# Asset pricing anomalies: Evidence from oil industry *

**Sofia B. Ramos**[†] **Helena Veiga**[‡] **Chih-Wei Wang**[§]

This Version: January 14, 2012

**ABSTRACT**

Recent research that has identified industry-related patterns finds that standard asset pricing models cannot explain effectively. This paper investigates whether industry commodity dependence affects the cross section of stock returns, using the case of the oil industry. The results show that in the period 1988-2009, a value (equally) weighted portfolio of high oil beta stocks outperforms a portfolio of low oil beta stocks by 1.1% (1.25%) in average per month, and approximately 13.24% (14.97%) in average annually. The oil premium is not pervasive, however, when we control for firm characteristics like size and book-to-market ratio. Using the common two-stage cross-sectional regression methodology, we confirm that oil is not priced cross-sectionally, supporting a mispricing explanation. In contrast, we find that firms with a low book-to-market ratio have a premium of 2.4% in average and that there is not a risk premium for small firms in this industry. The evidence seems consistent with a risk pricing explanation, in particular, with the argument that growth options are riskier than assets in place.

**JEL classification**: C23; G15; Q43.

**Keywords**: Anomalies; Asset Pricing; Growth Options; Oil and Natural Gas Industry; Oil Prices; Cross Sectional Tests.

*The authors acknowledge financial support from Fundacao para a Ciencia e Tecnologia PEst-OE/EGE/UI0315/2011 and from the Spanish Ministry of Education and Science, research projects ECO2009-08100 and MTM2009-13985-C02-01.

†Business Research Center/UNIDE, Lisbon University Institute (ISCTE-IUL), Avenida das Forças Armadas, 1600-083 Lisboa, Portugal. Email: sofia.ramos@iscte.pt. Corresponding author.

‡Universidad Carlos III de Madrid (Department of Statistics and Instituto Flores de Lemus), C/ Madrid 126, 28903 Getafe, Spain. UNIDE, Avenida das Forças Armadas, 1600-083 Lisboa, Portugal.

§Universidad Carlos III de Madrid, Department of Business, C/ Madrid 126, 28903 Getafe, Spain.

# I. Introduction

This paper investigates how commodity price risk affects asset pricing. We are motivated by the strand of the literature that analyzes how well industries are priced by common asset pricing models. Hou and Robinson (2006) focus on industry features like industry concentration and posit that the structure of product markets may affect stock returns. They argue that the structure of product markets may affect the risk of a firm's cash flows, and hence a firm's equilibrium rate of return. Their results reveal that firms in concentrated industries earn lower returns. Lewellen et al. (2010) show that several risk-based asset pricing models are rejected because they fail to explain the cross-section of returns on industry portfolios. Chou et al. (2012) show that industry portfolio returns cannot be explained fully by well-known asset pricing models.

Moreover, empirical evidence finds for some particular industries evidence that other factors are also priced. For instance, the interest rate is an important factor for the banking sector. Viale et al. (2009) find no evidence that firm specific factors such as size and book-to-market ratios are priced in the bank sector; however, shocks to the slope of the yield curve are useful in explaining banking stock returns. Also Zeng et al. (2010) support the existence of the banking risk premium for public firms in the U.S. market.

We take the case of the oil industry. Using time series analysis, several papers find that oil is a determinant factor of oil industry returns, however there is a void on the cross section results.[1] From the theoretical perspective, the Intertemporal Capital Asset pricing Model (ICAPM) of Merton (1973) states that if investment opportunities change over time, then assets' exposures to these changes are important determinants of average returns in addition to the market beta. Given that oil has such a pivotal role in this industry, we analyze the hypothesis that oil is important for average returns of the oil and natural gas industry.

Some papers already have tested oil as a pricing factor in the framework of macroeconomic

[1] A strand of the literature uses Arbitrage Pricing Theory (APT) or Vector Autoregression (VaR) models to analyze the risk factors of the oil industry. Several papers document that oil is an important driver of the oil industry (see for example, Faff and Brailsford, 1999; Sadorsky, 2001; El-Sharif et al., 2005; Al-Mudaf and Goodwin, 1993; Hammoudeh et al., 2004; Park and Ratti, 2008; Boyer and Filion, 2007; Oberndorfer, 2009; Ramos and Veiga, 2011). However, all these papers are only based on time series analysis

innovations, due to the strong evidence that oil price increases accounted partially for every U.S. recession after World War II (Hamilton, 1983). Based on this result, many researchers have used oil as proxy of macroeconomic conditions. Chen et al. (1986) is one of the first papers to investigate the impact of macroeconomic innovations on stock price returns. They do not, however, find any evidence that oil price risk is rewarded by the stock market. Hamao (1989) applied the approach of Chen et al. (1986) to a sample of Japanese equity data and also found no evidence for the pricing of an oil factor.

