1.03	1.00	1.02	1.00	0.93	0.52
Autos	1.37*	1.20	1.78**	1.58*	1.79*	1.71*	1.77*	1.56*	1.52*	1.32*
Aero	0.82	0.66	0.79	0.92	0.96	0.96	0.96	0.82	0.59	0.39
Ships	0.75	0.90	0.98	0.96	0.15	0.94	0.17	1.00	0.25	0.49
Guns	0.32	0.20	-0.29	0.28	0.28	0.03	0.38	-0.03	-0.67	0.18
Gold	0.53	0.46	-0.18	0.34	0.45	0.45	0.39	-0.28	-0.48	0.30
Mines	1.21	1.17	0.78	1.20	0.81	0.98	1.10	0.63	1.02	0.97
Coal	-0.82	-0.74	-0.70	-0.90	-0.23	-0.85	-0.17	0.01	-0.29	-0.24

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	DP	DY	EP	BM	LTY	TMS	TBL	DFY	LTR	Spot
Util	-0.31	-0.38	-0.99	-0.68	-0.45	-0.44	-0.67	-0.53	-0.26	0.04
Telcm	-0.22	-0.29	-0.15	-0.02	0.73	0.88	0.73	0.86	0.82	0.34
PerSv	0.42	0.38	0.64	0.73	1.01	0.79	0.98	1.00	0.51	-0.96
BusSv	1.12	1.02	1.16	1.31	1.47*	1.47*	1.48*	1.48*	1.39*	0.70
Hardw	1.46*	1.45*	1.42*	1.42*	1.33*	1.43*	1.39*	1.44*	1.26	1.15
Softw	1.06	1.06	1.23	1.22	1.12	1.20	1.19	1.20	1.23	0.60
Chips	1.41*	1.39*	1.53*	1.53*	1.51*	1.49*	1.48*	1.48*	1.51*	0.97
LabEq	1.03	0.96	1.07	1.11	0.93	1.09	1.01	1.09	1.09	0.66
Paper	-0.55	-0.63	0.37	-0.40	0.33	0.43	0.39	0.20	0.04	0.42
Boxes	-0.10	-0.16	0.59	0.33	0.80	0.79	0.80	0.15	0.79	0.09
Trans	1.01	0.94	1.11	1.13	1.34*	1.36*	1.34*	1.34*	1.06	1.15
Whlsl	0.11	-0.04	0.43	0.18	0.87	0.87	0.88	0.79	-0.15	0.30
Rtail	1.61*	1.54*	1.81**	1.75**	1.97**	1.94**	1.97**	1.96**	1.79**	1.14
Meals	1.45*	1.34*	1.55*	1.53*	1.69**	1.70**	1.67**	1.69**	1.33*	0.45
Banks	0.54	0.42	0.79	0.75	0.80	0.92	0.81	0.57	0.82	0.70
Insu	0.43	0.33	0.44	0.54	0.73	0.82	0.69	0.61	-0.12	0.42
RlEst	1.78**	1.76**	1.07	1.78**	1.29*	1.28*	0.83	1.64*	0.77	1.39*
Fin	1.19	1.09	1.33*	1.29*	1.32*	1.17	1.28*	1.33*	1.13	1.15
Other	1.02	0.98	0.79	1.04	1.35*	1.19	1.28*	1.25	1.35*	1.19
OG	-0.15	-0.18	-0.52	-0.12	0.01	-0.62	-0.23	-0.30	-0.21	0.01
OGEP	-0.06	-0.09	-0.04	-0.03	-0.20	-0.36	0.01	-0.10	-0.03	-0.26
IOG	-0.19	-0.19	-1.00	-0.26	-0.11	-0.68	-0.41	-0.46	-0.18	-0.14
OES	0.11	0.13	0.14	-0.22	-0.20	-0.77	0.01	-0.13	-0.34	-0.38
Oil	-0.09	-0.11	-0.57	-0.14	-0.02	-0.57	-0.31	-0.32	-0.21	-0.09

