Oil Prices and the Cross-Section of Stock Returns

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Abstract

We document a novel stock price momentum effect related to oil. A portfolio that buys low-oil-beta stocks and sells high-oil-beta stocks earns abnormal returns of -1.08% per month from 1986 to 2011, with majority of abnormal returns arising from 2002 to 2011, and 1.58% per month from 2012 to 2015. Our results are robust after controlling for size, value, asset growth, profitability, momentum, and total volatility in two-dimensional sorting, and after removing the oil price fluctuations that are driven by aggregate demand shocks. Oil beta is insignificant in forecasting future returns before 2002 in cross-sectional regressions and becomes significant since 2002. Our findings are consistent with the notion that investors underestimate the magnitude of the boom and bust of oil prices.

Keywords: Oil prices, return spread, cross section, factor model
JEL classification: G12

1 Introduction

Oil prices have been volatile, especially in the past decade. Figure 1 presents the daily nominal prices of West Texas Intermediate crude oil over the sample period from January 1, 1986 (the earliest date when the daily oil price data is available) to December 31, 2015. Oil prices were around $20 per barrel until the end of 2001. Over the next six years, oil prices skyrocketed, reaching more than $140 per barrel in the middle of 2007, and then crashed, falling sharply to around $40 per barrel in July 2008. Oil prices gradually rose to around $100 per barrel in mid-2014 and plummeted to around $30 per barrel in the end of 2015.

Oil prices affect the macroeconomy (see Hamilton (2009) and Blanchard and Gali (2009) among others) and hence should be related to aggregate stock market movements. Bernanke (2016) finds that oil price changes and aggregate stock returns were positively correlated in the past five years and this positive correlation is puzzling because a decrease in oil prices should be good news for oil-importing economies such as the US. This issue has received a considerable amount of attention in both the academia and the general public and most discussions have been focused on the relationship between oil prices and aggregate stock returns. The impact of oil price changes on the cross-section of stock returns has been underexplored. The goal of our paper is to investigate this issue.

There are several reasons to believe that exposure to oil price fluctuations is relevant for individual stock returns. First, oil is an input used by some firms and is an output from some other firms. As oil price swings up and down, it affects the profitability and cash flows of these firms and thus it has a direct effect on their stock prices. Second, oil prices can be treated as a proxy for prices of general inputs. After all, oil prices and prices of other inputs such as cement, copper, lubber, and steel are highly correlated, as shown in Tang and Xiong (2012). From this perspective, oil price changes matter for not only firms who are directly exposed to oil, but also firms who use any raw materials as inputs for their production. Third, as Hamiltion (2009) argues, almost all recessions are preceded by a spike in oil prices during the post-war period. Hence, oil prices may serve as a state variable that informs us about the future state of the economy and the shocks driving oil price changes may be a priced factor.

We first document empirical evidence on the cross-sectional variation of stock returns of firms with different exposures to oil price changes. We then use the Fama and French (2015) five-factor model to study whether risk-based theory can explain this cross-sectional variation. We use oil beta to measure the exposure to oil price changes by regressing a stock's excess returns on the market excess returns and oil price changes in in excess of the risk-free rate. At the end of each month, we conduct such regressions for each stock using daily data over the previous 12 months and the slope on the excess return on oil is our oil beta. We form decile portfolios based on the oil betas at the end of the month and follow each portfolio's excess returns in the next month.

We find that the return spread between decile 1 of stocks with the lowest oil betas and decile 10 of stocks with the highest oil betas is -0.22% per month (t-value = -0.68) in our full sample from 1986 to 2015. The spread is small and statistically insignificant. It is also equal to the return on the so called LHMO portfolio formed by buying decile 1 of stocks and selling decile 10 of stocks. The alpha of this portfolio relative to the Fama-French five-factor models is -0.69% (t-value = -2.08).

To examine why the return on the LMHO portfolio from 1986 to 2015 is low, we compute the average return in each year and find that it alternates between positive and negative signs before 2002, stays negative between 2002 and 2011, and stays positive between 2012 and 2015. From 1986 to 2001, the average return on the LMHO portfolio is small (-0.50%) and statistically insignificant with a t-value of -1.39. During this period, oil prices do not fluctuate much with an average growth rate of 0.2% per month and hence do not have a significant effect on the cross-section of stock returns.

The average return on the LMHO portfolio from 2002 to 2011 is a large number of -1.43% and statistically significant with a t-value of -2.27. The Fama-French five-factor alpha is also large at -1.45% and significant with a t-value of -2.15. During this period, oil prices exhibit an upward trend with an average monthly growth rate of 1%, even though there is a crash in 2008. In contrast, oil prices exhibit a downward trend with an average monthly growth rate of -1.4% during the period from 2012 to 2015. The average return on the LMHO portfolio during this period is a large positive number of 1.55% with a t-value of 2.13 and its alpha is 1.58% (t-value = 2.36). The p-values of GRS statistics for both subsamples 1986-2011 and 2012-2015 are around 9%.

The challenge is that, after adjusting for the required return prescribed by the five factors, there are large abnormal returns left among the extreme oil portfolios. Its implication for investing is that an arbitrager can always design a long-short strategy to capture these alphas. We then augment the Fama-French five factors with a momentum factor of Carhart (1997) and a total volatility factor to see whether they can reduce alphas. We find that the total volatility factor changes our results little. While the momentum factor does not have a large effect on the alphas of extreme portfolios, it reduces the GRS statistics to a point where we cannot reject the null of zero abnormal returns, as p-values are larger than 10%. At a first sight, it seems that momentum helps explain returns on oil portfolios, but we show that actually the opposite holds in the subsample from 2012 to 2015.

To disentangle the return on the LMHO portfolio from the return of momentum trading, we first remove high-oil-beta stocks from winner portfolios and low-oil-beta stocks from loser portfolios for the subsample from 2002 to 2011 and implement an opposite algorithm for the subsample from 2012 to 2015. We find that this procedure reduces the profit of momentum trading. In particular, profits from momentum trading disappear during the period from 2012 to 2015 when high-oil-beta stocks are removed from losers. This suggests that momentum is driven by oil price changes during that period.

We next remove winner stocks from high-oil-beta stocks portfolios and loser stocks from low-oil-beta stocks portfolio for the subsample from 2002 to 2011, and remove loser stocks from high-oil-beta stocks portfolios and winner stocks from low-oil-beta stocks portfolios for the subsample from 2012 to 2015. We find that the return on the LHMO portfolio changes little. This result suggests that momentum is not the main driver of the average return on the LHMO portfolio for the two subsamples.

To further show that the return on the LMHO portfolio is unique and novel, we control for some well-known firm fundamentals and other characteristics that forecast future stock returns. We control for size, value, asset growth, operating profitability, and total volatility. We find that they do not reduce the abnormal returns on the LHMO portfolio. Our finding is further supported by results from the Fama-MacBeth regression of future returns on firm characteristics and oil betas. Between 2002 and 2011, oil beta has a coefficient of 0.025 (t-value = 2.11). Asset growth, profitability and total volatility are also significant in this period. From 2012 to 2015, oil beta has a coefficient of -0.0337 (t-value = -2.17). The only control variable that is significant is profitability.

At the industry level, we find that large industries with high oil betas (positive) are petroleum industry and machinery industry, and large industries that have low oil betas (negative) are Retail, Transportation and Pharmaceutical industries. The oil sensitive industries before 2012 remain to be oil sensitive since 2012. It indicates that there is not much news with oil betas. It is the surprise in oil prices that drive the fluctuation in the return on stocks that have different sensitivities to shocks in oil prices.

It is possible that stock returns and oil prices move together simply because they both react to some other common forces. For instance, as aggregate demand decreases, oil prices go down and stock prices go down too. From this perspective, oil is simply a proxy for aggregate demand. Once aggregate demand is properly accounted for, there is nothing unique about oil. To address this issue, we estimate the oil price changes associated with changes in aggregate demand and remove them from the original oil price changes. We then re-estimate oil betas. The changes in aggregate demand are captured by copper price changes, changes in 10-year Treasury bond yield, and changes in the U.S. dollar exchange rate, as argued by Hamilton (2016) and Bernanke (2016). This method is different from that in Kilian (2009) and Ready (2015) where a structural VAR for the full sample is used. Since we form portfolios each month and it is improper to use future information to construct oil betas that have look-ahead bias, the full sample VAR approach cannot be applied. We find that removing the demand related changes in oil prices actually strengthens our results. It indicates that the return on the LMHO portfolio is indeed related specifically to oil, not necessarily to aggregate demand. [1]

2 Data and Methodology

2.1 Data

Oil price refers to the price of West Texas Intermediate Oil. They are daily from January 1, 1986 to December 31, 2015 and taken from the Federal Reserve Bank of St. Louis. We compute the daily percentage oil price changes (or return on oil) as $R_{OIL,t} = \ln(p_t/p_{t-1})$, where p_t is the oil price at date t.

Our stock returns data correspond to CRSP common shares (SHRCD = 10 or 11) from the NYSE, AMEX and Nasdaq (EXCH = 1 or 2 or 3). The risk-free rate R_{ft} is the 3-month Treasury bill rate. Firm fundamentals and accounting variables are taken from the Compustat database. We consider the following four fundamental variables following Fama and French (2008, 2015), Novy-Marx (2013), and Hou, Xue and Zhang (2015): firm size, book-to-market ratio, operating-profit-to-book-equity ratio, and asset growth. [2] Other control variables we use include the stock

[1] In unreported results we also perform a battery of other robustness checks. We re-estimate oil betas using the previous one month of data, not previous 12 months of data. We drop petroleum industry in the whole analysis. We find that results are qualitatively similar.

[2] Firm size (MC) is defined as the market capitalization at the end of June in each year. It is the product of the number of shares outstanding and the share price from the CRSP. This MC is used for the following four quarters. Book equity is stockholders' book equity, plus balance sheet deferred taxes (Compustat item ITCB) and investment tax credit (TXDB) if available, minus the book value of preferred stocks. We employ tiered definitions largely consistent with those used in Davis, Fama, and French (2000), Novy-Marx (2013), and Hou, Xue, and Zhang

price momentum and individual stock's total volatility. Following Jegadeesh and Titman (1993), at the end of each month *t*, we compute each stock's cumulative return from month *t*-13 to *t*-2, and take it as the stock price momentum. Similarly, the total volatility of each stock is the variance of daily stock returns in each month.