The perspective in this paper is different. Commodity price risk is important for companies in natural resources industries (Hong and Sarkar, 2008), thus it is important to understand how commodity price risk relates with asset pricing. Firm profitability is directly linked with the price of the commodity. So we presume that the market value of companies should vary with the price of commodity. We take the case of the oil and natural gas industry, a commodity dependent industry. The question we address is whether oil is priced in the cross section, i.e., if the average returns of these companies are related with oil returns.

Moreover, there are other conflicting effects. If the assumption that firm profitability is affected by oil prices is correct, then when oil price increases market capitalization increases and the book to market (B/M) ratio decreases. Thus, if oil price changes matter for market returns, we might observe simultaneously that large firms and growth firms provide abnormal returns. Overall, the problem is challenging as firm size and B/M have been found to be priced risk factors in the literature. So this paper aims to understand whether oil is a priced factor, and disentangle this effect from the B/M ratio and size effect.

Additionally, we cannot dismiss that other industry features such as the market structure of the industry or inelastic demand can affect asset pricing (Hou and Robinson, 2006).

Using a sample of around 260 firms of the oil and natural gas industry in the period 1989-2009, we start by building portfolios sorted on previous-month oil sensitivity. We find that raw value-weighted portfolio (VW) annualized returns for firms in the lowest oil beta decile are on average 0.914% monthly, while VW returns for firms in the highest oil beta decile are on average higher 2.018% monthly. The spread between high and low oil sensitivity portfolios is 13.24% annually and for the value-equally-weight portfolio (EW) is 14.97% annually. Analyzing the features of the oil portfolios, we confirm an inverse relation between oil sensitivity and the B/M ratio. To gauge the robustness of our results, we repeat our analysis across different grouped portfolios. We find that the oil premium is mitigated when we control for market capitalization and the B/M ratio. To be more concrete, we find that the spread is positive for low B/M firms and negative for high B/M firms.

To understand the result, we construct factor mimicking portfolios on the characteristics that seem to be related with abnormal returns: size, B/M and oil loading. The oil mimicking portfolio performs well in the time series analysis, but in the cross section the estimation confirms that only low B/M firms provide a positive risk premium. The spread on oil portfolios is then explained by market mispricing.

To distinguish a risk from a behavioral explanation for the growth premium, we test whether variation in $HML$ factor loadings after controlling for the B/M characteristic still predicts returns. Following Daniel and Titman (1997) and Hou et al. (2011), we sort stocks into portfolios based on both the level of B/M and the level of loadings on the $HML$ mimicking factor. We find that after controlling for the firm characteristic (B/M), having a higher level of risk ($HML$ loading) is associated with higher average returns. This finding does not contradict the hypothesis that rational factor pricing explains the growth anomaly.

Several rational explanations can justify the spread of low B/M firms. First, low B/M firms in this industry are not 'typical ' growth firms. The impact of current profitability decreases the B/M ratio like in the model of Gomes, Kogan, and Zhang (2003) that finds a negative relation between the B/M and firm profitability.

The question that remains is why they offer a risk premium? The evidence offered in this paper is consistent with the presence and riskiness of growth options in this industry. Hence, our evidence is in line with the model of Gomes et al. (2003) that contends that growth stocks, which derive market values more from growth options, are riskier than value stocks.

Also market structure, namely industry concentration, might affect asset pricing. In a rational framework, the $HML$ factor is commonly presented as representing distress risk. The work of Hou and Robinson (2006) posit that industries with high entry barriers insulate firms from distress risk. Given that, the oil industry has entry barriers as capital intensity, the acquisition of oil fields is limited by many factors like availability, leases, state and governmental licences, environmental licences among others. Thus distress risk might be less important in this industry and thus there is not compensation for it.

To our knowledge, this is the first paper to analyze commodity dependence and the cross section variation industry returns. This paper makes a contributions to the literature that relates industry features (e.g. market structure) and asset pricing. The evidence suggests that commodity price risk is not priced but but affects stock returns due to market mispricing. Moreover, our evidence does not provide support of the value premium, and is consistent with the arguing of the riskiness of growth options in line with Gomes et al. (2003) model.