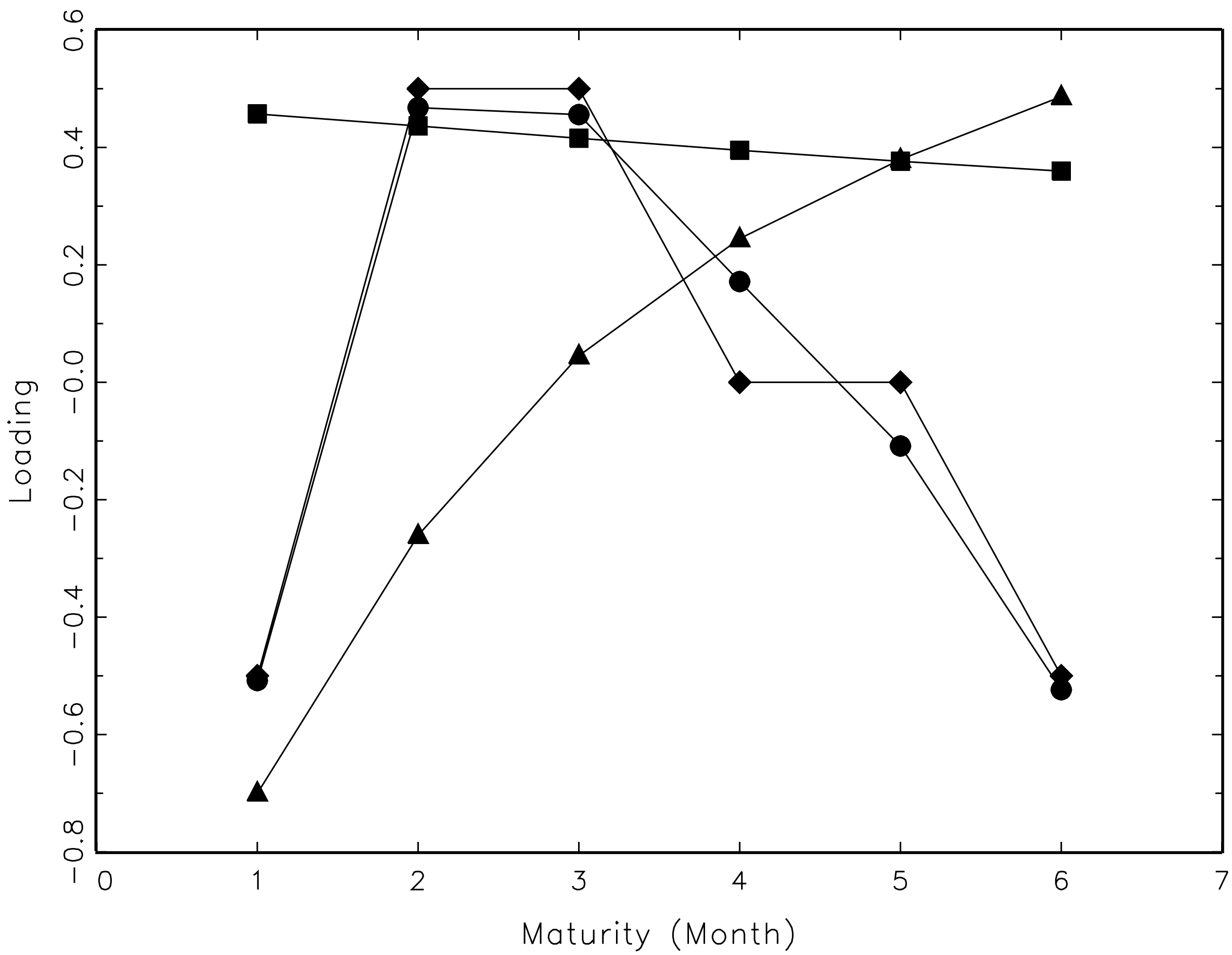

Figure 1: Curvature factor (diamonds), and the first (squares), second (triangles), and third (circles) principal components.