The five factors of Fama and French (2015) include the original three factors of Fama and French (1996) and two new factors. The original three factors are the market excess return (MKT), a size factor (SMB), and a value factor (HML). The additions are an asset growth factor (CMA) and a profitability factor (RMW). Additional common factors used in our analysis are: a momentum factor which is the return on a portfolio that buys the past winner and sells the past loser, and a total volatility factor which is the return on a portfolio that buys the stocks with high total volatility and sells the stocks with low total volatility. [3]

To estimate the demand component of oil price changes, we use the daily data of copper futures from Genesis Financial Technologies, the yields of the US 10 year T-bond and the U.S. dollar exchange rate from the Federal Reserve Bank of St. Louis.

(2015) to construct stockholders' equity and book value of preferred stocks. Stockholders equity is as given in Compustat (SEQ) if available, or else common equity (CEQ) plus the book value of preferred stocks, or else total assets minus total liabilities (AT–LT). Book value of preferred stocks is redemption value (PSTKRV) if available, or else liquidating value (PSTKL) if available, or else par value (PSTK). Book-to-market ratio in year *t*-1 is computed as book equity for the fiscal year ending in calendar year *t*-1 divided by the market capitalization at the end of December of year *t*-1. Stocks with missing book values or negative book-values are deleted. Following Fama and French (2015), we measure operating profit in year *t*-1 as year *t*-1 gross profit (Compustat item GP), minus selling, general, and administrative expenses (XSGA) if available, minus interest expense (XINT) if available, all divided by year *t*-1 book equity. Following Cooper, Gulen, and Schill (2008), we compute asset growth in year *t*-1 as total assets (AT) for the fiscal year ending in calendar year *t*-1 divided by total assets for the fiscal year ending in calendar year *t*-2, minus one.

[3] All these factor data are downloaded from Ken French's website (http://mba.tuck.dartmouth.edu).

2.2 Methodology

We first estimate oil betas using daily data over the previous 12 months. At the end of each month, we regress daily stock returns on daily market excess returns and daily returns of oil in excess of the risk free rate using the following equation

$$R_{it} - R_{ft} = a_{i0} + b_{i1}MKT_t + b_{i2}(R_{OIL,t} - R_{ft}) + \varepsilon_{it}, \tag{1}$$

where R_{it} is the return on stock i between date t-1 and date t. The slope b_{i2} on the return on oil is the oil beta. The estimated oil beta may vary across months.

Using these oil betas, we rank all firms from low oil betas to high oil betas in each month and follow their excess returns in the following month. We then form 10 portfolios based on the rank of oil betas. The return on a portfolio is the value-weighted average of the returns on all firms in that portfolio. The LMHO portfolio is the one that longs portfolio 1 with the lowest oil betas and shorts portfolio 10 with the highest oil betas. The return on the LMHO portfolio is equal to the return spread between portfolio 1 and portfolio 10.

At the time of portfolio formation, we delete firms whose prices are less than five dollars, and firms whose market capitalization are less than the 10 percentile of market capitalization of NYSE firms. The market capitalization breakpoints of NYSE firms are available at Kenneth French's website. We drop these firms to avoid micro-structure issues as they are hard to trade. Our results are stronger when we include these micro-cap firms.

Our main testing methods follow the classical method of Fama and French (1996, 2015). We test if the excess returns on decile portfolios formed on oil betas can be explained by the recently proposed five factors of Fama and French (2015) using time-series regressions with monthly data. If the returns on oil portfolios can be explained by these five common factors, the joint test on the abnormal returns or alphas using the GRS test of Gibbons, Ross and Shanken (1986) should be insignificant. At the same time, we check if the absolute values of alphas are small, especially for the extreme portfolios, as they are the ones that typically pose challenges to common factor models. We also expand the five factors to include a stock price momentum factor or a total volatility factor to check if the return on the LMHO portfolio is subsumed by momentum or total volatility.

To control for other firm fundamentals or characteristics, we perform double sorting, in which we first sort on oil betas, and then independently sort on a fundamental or a characteristic, and we take the intersections of the two sorts to form portfolios. We track the return on the portfolios in the following month. We also rely on the Fama and MacBeth (1973) regression to identify if oil beta has incremental power to explain future stock returns.

As a robustness check, we decompose oil price changes into a component due to changes in aggregate demand and a component due to changes in aggregate supply or other factors, as in Bernanke (2016). In each month, with past 12 months of data, we project daily oil price changes on daily copper price changes $R_{COPPER,t}$, daily changes in 10-year Treasury bond rate ΔINT_t, and daily percentage changes in the dollar exchange rate ΔE_t using the following regression

$$R_{OIL,t} - R_{ft} = c_0 + c_1(R_{COPPER,t} - R_{ft}) + c_2\Delta INT_t + c_3\Delta E_t + \epsilon_t. \quad (2)$$

We take the fitted value as oil price changes related to demand ($R^d_{OIL,t}$) and the residuals as oil price changes related to supply and other factors ($R^s_{OIL,t}$). We replace the return on oil in equation (1) with these alternative estimates and re-estimate each firm's oil betas. Based on the oil betas estimated using oil price changes related to demand and oil prices changes related to residuals, we form new sets of oil portfolios and repeat previous analyses.

3 Empirical Results

3.1. Results from One-Dimensional Sorting

If the return on oil affects the cross-section of stock returns, we should find that firms with different exposures to oil price changes earn different returns. We first examine this issue in the full sample from 1986 to 2015. The first row of Table 1 presents the average monthly excess returns on the decile portfolios sorted on the past oil betas over the previous month. This row shows that portfolio 1 with the lowest oil betas earns an average return of 0.51% per month (t-value = 1.58) and portfolio 10 with the highest oil betas earn an average return of 0.73% per month (t-value = 2.16). The return spread between portfolio 1 and portfolio 10 (LMHO) is -0.22% per month (t-value = -0.68). The low t-value shows that the return spread is insignificant. Nevertheless, in the second panel of table 1, we show that, after adjusting for risk exposures to the Fama-French five factors, the return spread is -0.69% per month (t-value = -2.08). Portfolio 10 has positive alpha and portfolio 1 has negative alpha. It suggests that portfolio 10 earns a higher return than the required return prescribed by its risk exposures, and portfolio 1 earns a lower return than the required return prescribed by its risk exposures. Thus the Fama-French five factors underestimate overall risks of portfolio 10 and overestimate overall risks of portfolio 1.

To see why the average return spread is small in the full sample intuitively, we compute the annual return spreads from 1986 to 2015, using the average of the monthly spreads. Figure 2 presents the result and shows that the return spread varies over time. It alternates between positive and negative signs from 1986 to 2001, stays negative from 2002 to 2011, and becomes positive from 2012 to 2015. This pattern shows that there is almost no difference in average returns between low-oil-beta stocks and high-oil-beta stocks in the full sample and suggests that the weak result in the full sample is driven by the sign switching of the return spread. We thus focus our analyses on two subsamples, 1986-2011 and 2012-2015, for brevity of presentation, and when relevant and needed for robustness, we break the sample into three subsamples, 1986-2001, 2002-2011, and 2012-2015.

Table 1 presents the spreads in excess returns and in alphas for the two subsamples. We find the following result. From 1986 to 2011, the spread in excess returns is -0.50% per month (t-value = -1.39) and the spread in alphas based on the Fama-French five-factor model is -1.08% per month (t-value = -3.05). In contrast, from 2012 to 2015, the spread is 1.55% (t-value = 2.13) and its alpha is 1.58% (t-value = 2.36). The GRS joint test does not reject the null of zero alphas in the full sample, and marginally reject joint zero alphas in each of the subsamples at the 10% significance level. The intriguing part is that the abnormal returns on the LMHO portfolios are economically large.

The third panel of table 1 shows the oil betas at the time of portfolio formation for each oil portfolio. The value-weighed oil beta is -0.14 for low-oil-beta stocks, and 0.21 for high-oil-beta stocks for the full sample. The oil betas become slightly larger in 2012 to 2015. These betas are highly significant and t-values are not reported for brevity.

The fourth panel of table 1 shows how the return on the LMHO portfolios correlates with the five factors of Fama and French (2015), as well as the momentum factor and a factor constructed from buying stocks with high total volatility and selling stocks with low total volatility. Before 2012, the highest correlation is 0.34, between the return on the LMHO portfolio and the asset growth factor. Since 2012, the highest correlation is 0.44 between the return on the LMHO portfolio and the momentum factor, and the lowest correlation is -0.45 between the return on the LMHO portfolio and the value factor. The fifth panel presents the mean and t-values of factors used in this paper. It appears that all factors have expected signs and significance before 2012 and none of them, except the market factor, is significant since 2012.

Table 2 examines betas on the five factors of the portfolios formed on oil beta. In the subsample from 1986 to 2011, low-oil-beta stocks (portfolio 1) load positively on the asset growth factor with a coefficient of 0.26 (t-value = 2.92), and high-oil-beta stocks (portfolio 10) load negatively on the asset growth factor with a coefficient of -0.60 (t-value = -5.74). The net result is that the LMHO portfolio loads positively on the asset growth. The negative loading suggests that high-oil-beta stocks earn low risk premium on the asset growth factor. Consequentially, high-oil-beta stocks can have large a positive alpha. Low-oil-beta stocks, relative to high-oil-beta stocks, also have larger loadings on the market factor and the HML factor. These factor loadings suggest that low-oil-beta stocks earn high risk premiums on the market factor and the HML factor, which help explain their negative alphas, once risk premiums are subtracted from their realized returns.