The rest of this article is organized as follows: In Section II, we relate relevant literature to CAPM and Three-Factor model. Then in Section III, we define our data. Section IV explains the methodology (time series vs cross-sectional regression), and Section V reports the main results of the paper and a discussion. In section VI we check robustness of our results. Finally, we conclude in Section VII.

## II. Review of the Literature

There is a vast literature on asset pricing starting with milestones works like Sharpe (1964), Lintner (1965) and Black (1972). Miller (1999) is one of the first works to point out that there is agreement among academics that a single factor, as defined as market beta, is insufficient to describe the cross section of expected returns. Several other papers document anomalies, other variables that seem to explain the cross section of returns: Monday dummy (French, 1980), January dummy (Roll, 1983; Reinganum, 1983), earnings-price ratio (Basu, 1977; Ball, 1978; Jaffe et al., 1989), firm size (Banz, 1981; Basu, 1983), long-term reversals (De Bondt and Thaler, 1985), B/M ratio (Stattman, 1980; Rosenberg et al., 1985), leverage (Bhandari, 1988) and momentum (Jegadeesh, 1990; Jegadeesh and Titman, 1993).

A turning point in the literature is when Fama and French (1992) find that size and book-to-market ratio could explain the cross section variation of equity returns. Later, Fama and French (1993, 1996) propose a three-factor model that improves average CAPM pricing errors by including a size and a book-to-market factor. The basic three factor-model is given by:

$$R_{it} = \alpha_i + \beta_{0i} market_t + \beta_{1i} SMB_t + \beta_{2i} HML_t + \varepsilon_{it}, \tag{1}$$

where $R_{it}$ is the return in U.S. dollars of firm $i$ in excess of the one-month U.S. T-bill in month $t$; $market_t$ is the excess return in U.S. dollars on the domestic market in month $t$; SMB (Small minus Big) is the average return on the small capitalization portfolios minus the average return on the large capitalization portfolios; HML (High minus Low) is the difference in return between the portfolio with high book-to-market stocks and the portfolio with low book-to-market stocks.

A strand of literature has investigated whether the Fama and French model applies to specific industries. Demsetz and Strahan (1995, 1997) show that there are significant differences in the diversification and financial leverage strategies of large and small banks. Viale et al. (2009) document that firm specific factors such as size and B/M ratios cannot explain bank stock returns, while the stock market excess returns and shocks to the slope of the yield curve are priced in the cross-section of bank stock returns. Zeng et al. (2010) support the existence of a banking factor in explaining the returns of firms in the U.S. market. Elyasiani et al. (2007) examine market betas for U.S. banks and report that the systematic risk exposure of larger banks is larger.

Our work is more closely related with the bulk of literature that focus on how industry specificities affect asset pricing. A series of papers demonstrate that a wide range of asset pricing phenomena have important industry components (Asness et al., 2000; Cohen et al., 2003; Hou, 2003; Moskowitz and Grinblatt, 1999). Hou and Robinson (2006) focus on industry features like industry concentration and posit that the structure of product markets may affect stock returns. They argue that operating decisions arise from an equilibrium in the product market that potentially reflects strategic interactions among market participants. Therefore, the structure of product markets may affect the risk of a firm's cash flows, and hence a firm's equilibrium rate of return. If the structure of product markets affects asset prices, then either market structure affects risk directly or it is somehow correlated with investor perceptions in a way that links it to behavioral phenomena. Their results reveal that firms in concentrated industries earn lower returns. Lewellen et al. (2010) show that several risk-based asset pricing models are rejected because they fail to explain the cross-section of returns on industry portfolios. Chou et al. (2012) show that industry portfolio returns cannot be explained fully by well-known asset pricing models.

The paper also relates with another two different strands of the literature. The first analyzes commodity exposure. Hong and Sarkar (2008) models commodity beta in a contingent-claim framework. Commodity beta is predicted to be an increasing function of the operating and financial leverage of the firm and a decreasing function of the company's tax rate and the level, volatility and speed of reversion of the commodity price.

The second strand of literature has tested oil as a pricing factor in the framework of macroeconomic innovations, due to the evidence that oil price increases accounted partially for every U.S. recession after World War II (Hamilton, 1983). Based on this result, many researchers use oil as proxy of macroeconomic conditions. Chen et al. (1986) is one of the first papers to investigate the impact of macroeconomic innovations on stock price returns. They do not, however, find any evidence that oil price risk is rewarded by the stock market. Hamao (1989) applies the approach of Chen et al. (1986) to a sample of Japanese equity data and also finds no evidence that an oil price factor is priced. More recently, Driesprong et al. (2008) find that changes in oil prices predict stock market returns worldwide. They find significant predictability in both developed and emerging markets. They conclude that investors seem to underreact to information on the price of oil.