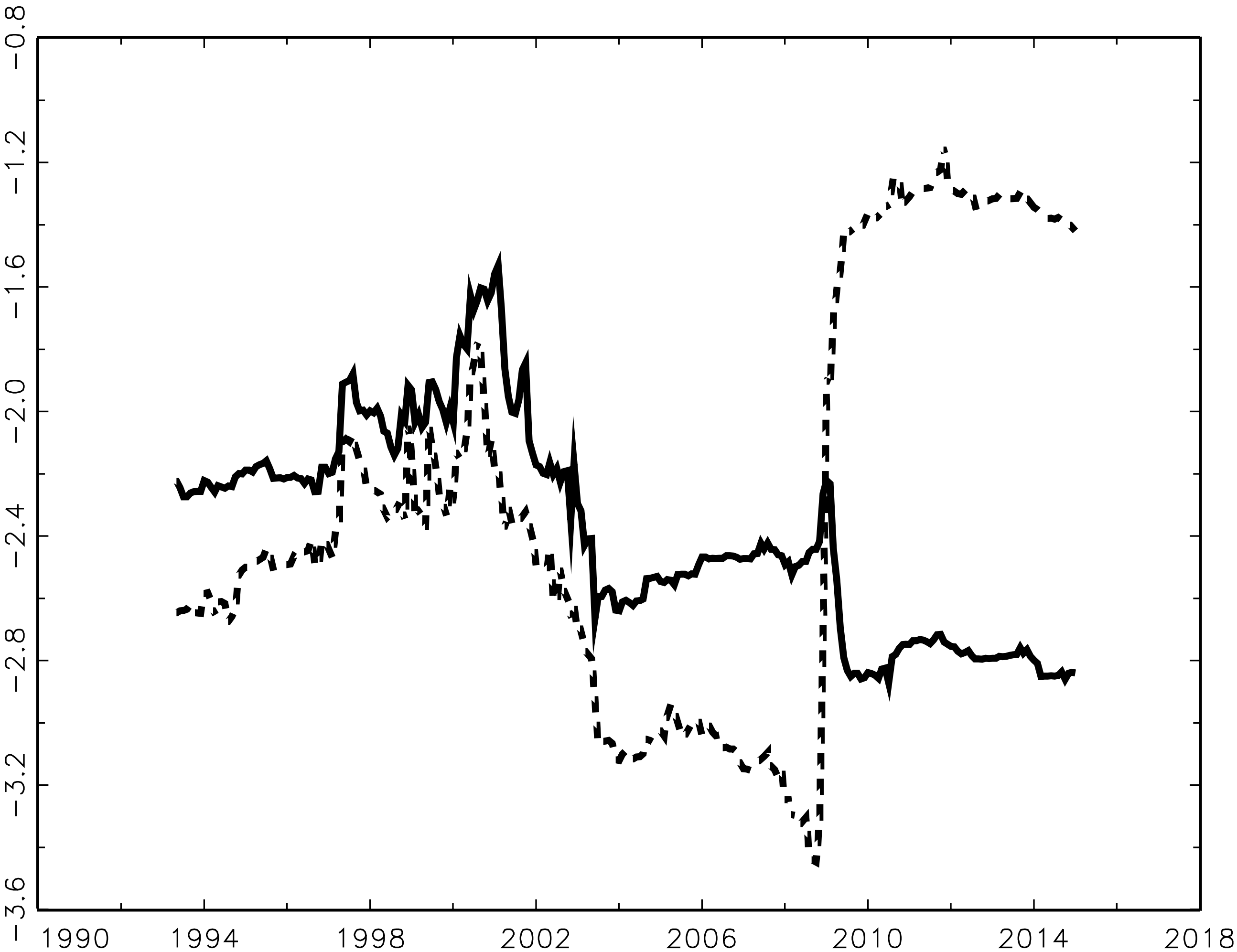

Figure 2: t-ratios from expanding window regressions of monthly market return on lagged spot oil price return (dashed curve) and curvature (solid curve).