In the subsample from 2012 to 2015, high-oil-beta stocks load positively on the value factor with a coefficient of 1.76 (t-value = 5.34) and negatively on the profitability factor with a coefficient of -1.81 (t-value = -3.39). This result indicates that returns on high-oil-beta stocks behave like those of value firms or firms with weak profitability in this subsample. Low-oil-beta stocks load negatively on the asset growth factor with a coefficient of -0.87 (t-value = -2.79). It suggests that returns on low-oil-beta stocks behave like those of firms with aggressive asset growth in this subsample. The problem is that, as shown in table 1, the realized risk premium of all these factors, except the market factor, is small and has opposite signs to those in 1986 to 2011. Hence, the risk adjustment from the five factors excluding the market factor does not have much effect on the abnormal returns. High-oil-beta stocks have a market beta of 1.26. When multiplied by the market risk premium of 1.23% per month in this period, it implies that high-oil-beta stocks should earn a risk premium of 1.55% per month on the market factor and it contributes to their large negative alphas. Similarly, low-oil-beta stocks should earn a risk premium of 1.22% per month (market beta of 0.99 times market risk premium of 1.23%) on the market factor and it helps to explain their small positive alphas.

In short, it appears that the Fama-French five factors do not explain fully the returns on portfolios formed on oil betas. We find that risk exposures and risk premiums often go in the wrong direction in the two subsamples. Before 2012, to explain why high-oil-beta stocks earn high returns, we should expect them to have high betas on some of the five factors, but we do not find that. Since 2012, we need to explain why high-oil-beta stocks earn low returns. The problem is that the realized risk premium on the size, value, asset growth and profitability factors are negative. To explain why high-oil-beta stocks earn lower returns relative to low-oil-beta stocks, they should have smaller market betas. But this is not what we find. The market beta is 1.26 for high-oil-beta stocks and it is 0.99 for low-oil-beta stocks. The required returns prescribed by the Fama-French five-factor model are similar for high-oil-beta stocks and low-oil-beta stocks and hence they do not help explain the return on the LMHO portfolio from a risk perspective.

3.2 Removing Risk Exposure Using Alternative Factors

In this subsection we provide further results to show that the return on the LHMO portfolio is new and robust. In table 3 we show the abnormal returns on decile portfolios formed on oil beta by adding a momentum factor or a volatility factor to the five factors.

The first panel of table 3 shows that, when the momentum factor is included, the GRS statistic is 1.56 (p-value = 0.12) for 1986-2011, and 1.44 (p-value = 0.21) for 2012-2015. The large p-values indicate that return on the LMHO portfolio may be subsumed by the momentum factor. Nevertheless, the challenge is that the alphas of the LMHO portfolio are significant and equal to -0.89% (t-value = -2.60) and 1.29% (t-value = 1.87) for these two subsamples. We will revisit this issue and show that the momentum factor and the return on the LMHO portfolio represent different phenomena.

As tables 1 and 3 show, compared to the sample from 2012 to 2015, the raw return and the abnormal return on the LMHO portfolio are quite small from 1986 to 2011, suggesting that oil does not have a large effect during that period. However, during the period between 2002 and 2011, the alpha after adjusting for the Fama-French five factors plus the momentum factor is large (-1.82%) and significant (t-value = -3.95), and the GRS test has a p-value of zero. This result shows that oil plays an important role during the period from 2002 to 2011.

Our results are similar when we include a volatility factor and the Fama-French five factors, as the second panel of table 3 shows. But unlike the momentum factor, the abnormal returns are significant for each subsample and the GRS test is also significant at the 10% significance level. This suggests that including the volatility factor does not help much explain the return on the LHMO portfolio. In unreported results we also remove the oil industry from our sample and find qualitatively similar results.

Overall, oil seems to play a negligible role in driving cross-sectional stock returns before 2002, but has a large effect since 2002. High-oil-beta stocks earn high returns between 2002 and 2011, as oil price trends up, and earn low returns between 2012 and 2015, as oil price stabilizes and crashes.

Finally, we show that, to reduce alphas of portfolios formed on oil beta, one can use an ad hoc model that combines the market factor and the return on the LMHO portfolio. For brevity we only present results for the full sample in the last panel of table 3. We find that the abnormal returns are negligible. This result also holds true for the subsamples considered earlier.

3.3 Revisit Returns on LMHO and Momentum

Results from table 3 seem to suggest that the return on the LMHO portfolio is subsumed by the momentum factor. This section attempts to distinguish between the two and tests which one is more dominant. We will show that it is not winner stocks that drive the returns on high-oil-beta stocks and it is not loser stocks that drive the returns on low-oil-beta stocks. Winner stocks and high-oil-beta stocks may be the same stocks or different stocks. It is possible that returns on high-oil-beta stocks simply coincide with returns on winners so that the GRS statistic is small when momentum is included as a factor to explain returns on portfolios formed on oil beta.

To proceed, we form a decile of momentum portfolios based on price performance in the past 12 months. The LMH return for the row labeled MOM is the return from buying past losers (decile 1) and selling past winners (decile 10). We also construct a new decile of portfolios based on the preceding momentum decile as follows. For years 1986-2011, at the time of portfolio formation, we drop stocks that have high oil betas from the winners. Similarly, we drop stocks that have low oil betas from the losers. In contrast, for years 2012-2015, at the time of portfolio formation, we drop stocks that have *low* oil betas from the winners. Similarly, we drop stocks that have *high* oil betas from the losers. Rankings of oil betas are from independent sorts. High-oil-beta stocks include stocks from deciles 8, 9 and 10 based on oil beta sorting, and low-oil-beta stocks include stocks from deciles 1, 2 and 3. This procedure allows us to identify the contribution of high- and low-oil-beta stocks to momentum. If returns on extreme momentum portfolios are distinct, we expect them to be not affected when we remove high- and low-oil-beta stocks from the corresponding bins.

Table 4 presents our results. From 1986 to 2001, the LMH return for the momentum decile shown in the row labeled MOM is -1.11% (t-value = -1.80) and its Fama-French five-factor alpha is -0.82% (t-value = -1.42). The modified LMH return for the new momentum decile presented in the row labeled MOMA is -1.47% (t-value = -2.28) and its five-factor alpha is -0.90% (t-value = -1.48). In the first 16 years of our sample, momentum is strong and oil seems to have negligible effect on momentum.

The results for the next 14 years are strikingly different. From 2002 to 2011, the LMH return for the momentum decile is -0.21% (t-value = -0.31) and its Fama-French five-factor alpha is 0.30% (t-value = 0.48). Thus momentum is weak in this subsample as it covers the 2008-2009 financial crisis, a period that momentum crashes. Removing high- and low-oil-beta stocks, nevertheless, further worsens the performance of momentum trading. In particular, the LMH return for the new momentum decile presented in the row labeled MOMA is 0.17% (t-value = 0.26) and its five factor alpha is 0.90% (t-value = 1.57). The difference is 0.38% per month, implying that restating high- and low-oil-beta stocks in their corresponding bins help achieve the original -0.21% return in momentum trading.

By contrast, from 2012 to 2015, the LMH return for the momentum decile is -0.99% (t-value = -1.43) and its Fama-French five-factor alpha is -1.28% (t-value = -2.02). The LMH return for the new momentum decile is -0.12% (t-value = -0.18) and its Fama-French five factor alpha is -0.29% (t-value = -0.42). This result shows that removing high-oil-beta stocks from the loser portfolio totally destroys momentum. In this subsample, high oil betas stocks among the loser portfolios are the ones that deliver abysmal low returns.

We apply an analogous procedure to the returns on the decile portfolios formed on oil betas. The row labeled LMHO presents results computed as in table 1. We then construct a new decile of oil portfolios as follows. For years 1986-2011, at the time of portfolio formation, we drop stocks that performed well in the past, from decile 10 of the oil portfolios. Similarly, we drop stocks that performed poorly in the past from decile 1 of the oil portfolios. In contrast, for years 2012-2015, at the time of portfolio formation, we drop stocks that performed *poorly* in the past from decile 10 of oil portfolios. Similarly, we drop stocks that performed *well* in the past from the decile 1 of oil portfolios. Stocks performed well in the past are from deciles 8, 9, and 10, and stocks performed poorly in the past are from deciles 1, 2, and 3, formed on the price momentum in the past 12 months.

If the return spread for the oil portfolios presented in row labeled LMHO is unique and robust, we should expect it to be not different from the return spread for the modified oil portfolios presented in the row labeled LMHOA. The bottom two blocks of table 4 present our results. From 1986 to 2001, the LMH return for the oil portfolios in the row labeled LMHO is 0.09% (t-value = 0.22) and the Fama-French five-factor alpha is -0.51% (t-value = -1.36). The LMH return for the modified oil portfolios presented in the row labeled LMHOA is 0.35% (t-value = 0.81) and its five factor alpha is -0.17% (t-value = -0.39). Removing winner stocks from high-oil-beta portfolio lowers the return on the high-oil-beta portfolio and raises the return on the LMHO portfolio from 0.09% to 0.35%. This suggests that momentum helps to explain the returns on the LMHO portfolio, but the magnitude is on par with those we get when we remove high-oil-beta stocks from the winner portfolio in the same sample period, which is 0.30%.

From 2002 to 2011, the return on the LMHO portfolio is -1.43% (t-value = -2.27) and the Fama-French five-factor alpha is -1.45% (t-value = -2.15). The LMH return on the modified LMHO portfolio presented in the row labeled LMHOA is -1.14% (t-value = -1.86) and the Fama-French five-factor alpha is -1.39% (t-value = -2.15). The results suggest that the return on the LMHO portfolio is not much different from the return on the modified LMHO portfolio. From 2012 to 2015, the return on the LMHO portfolio is 1.55% (t-value = 2.13) and the Fama-French five-factor alpha is 1.58% (t-value = 2.36). The LMH return on the modified LMHO portfolio is 1.23% (t-value = 1.63) and the Fama-French five-factor alpha is -1.30% (t-value = 1.70). Again removing loser stocks from the high oil beta portfolio and removing winner stocks from the low oil beta portfolio does not produce material changes in the economical magnitude of alphas.

In summary, our evidence points to the fact that momentum and return on the LMHO portfolio are driven by different stocks. Before 2012, one helps explain the other, but since 2012, it is the return on the oil portfolios that explains momentum. Therefore, we view our findings as documenting a novel stock price momentum effect related to oil. In the following section we will further show that the five-factor alphas of the LMHO portfolio are unique via two-dimensional sorting.