# III. Data and Portfolio Returns

## A. Data

We select firms that are directly related with crude oil. The firm's stock returns are obtained from the following SIC codes: 1311, 138 (including 1381, 1382, and 1389), 2911, 2990 and 3533, a total of seven oil related industries available on the Center for Research in Security Prices (CRSP). Table I reports all the information available on SIC codes and firms.

From Compustat, we extract the following monthly company items: the adjusted return at the end of the month, the market capitalization and the book-to-market ratio. The sample period is from December 1988 to June 2009. Similar to previous works we impose some filters on our data. To avoid potential bias in our analysis, we kept firms that have data on Compustat for more than two consecutive years (see Viale et al., 2009, among others).

Table I presents the descriptive statistics by each industry SIC code, i.e., statistics on the number of firms, the market capitalization, the monthly returns and the B/M ratio. The panel is unbalanced, the number of firms is not fixed, it changes across time. The industry with the largest number of firms is Crude Petroleum & Natural Gas (SIC Code 1311). The number of firms ranges from 81 to 148 and the average is 108. The market capitalization is very disperse, due to Petroleum Refiners (SIC Code 2911) whose average market capitalization is almost two million. Raw returns are higher for SIC code 1389 (a monthly average of 1.55%) and negative for Miscellaneous Products of Petroleum & Coal (SIC Code 2990). Petroleum Refiners raw returns standard deviation is the lowest in the sample. A high B/M ratio means that market values are very low regarding the book value, and is commonly interpreted as stocks being underpriced. The standard deviation of B/M in Drilling Oil & Gas Wells industry (SIC code 1381) is higher than those of other industries.

Finally, we take care of the most extreme observations, replacing the observations in the 1st and 99th percentiles by the values of the respective percentiles. Winsorizing ensures that extreme outliers do not drive the results and it is currently used in cross-section regressions (see Knez and Ready, 1997; Ang et al., 2006, among others). Winsorizing results particularly useful for the B/M observations because extremely large B/M values are sometimes observed due to low prices, particularly before a firm delists.[2]

## B. Portfolios Returns

This section analyzes the performance of portfolios formed based on the oil returns. If commodity price risk is a priced factor we should observe a relation between oil risk and returns of portfolios ranked on the oil returns. Price commodity risk is proxied by sensitivity or loadings to the logarithmic change in oil prices. Thus at end of each month $t$, we estimate oil betas for each firm using the following equation:

$$R_{it} = \alpha_i + \beta_{oil} R_{oil,t} + \varepsilon_{it}, \tag{2}$$

where $R_{it}$ is the excess return of stock $i$ at time $t$ and $R_{oil,t}$ is the oil return at time $t$. Oil prices are from the settlement price of the NYMEX oil futures contract, the most widely traded futures contract on oil. Data are from Datastream. The estimation is done with a 36-month rolling window regression. Then, five portfolios are constructed and firms are allocated into one of the five portfolios based on their oil beta. We compute VW portfolios and EW portfolios excess returns for $t + 1$.[3] We repeat the estimation for every $t$. At the end of the estimation procedure we obtain a time series of monthly excess returns for the five portfolios.

Table II shows average monthly excess returns from portfolios formed from one-dimensional sorts of stocks on $\beta_{oil}$ by using rolling regression over the period January 1992 through June 2009 (210 months). Panel A shows the results for a VW portfolio and Panel B for an EW portfolio.

[2]Knez and Ready (1997) show that the size effect is driven by the extreme 1% of the observations. They trim the extreme 1% of the observations and the coefficient of firm size changes signal.

[3]Fama and French (2008) cautions against drawing strong conclusions from the spread in equal-weighted portfolio returns, since they are likely to be heavily influenced by micro stocks.

The average return on the lowest quintile is around 0.914% and on the highest quintile is 2.018% (24.22% annually). The spread is positive and equal to 1.104%. Panel B shows the results for an EW portfolio. Portfolio returns are increasing with oil beta. The increase in returns from the lowest quintile to the highest quintile in the equal-weighted portfolios is 1.248% (14.97% annually). Despite the economic relevance of the spreads, the difference is not statistically significant which maybe due to the large standard deviation of oil returns. We also note that firms in the lowest oil beta quintile have negative betas, i.e., they are countercyclical in relation to the price of oil. Moreover, the spread between the VW and EW portfolio tends to be positive, that is, for the same oil beta quintile, VW portfolios offer higher returns suggesting that large firms provide higher returns. Table II - Panel C displays some features of firms included in the portfolios, such as, the average market capitalization and the B/M ratio. The smallest firms are also the firms with the lowest oil betas, while the largest firms are those in medium oil beta quintiles. We also observe that the B/M is decreasing with oil sensitivity. Growth firms have usually the highest oil beta while value firms the lowest oil beta.

To see the robustness of the spread to firm characteristics, in particular, to check if the result is not driven by the B/M, we construct triple sorted portfolios similar to approach of Daniel and Titman (1997). Because our sample narrows to the oil industry, we cannot create many portfolios, they would be composed of a reduced number of firms and consequently there will be too much noise. Thus, we compute 12 portfolios on market capitalization, B/M and oil sensitivity (on small and large market capitalization, high, medium and low B/M ratio and high and low oil sensitivity).

Table III shows the results. For value firms the return spread of oil loading (High-Low) is negative and for growth firms the spread High-Low is positive. For small minus big firms the spread is larger. So, the oil spread is not persistent when we control for the B/M ratio.

# IV. Methodology

Our results on section III suggest that the spread on oil portfolios is mitigated when we control for firm characteristics, in particular for the book-to-market ratio. In this section, we analyze better this result and investigate what is priced in the cross section of returns.

The base asset pricing model is the three factor model of Fama and French. Fama and French (1993, 1996) propose a three-factor model that improves average CAPM pricing errors by including a size and a B/M factor. The model is the following:

$$R_{it} = \alpha_i + \beta_{0i} market_t + \beta_{1i} SMB_t + \beta_{2i} HML_t + \varepsilon_{it}, \tag{3}$$

where $R_{it}$ is the return of portfolio $i$ in excess of a risk free rate in month $t$; $market_t$ is the excess return on the domestic market in month $t$; SMB (Small minus Big) is the average return on the small capitalization portfolios minus the average return on the large capitalization portfolios; HML (High minus Low) is the difference in return between the portfolio with high B/M ratio stocks and the portfolio with low B/M ratio stocks. We extend this base model by including as a fourth factor $OIL$ and the analysis will compare the two models.

Following Fama and French (1992), we construct 12 portfolios based on firm features like market capitalization, the B/M ratio and the oil sensitivity (see appendix A). Firm size in a particular year refers to market capitalization at the end of June of this year and the B/M ratio is calculated by the book value of common equity for the fiscal year ended in previous calendar year divided by the market value of equity at the end of December of the previous year.[4] Regarding the oil sensitivity, we use the first 36 months to estimate loadings of firms' excess returns with respect to oil returns by using rolling regressions. Hence, in our 12 portfolios, the sample period is from January 1992 to June 2009.

Firm excess returns are ranked in terms of firm size, B/M and oil sensitivity, and twelve portfolios are formed from the intersections of market capitalization (small and big), three different

[4] By following Cohen et al. (2003), we replace negative BE values by small positive values of 1 to ensure that the market-to-book ratios are in the right, not the left, tail of the distribution.

B/M ratios (high, median, and low) and oil sensitivity (high and low). Let XYZ represent one of the twelve portfolios, where X is either S or B, indicating small size and big size, respectively; Y could be H, M, or L, indicating high, median, and low B/M ratio; Z is either H or L, indicating high and low oil sensitivity. For example, SHH represents the average return of the portfolio with small market capitalization, high B/M ratio and high oil sensitivity.

The VW monthly excess returns on these twelve portfolios are the dependent variables in time-series and cross-sectional regressions.[5] Figure 1 shows the cumulative returns of portfolios. We normalize all portfolios to 100 for the first date of the sample. The four portfolios with the best performance are SLH, BLH, SLL and BLL. These portfolios share the fact of owing low B/M firms. The ones that have the worse performance, the final value is below 100, are SHH, SHL and BHH, all with firms with high B/M ratios.

## A. Time-Series Analysis

Hou et al. (2011) state that the success of the factor pricing model in the time series test is a necessary but not sufficient condition for rational risk pricing to be confirmed. In a factor pricing model, mean returns increase with factor loadings, and the factor premium for a given zero-investment factor is equal to the mean return on that factor (or, for the market factor, the mean return in excess of the risk-free rate). In consequence, in a time series regression of a portfolio's excess returns on zero-investment or excess factor returns, the intercept term measures the mean abnormal return, or the return in excess of that predicted by the factor pricing model.