3.4 Results from Two-Dimensional Sorting

It is possible that the abnormal return on the LMHO portfolio disappears once we control for other existing variables that are known to forecast future returns. To address this issue, we perform two-dimensional independent sorting and intersect oil betas with one of the following control variables: June market capitalization (MC), book-to-market ratio (BM), asset growth (AG), operating profitability (OPE), momentum (MOM), and total volatility (TVOL).

At the end of month *t-1*, we form quintile portfolios based on oil betas of each stock, and independently form quintile portfolios based on one of the controlling variables. Portfolio components are intersections from the two independent sorts. The portfolio excess return next month is the value-weighted average of the returns on stocks in each portfolio. For each quintile along one of the control variables, we have a LMHO portfolio that buys low oil betas stocks (quintile 1) and sells high-oil-beta stocks (quintile 5). Similarly, for each quintile along the dimension of oil betas, we form a LMH portfolio that buys quintile 1 and sells quintile 5, for each control variable. We compute the alphas of these LMHO portfolios and LMH portfolios using the Fama and French (2015) five factors.

Table 5 shows our results, and for brevity we report results for 1986 to 2011, and 2012 to 2015. Panel A is for the sub-sample from 1986 to 2011. The five-factor alphas of LMHO portfolios are large in most of the quintile. For instance, among profitability quintiles, the alphas of LMHO portfolios are -0.96%, -0.85%, -0.92%, -0.42% and -0.49% (t-value = -2.94, -2.36, -2.56, -1.39, -1.58). These five alphas have a joint GRS value of 1.99 (p-value = 0.08). In contrast, in the bottom panel of panel A, among oil beta quintiles, the alphas of portfolios formed on profitability are -0.81%, -0.08%, 0.01%, -0.10% and -0.34% (t-value = -3.54, -0.44, -0.03, -0.49, -1.14). The GRS statistic is 2.75 (p-value = 0.02). As Fama and French (2015) show, it is incomplete or sometimes perilous to make inference solely relying on one criterion such as the GRS test, as the GRS test utilizes the variance covariance matrix in its calculation. In our case, the GRS test has a p-value of 0.45 for the LMH portfolio formed on momentum and a p-value of 0.90 for the LMH portfolio formed on total volatility. They advise to report alternative metrics such as absolute alphas. To this end, we find that the average absolute alphas of LMHO portfolios are 0.54%, 0.66%, 0.82%, 0.73%, 0.56% and 0.71% among quintile portfolios formed on size, value, asset growth, profitability, momentum, and total volatility, respectively. In contrast, the average absolute alphas of LMH portfolio formed on the same controlling variables are 0.20%, 0.24%, 0.29%, 0.27%, 0.42%, and 0.11% across quintile portfolios formed on oil betas. It is evident that the alphas of the LMHO portfolio are large.

The results in panel B of table 5 for the subsample from 2012 to 2015 are more dramatic. The five factor absolute alphas of LMHO portfolios on average are 1.23%, 1.26%, 1.21%, 1.22%, 1.14%, and 1.44%. And they are 0.24%, 0.25%, 0.32%, 0.16%, 0.54% and 0.31% for LMH portfolios. Not surprisingly, the GRS statistic rejects the null of zero alphas of LMHO portfolios, and cannot reject zero alphas of LMH portfolios.

The stronger results for the second subsample arise probably because the well-known forecasting variables do not function properly in this period, i.e., these factors do not earn premiums. Our results show that, not only oil exposures are dominant in driving future returns since 2012, but also they have a material effect in determining future returns prior to 2012, when these common forecasting variables are known to be able to forecast future returns. In short, control variables do not reduce the five-factor alphas of LMHO portfolios.

3.5 Results from Cross-Sectional Regressions

What types of firms have high oil betas? We run the Fama and MacBeth (1973) regressions as follows. We regress oil betas at the time of portfolio formation, by sample periods, on the fundamentals including market capitalization, book-to-market ratio, asset growth, operating profitability, price momentum in the past 12 months, and each stock's total volatility at the time of portfolio formation. Table 6 presents the results. Panel A shows that, in the full sample from 1986 to 2015, high-oil-beta stocks tend to be large stocks, value stocks, stocks that grow investments aggressively, stocks that have weak profitability, and stocks that are volatile. These results generally hold in both subsamples. The exceptions are as follows. Before 2012, high oil betas stocks tend to be momentum stocks. On and after 2012, high oil betas stocks are not related to profitability and tend to be loser stocks. Between 2002 and 2011, high oil betas stocks tend to be large firms, value firms, firms with aggressive investment, and firms with weak profitability.

How does the oil beta perform in predicting future returns? Following Fama and MacBeth (1973), we regress future one-month returns on current oil betas, fundamentals, and other control variables. Panel B of Table 6 presents the results. In the full sample from 1986 to 2015, oil beta has a coefficient of -0.004 (t-value = -0.06). Among the control variables, asset growth, profitability, and total volatility are significant. From 1986 to 2011, oil beta has a coefficient of 0.0048 (t-value = 0.76). Asset growth, profitability and total volatility are significant in this period. From 2012 to 2015, oil beta has a coefficient of -0.0337 (t-value = -

2.17). The only control variable that is significant is profitability. Between 2002 and 2011, oil beta has a coefficient of 0.025 (t-value = 2.11). Asset growth, profitability and total volatility are also significant in this period.

How do we interpret these results? Before 2012, the insignificant coefficient resonates with the relatively small return on the LMHO portfolio in this period. Since 2012, oil beta and profitability have distinct forecasting ability for future returns, as both are significant, and high-oil-beta stocks are not necessarily firms with strong or weak profitability.

3.6 Oil Betas and Industry Returns

We consider 48 industries identified by the SIC codes as in Fama and French (1997). Table 7 presents the average oil betas by industries. We find that, from 1986 to 2011, the 10 industries with the largest oil betas are the following: Coal, Precious Metals, Petroleum and Natural Gas, Mine, Steel, Machinery, Construction, Fabricated Products, Utilities and Electrical Equipment. These industries have positive oil betas and high alphas in the following month. Considering the number of firms and market capitalization, we find that the three industries having large positive alphas point to Petroleum and Natural Gas, Machinery, and Chips. The average alphas of firms in these industries are around 1.14%.

The 10 industries with the smallest oil betas, from the lowest to the highest, are Retail, Banks, Meals, Transportation, Insurance, Soda, Drugs, Entertainment, Trading and Defense. These industries have negative oil betas and small alphas in the following month.

Turing to the results after 2012, we find that, industries that are sensitive to oil prices prior to 2012 continue to be sensitive. In this subsample, high-oil-beta industries have low alphas and low-oil-betas industries have high alphas.

3.7. Controlling for the Effect of Demand on Oil Price Changes

Bernanke (2016) argues that the recent strong correlation between oil price changes and aggregate stock returns may be explained by the hypothesis that both are reacting to a common aggregate factor, namely, a softening of global aggregate demand, which hurts both corporate profits and demand for oil. Thus oil beta should be positive. From this perspective, one may argue that oil beta is not something unique, as it may be simply capturing how stock returns fluctuate relative to aggregate demand. In this subsection we follow Bernanke's (2016) methodology, which is originally suggested by Hamilton (2014), to decompose the changes in oil prices into a component due to demand shocks and a component that is regarded as the residual supposedly capturing the supply shocks or other factors. We differ from Bernanke (2016) in that our analysis focuses on the impact of oil price changes on the cross-section of stock returns instead of the aggregate market returns. If oil exposures indeed are relevant and provide additional information about future returns and alphas, we should expect that LMHO returns and alphas are significant after we remove the demand driven oil price changes from the total oil price changes.

We use copper futures prices, the US 10 year T-bond rate, and the U.S. dollar exchange rate to capture demand changes. The rational of using copper prices suggested by Hamilton

(2014) and Bernanke (2016) is that the drop of the price of copper has nothing to do with the success of people getting more oil out of the rocks in Texas and North Dakota. Softness in demand for commodities like copper may be an indicator of new weakness in the economy. Similarly, yields on 10-year US Treasury bond and weakening dollar indicate weakness in the world economy.

We regress the oil price changes on copper prices changes and the 10-year T-bond rate in each month using equation (2). The fitted value is the oil price changes as predicted by the demand changes. Using oil price changes related to demand and the residual, we calculate two corresponding oil betas. We form portfolios sorted on these two betas in the previous month. We then conduct a similar analysis as in previous subsections.

Table 8 presents the results. The first two blocks present the returns on portfolios formed on oil betas related to demand and oil betas related to the residual. From 1986 to 2011, the return on the LMHO portfolio related to the demand component of oil price changes is -0.08% (t-value = -0.23). Its alpha is -0.57% (t-value = -1.63). The return on the LMHO portfolio formed on oil betas related to the residual component of oil price changes is -0.36% per month (t-value = -1.06). The abnormal returns are- 0.95% per month (t-value = -2.86). From 2012 to 2015, the return on the LMHO portfolio formed on oil betas related to the demand component of oil price changes is 0.77% (t-value = 1.06). Its alpha is 1.07% (t-value = -1.78), while corresponding numbers are 1.76% (t-value = 2.49) and 1.63% (t-value = 2.22). These results indicate that removing the effect of demand-driven oil price changes does not alter our results.

3.8. Discussions

Our findings pose a challenge to the conventional risk-based explanations for cross-sectional asset returns using the Fama-French five-factor model. First, alphas from the five-factor model are not zero, especially for the extreme portfolios. Second, if the relation between oil prices and future economy is negative as described in Hamilton (2009), or the relation between oil prices and future stock returns is negative as shown in Driesprong, Jacobsen, and Maat (2008), then oil prices can be viewed as a state variable that captures future investment opportunities, and the innovation in oil prices may become a common risk factor. Stocks load highly on the oil factor will earn low returns because they hedge against future adverse outcomes.[4] From our findings, we find that this argument works for the sample since 2012, but not before 2012, and does not work for the full sample. In the full sample, high-oil-beta stocks stocks still earn high returns. Third, one may argue that oil is probably just a variation of a standard business cycle type risk factor that carries a positive risk premium. The challenge here is that it fails to work after 2012 and the raw return on the LMHO portfolio is only 0.22% per month in the full sample. In addition, we find that using returns on the LMHO portfolio as a factor reduces the alphas of oil portfolios to almost zero in the full sample, but, in unreported results, it does not lower much the alphas of portfolios formed on other characteristic such as asset growth or profitability. Whether oil price fluctuation is a common factor among asset returns is of less interest to us. It is akin to ask whether momentum returns or returns formed on mergers or acquisitions are factors. It also depends on the playing field. Our results indicate

[4] It is possible that stocks with high oil betas earn lower future returns because they pay well when future investment opportunities are worsened by the intertemporal capital asset pricing model of Merton (1973). If high-oil-beta stocks provide useful hedges, their expected returns should be lower. As Campbell et al (2012) point out, there are two types of deterioration in investment opportunities: declining expected returns and rising volatilities.

that the five-factor alpha of the LMHO portfolio is large, so it is natural to expect that the return on the LMHO portfolio will be able to explain returns of portfolios formed on oil betas.