Thus, time series tests of factor pricing models rely on the intercepts from time series regressions to provide inferences on how well the given model can explain the cross-section of average returns (see Gibbons et al., 1989; Fama and French, 1993, 1996, for example).[6]

In order to evaluate the overall ability of the specified model in explaining excess returns, we adopt the test proposed by Gibbons et al. (1989) (called GRS test henceforth). The null hypothesis of the GRS test assumes that all pricing errors are jointly equal to zero. The rejection

[5] In the robustness section we use different portfolio construction.

[6] Intercepts that are indistinguishable from zero are consistent with rational factor pricing (Merton (1973)).

of the null hypothesis indicates that at least one of the pricing errors from a specific model is not zero, and then the used pricing model is not enough to explain excess returns.[7]

The GRS test is mainly based on a finite-sample F-test presented as follows:

$$GRS = \frac{T-N-K}{N}\left[1+E_t(f_t)'\hat{\Omega}^{-1}E_t(f_t)\right]^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha} \equiv F_{N,T-N-K}, \tag{4}$$

where $T$ is the number of observations across time, $N$ is the number of portfolios, $K$ is the number of factors, $f_t$ is the factor vector at moment $t$, $\widehat{\Omega} = \frac{1}{T}\sum_{t=1}^{T}(f_t - E_T(f))(f_t - E_T(f))'$ (the factor covariance) and $\widehat{\Sigma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t'$ (the residual covariance).

## B. Cross-sectional Analysis

Fama and MacBeth (1973) propose a procedure to run cross-sectional regressions. The procedure consists in estimating the betas and the risk premium of any factor that is expected to determine asset prices.[8]

The procedure consist of finding beta estimates with time-series regression, by regressing each portfolio excess return against the proposed risk factors. Second, we run a cross-sectional regression at each time period with all portfolio excess returns against the estimated betas to determine the risk premium of each factor. We estimate two main equations:

$$\begin{aligned} R_t^i &= \hat{\beta}_{market,i}\lambda_{market,t} + \hat{\beta}_{SMB,i}\lambda_{SMB,t} + \hat{\beta}_{HML,i}\lambda_{HML,t} + \epsilon_{i,t} && (5) \\ R_t^i &= \hat{\beta}_{market,i}\lambda_{market,t} + \hat{\beta}_{SMB,i}\lambda_{SMB,t} + \hat{\beta}_{HML,i}\lambda_{HML,t} + \hat{\beta}_{OIL,i}\lambda_{OIL,t} + \epsilon_{i,t} && (6) \end{aligned}$$

$i = 1, ..., N$ for each $t$. $\hat{\beta}_{market,i}$, $\hat{\beta}_{SMB,i}$, $\hat{\beta}_{HML,i}$, and $\hat{\beta}_{OIL,i}$ are the factor loadings obtained in the time series regression. Equation (5) is our benchmark model for our mimicking portfolio and

[7]Time series regression tests have the advantage that the time series slopes are factor loadings with a clear interpretation. Besides this method can avoid the problem of error-in-variables because all the factors are observable in opposite to the cross-section methodology where the regressors are the estimated betas obtained from the time series step.

[8]The advantages of this method are allowing betas to change over time, to produce standard errors and test statistics.

equation (6) allows to test if oil is a priced factor.

We estimate the factor risk premia ($\lambda's$) and the pricing errors ($\epsilon's$) of equations (5) and (6) as the average of the cross-sectional estimates:

$$\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t \quad \text{and} \quad \hat{\epsilon}_i = \frac{1}{T}\sum_{t=1}^{T}\hat{\epsilon}_t \tag{7}$$

and the corresponding variances are:

$$\hat{\sigma}_{\lambda}^2 = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\lambda}_t - \hat{\lambda})^2 \quad \text{and} \quad \hat{\sigma}_{\epsilon_i}^2 = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\epsilon}_t - \hat{\epsilon}_i)^2. \tag{8}$$

If estimated betas are important determinants of average returns, then the risk premia of equations (5) and (6) should be significant.

The standard Fama-MacBeth standard errors presented in equation (8) do not take into account that the $\beta's$ are estimated. Therefore, we use the Shanken (1992)'s correction to obtain the correct asymptotic standard errors of the factor risk premia vector.

In order to test that all the pricing errors are jointly zero we assume that the pricing errors are *iid* over time and independent of the factors. The test-statistics is then

$$\hat{\epsilon}' cov(\hat{\epsilon})^{-1}\hat{\epsilon} \sim \chi^2_{N-K}.$$

**GLS cross-sectional regression** Instead of the Fama and MacBeth (1973) procedure described before, we can conduct cross-sectional regressions whose dependent variable is the portfolio average return on the factor risk premia vector and pricing errors:

$$E_T(R_t^i) = \hat{\beta}_{market,i}\lambda_{market} + \hat{\beta}_{SMB,i}\lambda_{SMB} + \hat{\beta}_{HML,i}\lambda_{HML} + \epsilon_i \tag{9}$$

$$E_T(R_t^i) = \hat{\beta}_{market,i}\lambda_{market} + \hat{\beta}_{SMB,i}\lambda_{SMB} + \hat{\beta}_{HML,i}\lambda_{HML} + \hat{\beta}_{OIL,i}\lambda_{OIL} + \epsilon_i, \tag{10}$$

$i = 1, ...N$. Since the errors in the cross-sectional regressions 9 and 10 are correlated with each other, we should run a GLS cross-sectional regression. The GLS estimates of the parameters and their variances that take into account the Shanken (1992)'s correction are

$$\begin{aligned} \hat{\lambda} &= (\beta'\Sigma^{-1}\beta)^{-1}\beta'\Sigma^{-1}E_T(R), \\ \hat{\epsilon} &= E_T(R) - \hat{\lambda}\beta \end{aligned} \tag{11}$$

and

$$\begin{aligned} \sigma^2_{\hat{\lambda}} &= \tfrac{1}{T}\left[(\hat{\beta}'\hat{\Sigma}^{-1}\hat{\beta})^{-1}(1 + \hat{\lambda}'\Sigma_f^{-1}\hat{\lambda}) + \hat{\Sigma}_f\right] \\ cov(\hat{\epsilon}) &= \tfrac{1}{T}(\hat{\Sigma} - \hat{\beta}(\hat{\beta}'\hat{\Sigma}^{-1}\hat{\beta})^{-1})\hat{\beta}')(1 + \hat{\lambda}'\Sigma_f^{-1}\hat{\lambda}), \end{aligned} \tag{12}$$

where $\Sigma_f$ is the factor covariance matrix and $\hat{\Sigma}$ is the residual covariance matrix of the time series regressions (see Cochrane, 2001, for details in the previous procedures).

## C. Mimicking Portfolios

Hou et al. (2011) refer that the factor mimicking approach is a method of extracting factors from the anomalous characteristic itself, which provides a systematic way of identifying the risk factor that is most closely related to the anomaly, if there is indeed a risk effect. To test, they follow the approach originally developed by Fama and French (1993) and Daniel and Titman (1997) constructing factor mimicking portfolios that load heavily on whatever risk factor is driving an anomaly. This procedure can be used to extract measures of risk even if the researcher does not directly observe the factor structure underlying stock returns.

Similar to refereed studies that dissect anomalies, we construct three mimicking portfolios based on the features of our sample. They are zero investment portfolios that are long on small firms and short on large firms ($SMB$) and long on high B/M and short on low B/M ($HML$) and long on high oil sensitivity and short on low oil sensitivity ($OIL$).

Table IV presents the summary statistics of the factors. The first column presents market excess returns. The mean of the market excess returns is positive around 0.37%. The following columns presents the statistics on the mimicking factors. The $SMB$ and $HML$ portfolios have negative returns, indicating that large firms and growth firms provide higher returns than small firms and value firms. The portfolio long on high oil beta and short on low oil beta has positive return of 0.18%. This is in line with the previous evidence that low B/M offer higher return than high B/M. The figure is statistically significant. Thus, a first inspection seems to indicate that the oil industry seems to be at odds, in the sense that large and growth firms tend to offer higher excess returns. The standard deviation of $SMB$ and $HML$ is lower than the factors $OIL$ and $market$.

Table V presents the Pearson correlation coefficient of the factors. $HML$ and $OIL$ are positively correlated with the market, but $HML$ and $OIL$ are negatively correlated between them.

# V. Empirical Results

This section analyzes whether oil is a priced risk factor.

## A. Time Series Regressions

Table VI shows the results of the estimation of the time series regression of equation (3). Panel A uses three factors: the excess returns of the market ($market$), the $SMB$ and $HML$ mimicking factors. The dependent variables are the twelve portfolios computed on the firm characteristics: Size, B/M and commodity risk (oil loading). The first six rows present the results of low oil beta sensitivity portfolios and the last six rows of high oil beta sensitivity portfolios. The columns present the values of the coefficients and the t-statistics.