Our evidence seems to suggest that investors underreact to the oil price movement or underreact to current information that helps forecast future oil price changes. For instance, this information from 2002 to 2011 can be gradually small demand shocks coupled with tight supply conditions as described in Kilian (2009); and this information from 2012 to 2015 can be weakening of emerging economy and the rise of shale producers. Investors either underestimate how high the oil price will rise, or underestimate how low the oil price will drop, and consequently underestimate the value of stocks that load differently on oil price movements.

Driesprong, Jacobsen, and Maat (2008) provide a behavioral story based on investors' underreaction to oil price changes to explain why the oil price changes predict future aggregate returns negatively. Sockin and Xiong (2015) argue that information frictions cause goods producers to erroneously estimate the demand for oil from emerging economies around the second half of 2007, and funds keep flowing into oil for the sake of diversification amid deteriorating U.S. economy and stock market performance at that time, which ultimately lead to another 40% increase of oil prices from the end of 2007 to June of 2008. Blanchard (2016) argues that herding behavior may explain the recent positive relation between aggregate stock returns and oil price changes. The recent decline of oil prices was associated with elevated uncertainty. When some investors sold stocks in panic, others followed suit, causing the stock market to fall.

Had investors fully expected the surge of oil prices from 2002 to 2011, they should have priced high-oil-beta stocks expensively immediately so that future returns on high-oil-beta stocks are not particularly large. Similarly, had investors fully expected the sharp fall of oil prices from 2012 to 2015, they should have priced high-oil-beta stocks cheaply immediately so that future returns on high-oil-beta stocks are not particularly small. It turns out that the market and investors failed to price oil portfolios correctly.

4 Conclusion

Irregularities in the stock market evolve. McLean and Pontiff (2016) show that anomalous returns are 58% lower after academic publications as investors learn mispricing from them. Our study finds mispricing related to changes in oil prices. The pivotal point for oil to matter seems to be 2002. The effect of oil prices on cross-sectional asset return is negligible before 2002. But high-oil-beta stocks, relative to low-oil-beta stocks, deliver superior performance between 2002 and 2011 when oil prices trend upward even with a crash in 2008, and inferior performance between 2012 and 2015 when oil prices trend downward. Moreover, stock price momentum driven by oil price changes since 2012 is stronger than or dominates the outcome from typical momentum trading of buying past winners and selling past losers.

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Table 1. Summary of Returns of Portfolios Formed on Oil Betas, 1986-2015

To estimate oil betas, we regress each stock's daily excess returns on the market excess return and daily percentage changes in the price of crude oil (WTI) in excess of the risk-free rate (oil excess return). The oil betas are slopes on the oil excess return. At the end of month *t-1*, we form decile portfolios based on the oil betas of all stocks, and track their returns in the following month. Portfolio excess return is value-weighted average of returns on stocks in each portfolio. Decile 1 (L) includes stocks that have the lowest oil betas and decile 10 (H) has the highest oil betas. Column LMHO lists returns on a portfolio that buys decile 1 and sells decile 10. At the time of portfolio formation, we delete firms that have negative or zero book-to-market ratio, that have prices less than five dollars, or whose market capitalizations are less than the 10 percentile market capitalization among the NYSE firms. Oil betas are winsorized at 1% and 99%. The upper panel lists excess returns (Ret) in monthly percentage and their t-values (t). Returns are in monthly percentage. The second panel reports the Fama-French (2015) five factor alphas. The GRS and its p-value are joint tests of alphas following Gibbons, Ross and Shanken (1989). The third panel reports the value-weighted oil beta for each oil portfolio. The fourth panel reports correlations of LMHO with returns of five factors (MKT, SMB, HML, CMA, RMW) of Fama and French (2015), return on the LMH portfolio formed on past price momentum (MOM), and return on the portfolio formed on individual stock's total volatility (TVOL). The fifth panel presents mean and t-values of factors used in each subsample. Stocks returns are from the CRSP. The risk-free rate, NYSE size breakpoints and other portfolio and factor data are obtained from Kenneth French's website. The WTI crude oil price is from the Saint Louis Fed at https://fred.stlouisfed.org/series/DCOILWTICO. The sample is daily from 1986 to 2015.

Sample	Var/Decile	1 (L)	2	3	4	5	6	7	8	9	10 (H)	LMHO	GRS	p-value
1986-2015	Ret	0.51	0.62	0.48	0.64	0.66	0.65	0.72	0.54	0.66	0.73	-0.22		
	t	1.58	2.34	2.06	2.67	2.80	2.75	2.86	1.88	2.23	2.16	-0.68		
1986-2011	Ret	0.34	0.48	0.33	0.52	0.58	0.52	0.64	0.43	0.62	0.84	-0.50		
	t	0.95	1.61	1.27	1.92	2.20	1.96	2.26	1.35	1.87	2.26	-1.39		
2012-2015	Ret	1.57	1.54	1.46	1.46	1.17	1.50	1.24	1.19	0.91	0.02	1.55		
	t	2.52	3.23	3.16	3.12	2.63	3.31	2.74	2.37	1.61	0.02	2.13		
1986-2015	Alpha	-0.29	-0.22	-0.21	-0.04	-0.03	0.06	0.17	0.13	0.14	0.40	-0.69	1.02	0.43
	t	-1.65	-1.99	-2.48	-0.42	-0.30	0.65	2.06	1.19	1.18	1.91	-2.09		
1986-2011	Alpha	-0.40	-0.32	-0.30	-0.09	-0.02	0.01	0.20	0.18	0.24	0.68	-1.08	1.67	0.09
	t	-2.13	-2.61	-3.16	-0.91	-0.23	0.11	2.12	1.47	1.89	3.01	-3.05		
2012-2015	Alpha	0.28	0.36	0.27	0.20	-0.04	0.32	0.08	-0.10	-0.48	-1.31	1.58	1.90	0.08
	t	0.73	1.54	1.42	1.23	-0.31	1.76	0.44	-0.50	-2.91	-2.88	2.36		
1986-2015	Oil Beta	-0.143	-0.082	-0.054	-0.033	-0.015	0.003	0.022	0.045	0.084	0.211	-0.355		
1986-2011	Oil Beta	-0.137	-0.080	-0.052	-0.031	-0.014	0.003	0.021	0.044	0.082	0.203	-0.341		
2012-2015	Oil Beta	-0.181	-0.097	-0.064	-0.039	-0.018	0.002	0.024	0.051	0.096	0.262	-0.443		

	1986-2011							2012-2015						
Corr	SMB	HML	CMA	RMW	MOM	TVOL	LMHO	SMB	HML	CMA	RMW	MOM	TVOL	LMHO
MKT	0.21	-0.29	-0.34	-0.39	-0.22	0.63	0.02	0.18	-0.06	-0.21	-0.07	-0.32	0.42	-0.10
SMB		-0.21	-0.47	-0.07	0.00	0.55	-0.15		0.01	-0.56	-0.12	-0.14	0.60	0.03
HML			0.40	0.67	-0.14	-0.50	0.25			0.00	0.70	-0.48	-0.21	-0.45
CMA				0.15	0.12	-0.68	0.34				0.19	0.06	-0.63	-0.15
RMW					0.08	-0.46	0.10					-0.25	-0.41	-0.11
MOM						-0.31	-0.25						-0.37	0.44
TVOL							-0.12							-0.04
	MKT	SMB	HML	CMA	RMW	MOM	TVOL	MKT	SMB	HML	CMA	RMW	MOM	TVOL
Mean	0.50	0.12	0.26	0.40	0.34	1.13	-0.57	1.23	-0.11	-0.16	-0.03	-0.04	1.06	0.02
t-value	1.87	0.65	1.41	2.73	2.81	2.42	-1.09	2.74	-0.34	-0.59	-0.16	-0.24	1.20	0.02

Table 2. Betas of Oil Portfolios using the Fama and French Five Factors

The table presents betas of decile portfolios formed on oil betas as testing assets. We use the Fama and French (2015) five-factor model that includes the market excess returns (MKT), a size factor (SMB), a value factor (HML), an asset growth factor (CMA), and a profitability factor (RMW). We present betas and their t-values. LMHO stands for the difference in returns between portfolio 1 and portfolio 10. Returns are in monthly percentage.

Panel A: 1986-2011										
	MKT	SMB	HML	CMA	RMW	t(MKT)	t(SMB)	t(HML)	t(CMA)	t(RMW)
1	1.19	0.15	0.40	0.26	-0.23	26.97	2.42	4.76	2.92	-1.87
2	1.11	0.06	0.22	0.35	0.10	39.06	1.53	4.02	6.16	1.34
3	0.98	-0.10	0.10	0.28	0.02	44.98	-3.04	2.43	6.37	0.39
4	1.01	-0.12	0.13	0.20	-0.01	46.28	-3.76	3.03	4.62	-0.11
5	0.98	-0.01	0.05	0.21	0.05	43.04	-0.30	1.10	4.63	0.84
6	0.94	0.02	-0.12	-0.02	0.22	40.75	0.54	-2.73	-0.37	3.44
7	0.99	-0.05	-0.06	-0.05	-0.04	44.62	-1.49	-1.47	-1.04	-0.59
8	0.98	-0.03	-0.08	-0.31	-0.27	34.51	-0.68	-1.43	-5.33	-3.41
9	1.05	0.00	-0.16	-0.23	-0.06	34.99	-0.11	-2.71	-3.75	-0.72
10	0.93	0.14	0.10	-0.60	-0.29	17.78	1.83	1.01	-5.74	-2.02
LMHO	0.26	0.02	0.30	0.86	0.06	3.19	0.14	1.91	5.20	0.28

Panel B: 2012-2015										
	MKT	SMB	HML	CMA	RMW	t(MKT)	t(SMB)	t(HML)	t(CMA)	t(RMW)
1	0.99	0.07	-0.45	-0.87	0.33	8.45	0.37	-1.60	-2.79	0.73
2	0.96	0.01	0.05	0.15	-0.16	13.34	0.07	0.32	0.80	-0.59
3	0.95	0.03	-0.33	-0.02	0.53	15.89	0.34	-2.33	-0.12	2.30
4	0.98	-0.15	-0.33	-0.22	0.47	19.09	-1.77	-2.69	-1.58	2.40
5	0.97	-0.06	-0.25	0.15	0.45	24.58	-0.87	-2.73	1.44	2.97
6	0.95	-0.09	-0.08	-0.08	0.28	16.80	-0.97	-0.61	-0.52	1.29
7	0.94	-0.01	-0.07	-0.08	0.18	16.53	-0.13	-0.51	-0.50	0.82
8	1.06	-0.01	0.18	0.23	-0.42	17.90	-0.11	1.30	1.47	-1.83
9	1.18	0.24	0.24	0.13	-0.26	23.07	2.74	2.02	0.98	-1.34
10	1.26	0.16	1.76	0.18	-1.81	9.04	0.70	5.34	0.48	-3.39
LMHO	-0.27	-0.09	-2.21	-1.05	2.14	-1.29	-0.26	-4.51	-1.91	2.70

Table 3. Adjusting for Risk Exposure Using Alternative Factors

This table presents abnormal returns (Alpha) of decile portfolios formed on oil betas by incorporating a momentum factor (FMOM) and a volatility factor (FTVOL) into the five factors of Fama and French (2015) for different sample periods. The momentum factor buys past winners and sells past losers; the volatility factor buys low volatility stocks and sells high volatility stocks. The bottom panel tests using the market factor and return on the LMHO portfolio. Returns are in monthly percentage.

Sample	Var/Decile	1 (L)	2	3	4	5	6	7	8	9	10 (H)	LMHO	GRS	p-value
							FF5 + MOM							
1986-2011	Alpha	-0.29	-0.27	-0.30	-0.07	-0.01	-0.01	0.18	0.20	0.24	0.60	-0.89	1.56	0.12
	t	-1.61	-2.28	-3.18	-0.79	-0.06	-0.10	1.89	1.66	1.85	2.69	-2.60		
2012-2015	Alpha	0.37	0.26	0.25	0.11	-0.02	0.34	0.00	-0.09	-0.40	-0.93	1.29	1.44	0.21
	t	0.91	1.07	1.21	0.67	-0.15	1.74	0.01	-0.44	-2.35	-2.15	1.87		
2002-2011	Alpha	-0.85	-0.72	-0.38	-0.07	0.23	-0.05	0.12	0.36	0.38	0.96	-1.82	3.95	0.00
	t	-2.93	-3.42	-2.41	-0.53	1.73	-0.35	0.84	2.46	1.93	2.39	-3.13		
							FF5 + TVOL							
1986-2011	Alpha	-0.38	-0.31	-0.30	-0.09	-0.03	0.00	0.20	0.18	0.25	0.68	-1.06	1.68	0.09
	t	-2.17	-2.59	-3.20	-0.95	-0.31	0.02	2.10	1.45	1.98	3.03	-3.03		
2012-2015	Alpha	0.37	0.30	0.21	0.17	-0.07	0.32	0.06	-0.11	-0.46	-1.08	1.45	1.88	0.09
	t	0.96	1.28	1.11	1.02	-0.55	1.72	0.32	-0.54	-2.73	-2.64	2.14		
2002-2011	Alpha	-0.71	-0.67	-0.36	-0.03	0.24	-0.04	0.10	0.36	0.34	0.77	-1.48	3.46	0.00
	t	-2.30	-3.05	-2.33	-0.25	1.89	-0.32	0.69	2.50	1.74	1.76	-2.22		
							MKT + LMHO							
1986-2015	Alpha	-0.07	0.08	-0.02	0.11	0.13	0.10	0.11	-0.15	-0.06	-0.07	0.00	0.00	1.00
	t	-0.65	0.91	-0.22	1.34	1.49	1.11	1.40	-1.36	-0.61	-0.65	inf		

Table 4. Revisit LMHO and Momentum

We form decile portfolios based on price performance in the past 12 months. The LMH return of MOM is the return from buying past losers and sell past winners. The return on the MOMA portfolio is computed as follows. For year 1986-2011 including year 1986-2001 and 2002-2011, at the time of formation, we drop stocks that have-high-oil betas from the winners. Similarly, we drop stocks that have low oil betas from the losers. In contrast, for year 2012-2015, at the time of formation, we drop stocks that have *low* oil betas from the winners. Similarly, we drop stocks that have *high* oil betas from the losers. Rankings of oil betas are from independent sorts. High-oil-beta stocks include stocks from deicles 8, 9 and 10 and low-oil-beta stocks include stocks from deciles 1, 2 and 3, from portfolios formed on oil betas. The return on the LMHOA portfolio modifies the components in LMHO and is computed as follows. For years 1986-2011, at the time of formation, we drop stocks that performed well in the past from decile 10 of oil beta portfolios. Similarly, we drop stocks that performed poorly in the past from decile 1 of oil beta portfolios. In contrast, for years 2012-2015, at the time of formation, we drop stocks that performed *poorly* in the past from decile 10 of oil beta portfolios. Similarly, we drop stocks that performed *well* in the past from decile 1 of oil beta portfolios. Stock performed well in the past are from deciles 8, 9, and 10, and stocks performed poorly in the past are from deciles 1, 2, and 3 of portfolios formed on price momentums in the past 12 months. In this table, variable LHM is low-minus-high, or selling portfolio 1 and buying portfolio 10. The alphas are the Fama and French (2015) five factor alpha. Returns (Ret) are in monthly percentage.

	Panel A: 1986-2001						Panel B: 2002-2011						Panel C: 2012-2015					
	Ret			Alpha			Ret			Alpha			Ret			Alpha		
	1	10	LMH	1	10	LMH	1	10	LMH	1	10	LMH	1	10	LMH	1	10	LMH
MOM	0.18	1.28	-1.11	-0.17	0.65	-0.82	-0.14	0.07	-0.21	-0.10	-0.40	0.30	0.40	1.39	-0.99	-1.22	0.06	-1.28
t	0.31	2.16	-1.80	-0.45	2.26	-1.42	-0.17	0.12	-0.31	-0.27	-1.15	0.48	0.48	2.46	-1.43	-2.38	0.20	-2.02
MOMA	0.09	1.55	-1.47	-0.14	0.75	-0.90	0.22	0.05	0.17	0.35	-0.55	0.90	1.32	1.44	-0.12	-0.13	0.16	-0.29
t	0.15	2.59	-2.28	-0.37	2.35	-1.48	0.28	0.09	0.26	1.00	-1.68	1.57	1.73	2.39	-0.18	-0.23	0.40	-0.42
LMHO	0.83	0.74	0.09	-0.06	0.44	-0.51	-0.42	1.01	-1.43	-0.67	0.78	-1.45	1.57	0.02	1.55	0.28	-1.31	1.58
t	1.97	1.60	0.22	-0.31	1.85	-1.36	-0.67	1.59	-2.27	-1.99	1.78	-2.15	2.52	0.02	2.13	0.73	-2.88	2.36
LMHOA	0.89	0.54	0.35	-0.01	0.16	-0.17	0.00	1.14	-1.14	-0.48	0.91	-1.39	1.41	0.18	1.23	0.12	-1.18	1.30
t	2.12	1.25	0.81	-0.03	0.51	-0.39	0.00	1.92	-1.86	-1.36	2.25	-2.15	2.17	0.24	1.63	0.25	-2.68	1.70

Table 5. LMHO and LMH Alphas from Double Sorting

At the end of month *t-1*, we form quintile portfolios based on the oil beta of each stock, and independently form quintile portfolios based on one of the following control variables: June market capitalization (MC), book-to-market ratio (BM), asset growth (AG), operating profitability (OPE), momentum (MOM), and total volatility (TVOL). Portfolios are intersections from the two previous independent sorts. Portfolio excess return (Ret) is value-weighted average of the returns of stocks in each portfolio. For each quintile along one of the control variables (Char/Quintile), we have a LMHO portfolio that buys low oil betas stocks (quintile 1) and sells high-oil-beta stocks (quintile 5). Similarly, for each quintile along the dimension of oil betas, we have a LMH portfolio that buys quintile 1 and sells quintile 5, for each control variable. We compute the alphas of these LMHO portfolios and LMH portfolios using the Fama and French (2015) five factors. The *t* represents t-values. The GRS and its p-value are joint tests of alphas following Gibbons, Ross and Shanken (1989). Panel A is for years from 1986 to 2011 and panel B is for years from 2012 to 2015. Returns are in monthly percentage.

Panel A: 1986-2011												
	LMHO Alpha					t-value					GRS	p-value
Char/Quintile	1	2	3	4	5	1	2	3	4	5		
MC	-0.32	-0.25	-0.58	-0.66	-0.88	-1.62	-1.25	-2.49	-2.71	-3.04	2.28	0.05
BM	-0.91	-0.34	-0.57	-0.79	-0.69	-3.18	-1.15	-1.79	-2.48	-2.11	2.94	0.01
AG	-0.45	-0.52	-0.99	-0.70	-1.44	-1.53	-1.91	-2.86	-1.92	-4.37	4.17	0.00
OPE	-0.96	-0.85	-0.92	-0.42	-0.49	-2.94	-2.35	-2.56	-1.39	-1.58	1.99	0.08
MOM	-0.59	-0.31	-0.49	-0.25	-1.17	-1.80	-1.01	-1.64	-0.90	-3.29	2.71	0.02
TVOL	-0.48	-0.50	-0.89	-0.92	-0.75	-2.05	-1.83	-2.61	-2.56	-2.19	1.89	0.10
	LMH Alpha					t-value					GRS	p-value
Char/Oil Quintile	OIL1	OIL2	OIL3	OIL4	OIL5	OIL1	OIL2	OIL3	OIL4	OIL5		
MC	0.24	0.35	-0.06	0.01	-0.33	1.26	2.29	-0.41	0.03	-1.50	2.24	0.05
BM	0.05	0.38	0.13	0.36	0.26	0.23	2.10	0.81	1.73	0.98	1.99	0.08
AG	0.28	0.18	-0.23	0.05	-0.70	1.20	0.96	-1.17	0.26	-3.30	3.08	0.01
OPE	-0.81	-0.08	0.01	-0.10	-0.34	-3.54	-0.44	0.03	-0.49	-1.14	2.75	0.02
MOM	-0.21	-0.46	-0.20	-0.44	-0.80	-0.50	-1.18	-0.50	-1.12	-1.84	0.95	0.45
TVOL	0.17	0.00	0.04	0.26	-0.10	0.53	0.00	0.12	0.90	-0.31	0.32	0.90

Panel B: 2012-2015												
	LMHO Alpha					t-value					GRS	p-value
Char/Quintile	1	2	3	4	5	1	2	3	4	5		
MC	0.79	1.49	1.14	1.41	1.30	1.75	3.82	2.32	2.66	2.49	3.30	0.01
BM	1.10	1.14	1.57	1.19	1.31	2.23	2.22	2.79	2.01	1.51	2.42	0.05
AG	1.04	0.53	1.23	1.55	1.73	1.99	0.81	2.26	2.89	2.42	2.47	0.05
OPE	1.48	1.94	0.55	1.13	1.02	2.19	2.98	0.91	2.23	2.21	2.97	0.02
MOM	1.83	1.66	0.25	0.72	1.26	2.35	3.00	0.45	1.38	2.17	3.16	0.02
TVOL	1.52	0.69	1.80	1.58	1.61	3.74	1.17	3.01	2.73	1.91	3.08	0.02
	LMH Alpha					t-value					GRS	p-value
Char/Oil	OIL1	OIL2	OIL3	OIL4	OIL5	OIL1	OIL2	OIL3	OIL4	OIL5		
MC	-0.10	0.04	0.21	0.45	0.41	-0.27	0.14	0.64	1.38	1.09	0.75	0.59
BM	-0.01	0.01	-0.14	-0.89	0.21	-0.01	0.02	-0.39	-2.64	0.34	1.34	0.27
AG	-0.16	0.02	-0.53	0.37	0.53	-0.31	0.04	-1.07	0.87	1.25	0.49	0.78
OPE	0.01	-0.02	-0.05	0.27	-0.45	0.03	-0.09	-0.18	0.86	-0.77	0.40	0.84
MOM	0.17	-0.28	-0.53	-1.31	-0.40	0.20	-0.48	-0.89	-2.10	-0.56	1.04	0.41
TVOL	0.47	0.06	-0.01	0.44	0.57	0.61	0.11	-0.02	0.78	0.97	0.27	0.93

Table 6. Oil Betas, Characteristics and Future Returns

Panel A presents slopes and t-values (t) from the Fama-MacBeth (1973) regression of regressing oil betas at the time of portfolio formation on stock characteristics. Panel B presents slopes and t-values (t), using the Fama-MacBeth regression, from regressing the next-month excess returns on the oil betas and controlling variables. The following accounting variables are used: June market capitalization, the book-to-market ratio, the asset growth and the operating profitability (MC, BM, AG, OPE). Additional control variables include the price momentum in the past 12 months (MOM) and stocks total volatility (TVOL). The Adj. R2 is the adjusted R-squared. The Obs. is the number of observations.

	Panel A: Explaining Oil Betas					Panel B: Forecasting Returns			
Sample/Var.	1986-2011	2012-2015	2002-2011	1986-2015		1986-2011	2012-2015	2002-2011	1986-2015
Intercept	-0.01	-0.04	-0.0343*	-0.01		0.0100**	0.01	0.01	0.0098**
t	-1.24	-1.09	-1.82	-1.61		2.11	1.03	1.23	2.30
Oil Beta						0.00	-0.0337**	0.0205**	0.00
t						0.76	-2.17	2.11	-0.06
MC	0.0015*	0.0074**	0.0039**	0.0023**		0.00	0.00	0.00	0.00
t	1.80	2.23	2.07	2.59		-0.81	0.53	-1.19	-0.66
BM	0.0034***	0.0147***	0.0045**	0.0049***		0.00	0.00	0.00	0.00
t	3.07	2.77	2.00	3.86		1.10	0.30	0.32	1.14
AG	0.0058***	0.0097***	0.0170***	0.0063***		-0.0019***	0.00	-0.0016**	-0.0016***
t	3.03	3.26	4.56	3.69		-3.76	0.60	-1.99	-3.15
OPE	-0.0013***	0.00	-0.0017***	-0.0011***		0.0006**	0.0002*	0.0006**	0.0005**
t	-5.43	0.13	-4.17	-5.13		2.23	1.99	2.46	2.36
MOM	0.0112**	-0.0676***	0.0294***	0.00		0.00	0.00	0.00	0.00
t	2.38	-3.92	2.72	0.09		1.10	1.00	-0.63	1.29
TVOL	2.5683***	16.7773***	6.0671***	4.4895***		-2.5717***	0.16	-2.1841**	-2.2018***
t	3.35	2.98	4.27	3.86		-4.95	0.27	-2.30	-4.70
Adj R2	0.040	0.121	0.071	0.051		0.053	0.057	0.059	0.054
Obs.	683764	92042	248826	775806		682065	91872	248333	773937

Table 7. Oil Betas and Industries

This table presents average value-weighted oil betas and the Fama-French five-factor alphas by industry. We present the oil betas, from high to low, of the 10 industries that have the highest oil betas and the lowest oil betas. The column "Ret" is the average of next month return. The column "Alpha" is value-weighted alpha of individual alphas. Their respective t-values are computed using all data in each industry. We compute the five-factor alphas for each stock before we take averages by industry. The column "Ind" indicates the numerical number of the industry in the Fama and French (1997) 48 industries. The column "Name" is the name and abbreviation for each industy. The column "MC" is the value-weighted average of June market capitalization. The column "Obs" is the number of firm-month observations in each industry.

				1986-2011					
Ind	Name	Oil Beta	Ret	Alpha	*t(Oil Beta)*	*t(Ret)*	*t(Alpha)*	MC	Obs
29	Coal Coal	0.32	0.34	3.67	*59.13*	*0.88*	*28.71*	7088	1530
27	Gold Precious Metals	0.22	0.30	1.81	*56.77*	*1.03*	*66.23*	17894	1780
30	Oil Petroleum and Natural Gas	0.21	0.65	1.00	*223.86*	*12.85*	*110.16*	127677	25975
28	Mines Non-Metallic and Industrial Metal Mining	0.12	0.52	1.80	*43.68*	*2.60*	*16.90*	9185	3252
19	Steel Steel Works Etc	0.07	0.26	1.55	*62.20*	*2.43*	*79.20*	11764	11507
21	Mach Machinery	0.05	0.10	1.14	*49.80*	*1.45*	*106.22*	61540	23380
18	Cnstr Construction	0.03	-0.06	0.69	*22.18*	*-0.47*	*7.42*	3682	8011
20	FabPr Fabricated Products	0.03	-0.20	1.51	*14.18*	*-0.78*	*27.24*	2805	1982
31	Util Utilities	0.02	0.47	1.49	*48.52*	*13.50*	*238.82*	9591	38057
36	Chips Electronic Equipment	0.01	-0.41	1.31	*17.32*	*-5.20*	*1.01*	81038	31518
26	Guns Defense	-0.03	0.52	0.84	*-23.98*	*2.74*	*32.36*	19059	1779
47	Fin Trading	-0.03	0.39	0.99	*-90.99*	*8.94*	*63.76*	39600	47464
7	Fun Entertainment	-0.03	0.06	1.20	*-36.68*	*0.51*	*53.24*	42220	6393
13	Drugs Pharmaceutical Products	-0.03	0.31	1.24	*-73.40*	*5.82*	*87.35*	88599	27377
3	Soda Candy & Soda	-0.03	0.48	0.52	*-42.79*	*3.98*	*74.03*	88563	2937
45	Insur Insurance	-0.03	0.10	0.12	*-88.45*	*1.92*	*10.73*	46547	28227
40	Trans Transportation	-0.03	0.42	0.48	*-30.53*	*5.92*	*24.64*	15053	16522
43	Meals Restaraunts, Hotels, Motels	-0.03	0.63	0.56	*-54.65*	*8.27*	*5.54*	21007	13645
44	Banks Banking	-0.05	-0.06	1.03	*-152.34*	*-1.45*	*84.19*	66664	47993
42	Rtail Retail	-0.06	0.37	0.39	*-161.91*	*7.84*	*26.22*	64322	36891

		2012-2015							
Ind	Name	Oil Beta	Ret	Alpha	*t(Oil Beta)*	*t(Ret)*	*t(Alpha)*	MC	Obs
27	Gold Precious Metals	0.21	-2.03	-1.58	*33.77*	*-2.27*	*-6.45*	25308	151
29	Coal Coal	0.21	-3.25	-4.79	*24.57*	*-3.75*	*-13.75*	6860	200
30	Oil Petroleum and Natural Gas	0.21	-0.07	0.62	*84.05*	*-0.62*	*5.71*	174273	3877
28	Mines Non-Metallic and Industrial Metal Mining	0.17	-0.77	-1.53	*23.21*	*-1.44*	*-11.99*	21236	340
21	Mach Machinery	0.05	0.72	-0.85	*24.48*	*6.22*	*-18.04*	106555	3023
20	FabPr Fabricated Products	0.05	0.10	-0.69	*5.37*	*0.11*	*-1.24*	2394	148
22	ElcEq Electrical Equipment	0.02	0.68	-1.69	*13.22*	*3.52*	*-11.49*	20331	1109
25	Ships Shipbuilding, Railroad Equipment	0.02	1.52	2.18	*4.79*	*3.42*	*17.01*	14307	260
19	Steel Steel Works Etc	0.02	0.07	-0.57	*9.35*	*0.32*	*-2.48*	26962	1284
31	Util Utilities	0.02	0.47	1.01	*17.04*	*5.29*	*21.92*	20948	3984
43	Meals Restaraunts, Hotels, Motels	-0.03	1.01	0.97	*-22.17*	*6.23*	*11.35*	48611	1596
10	Clths Apparel	-0.04	1.44	1.01	*-16.07*	*6.12*	*14.17*	28432	836
1	Agric Agriculture	-0.04	1.97	0.22	*-7.98*	*3.27*	*1.76*	2149	160
8	Books Printing and Publishing	-0.04	1.35	1.85	*-20.69*	*5.33*	*13.02*	26175	767
7	Fun Entertainment	-0.04	2.29	4.67	*-14.18*	*8.01*	*38.73*	52112	830
13	Drugs Pharmaceutical Products	-0.05	1.61	2.25	*-39.02*	*13.65*	*16.17*	119568	3686
26	Guns Defense	-0.05	1.81	5.37	*-14.80*	*4.98*	*58.58*	39811	214
42	Rtail Retail	-0.06	1.23	2.84	*-67.46*	*13.52*	*45.19*	79512	5185
40	Trans Transportation	-0.06	0.96	1.32	*-19.52*	*7.33*	*25.93*	36029	2411
16	Txtls Textiles	-0.07	1.85	-0.62	*-14.28*	*3.93*	*-3.82*	7339	187

Table 8. Returns and Abnormal Returns on Portfolios Formed on Alternative Oil Betas

This table presents returns on decile portfolios formed on alternative oil betas. The original oil betas are slopes from a regression of daily excess returns on the market excess return and daily percentage changes in the price of crude oil (WTI) in excess of the risk-free rate. The first set of oil betas are slopes from a regression in which the daily percentage changes in the oil price in the previous regression is replaced by the oil price changes related to demand. The second set of betas uses residual percentage oil price changes. To estimate percentage oil price changes related to demand, in each month, we regress daily percentage oil price changes on daily percentage changes the price of copper futures, the change in 10 year Treasury bond rate, and the daily percentage change in the value of dollar. The fitted value is treated as the oil price changes related to demand shocks and the difference between actual values and fitted values is our residual percentage change in oil prices. Decile 1 (L) includes stocks that have the lowest oil beta and decile 10 (H) has the highest oil betas. LMHO represents the return of a portfolio that buys decile 1 and sells decile 10. The copper futures price is from the Genesis Financial Technologies. The bond rate and dollar index are from the St. Louis Fed. The "Ret" is the excess return and the "Alpha" is the Fama and French five factor alpha. All returns are in monthly percentage.

Port.	1 (L)	2	3	4	5	6	7	8	9	10 (H)	LMHO
Panel A: Portfolios Formed on Oil Demand Beta 1986-2011											
Ret	0.36	0.32	0.41	0.48	0.51	0.64	0.57	0.65	0.58	0.44	-0.08
t	1.08	1.08	1.56	1.89	1.92	2.46	2.07	2.18	1.77	1.03	-0.23
Alpha	-0.30	-0.38	-0.16	-0.21	-0.09	0.09	0.07	0.17	0.17	0.27	-0.57
t	-1.62	-2.51	-1.47	-2.46	-0.93	0.95	0.77	1.51	1.14	1.17	-1.63
Panel B: Portfolios Formed on Oil Residual Beta 1986-2011											
Ret	0.42	0.53	0.54	0.62	0.49	0.52	0.57	0.40	0.63	0.78	-0.36
t	1.18	1.79	1.96	2.29	1.88	2.02	2.03	1.33	1.90	2.11	-1.06
Alpha	-0.39	-0.23	-0.16	-0.01	-0.13	0.00	0.18	0.10	0.38	0.56	-0.95
t	-2.32	-1.89	-1.70	-0.12	-1.38	0.03	2.03	0.91	2.90	2.52	-2.86
Panel C: Portfolios Formed on Oil Demand Beta 2012-2015											
Ret	1.14	1.21	1.32	1.37	1.40	1.04	1.19	1.41	1.21	0.37	0.77
t	2.26	2.74	2.84	2.89	3.46	2.23	2.36	2.71	2.00	0.48	1.06
Alpha	0.06	0.07	0.18	0.09	0.38	-0.15	-0.10	0.15	-0.19	-1.01	1.07
t	0.19	0.38	0.75	0.59	1.94	-0.90	-0.62	0.67	-0.76	-2.14	1.78
Panel D: Portfolios Formed on Oil Residual Beta 2012-2015											
Ret	1.84	1.66	1.56	1.26	1.28	1.20	1.15	1.44	0.85	0.08	1.76
t	2.63	3.31	3.33	2.80	2.95	2.82	2.44	3.24	1.56	0.10	2.49
Alpha	0.40	0.41	0.35	0.05	0.13	0.08	-0.04	0.28	-0.52	-1.23	1.63
t	0.96	1.95	1.92	0.30	0.85	0.56	-0.18	1.51	-2.06	-2.72	2.22

Figure 1. Daily WTI Crude Oil Prices, 1986 to 2015

This figure plots the daily nominal crude oil prices (Western Texas Intermediate) from 1986 to 2015. Data is from the Saint Louis Fed.

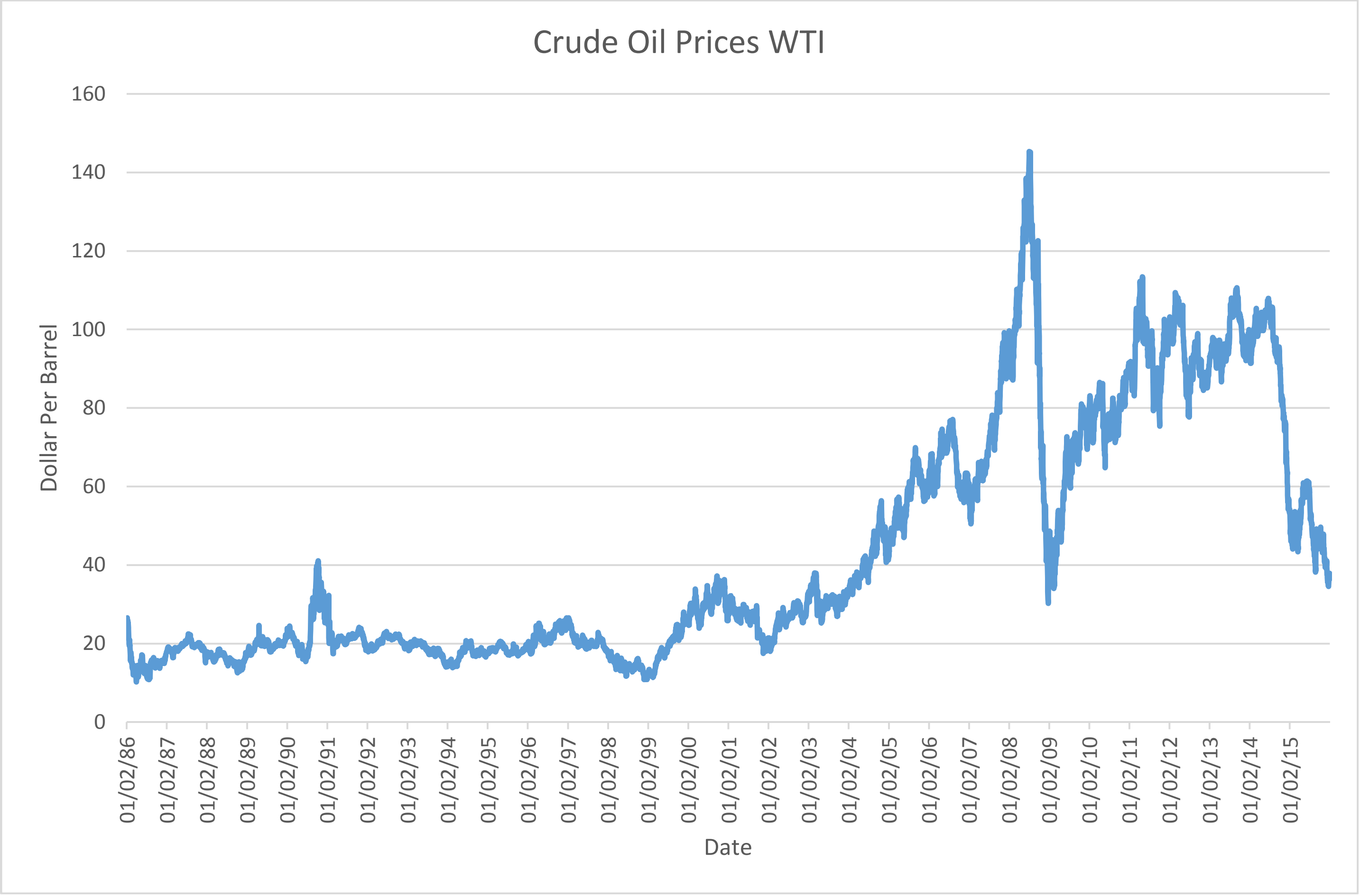

Figure 2. Returns of Portfolios Formed on Oil Betas, 1986-2015

To estimate oil betas, we regress daily excess returns on the market excess return and daily percentage changes in the price of crude oil (WTI) in excess of the risk-free rate. The slope on oil excess return is the oil beta. At the end of month *t-1*, we form decile portfolios based on the oil beta of each stock, and track their return in the following month. Portfolio excess return is value-weighted average of the returns of stocks in each portfolio. Decile 1 (L) includes stocks that have the lowest oil beta and decile 10 (H) has the highest oil betas. LMHO represents the return on a portfolio that buys decile 1 and sells decile 10. At the time of portfolio formation, we delete firms that have negative or zero book-to-market ratio, that have prices less than five dollars, or whose market capitalizations are less than the 10 percentile market capitalization among the NYSE firms. Stocks returns are from the CRSP. The risk-free rate and NYSE size breakpoints are from Kenneth French. The WTI crude oil price is from the Saint Louis Fed. The sample is daily from 1986 to 2015. We average monthly returns in each year to obtain returns by calendar years.