The coefficients on the market portfolio are positive and statistically significant. Portfolios with high oil beta also have a high oil beta. Regarding the factor $SMB$, coefficients are positive for small firms and negative for large firms, and are statistically significant. Coefficients of the mimicking $HML$ portfolio are decreasing from high B/M to low B/M, and are statistically significant for 10 out of the 12 portfolios (coefficients on median B/M portfolios tend to be not statistically significant).

The quality of the time series model is assessed by two items. The $R^2$ of the regressions that ranges between 0.272-0.402 and the pricing errors. None of the $\alpha's$ is statistically significant at standard levels of significance. Thus, the GRS test does not reject the null that all pricing errors are equal to zero.

The results for the four-factor model are presented in Panel B. The coefficients on the market excess return decrease when we include the oil mimicking portfolio, while the coefficients on $SMB$ are similar to those of Panel A. The coefficients on the $HML$ mimicking portfolio slightly increase, which supports the relation between B/M and oil.

The coefficients on the oil mimicking factor are positive and statistically significant. The t-statistic is larger than three in all portfolios, meaning that the oil factor indeed has explanatory power for oil firms' excess return. By comparing the $R^2$ with that of Panel A, adding $OIL$ increases substantially the explanatory power of the model. The $R^2$ increases substantially, and ranges from 0.391 to 0.736. The increase in $R^2$ is substantially large in high oil beta portfolios, i.e., with high commodity risk.

Looking at $\alpha's$, the pricing errors are now larger, and more positive, but according to the t-statistic some $\alpha's$ are statistically significant. Despite that, the GRS test does not reject the null at 5% confidence level.

Overall, including the oil mimicking portfolio in the model increases substantially the explanatory power of the model, but at the same time increases mispricing since portfolios returns are overpriced.

## B. Cross Sectional Regressions

Table VIII displays the results of the 2-step estimation of Fama and MacBeth (1973), equations (5) and 6. The quality of the asset pricing model is assessed by the null hypothesis that there is no mispricing in cross-sectional analysis. If the model is correctly specified we should not reject the null hypothesis.

We recall that in Table IV, the average of the factors is positive for the *market* and $OIL$ and negative for $SMB$ and $HML$. Accordingly, to be a priced factor, the risk premium ($\lambda$) needs to be statistically significant and positive for the *market* and oil mimicking portfolio, and negative for the $SMB$ and $HML$ factors.

Panel A shows the results for the model where the *market*, $SMB$ and $HML$ mimicking portfolios are the factors. The $\lambda$ of the market is positive but not statistically significant. The $\lambda's$ of $SMB$ and $HML$ factor are negative, consistent with previous results that show that large and growth firms have higher returns (Table IV). However, the $\lambda$ is only statistically significant for the $HML$ factor. The null of no mispricing is not rejected with an adjusted p-value of 0.126.

Panel B adds the oil mimicking factor in the cross-sectional regression. The $SMB$ and $HML$ risk premiums do not change, but $HML$ is the only statistically significant priced factor, besides the market. The coefficient of $OIL$ is positive but not statistically significant. Thus, $OIL$ is not a priced factor.

Table IX shows the results of the GLS estimation. This estimation corrects for errors in variables given that the regressors of the cross-sectional regressions are the parameter estimates of the time series regressions ($\beta's$). In Panel A, the only $\lambda$ that is statistically significant is that of HML portfolio. The $\lambda$ is negative, confirming the premium on low B/M firms. Panel B adds $OIL$ as a factor, and the risk premium although positive is not statistically significant.

Our study finds a risk compensation for low B/M firms, that there is not a risk premium for the risk of small firms and that oil returns create mispricing in industry returns. The next paragraphs discuss better these results.

Regarding the small firm premium, the empirical evidence is not unanimous on the pervasiveness of such premium and our finding is in line with these studies. Authors like Eleswarapu and Reinganum (1993), Dichev (1998), Chan et al. (2000), Horowitz and Loughran (2000b,a) and Amihud (2002) find no size premium. Hirshleifer (2001) contends that the size effect vanished after 1983. Schwert (2003) suggests that the size anomaly disappeared around the time of its discovery because practitioners began to use investment vehicles that tried to exploit the anomaly. Evidence outside the U.S. goes in the same direction. Dimson and Marsh (1998) show that the size premium is reversed in the U.K., small stocks underperformed large stocks by 2.4% between 1983 and 1997. Dimson et al. (2002) using an international sample of 19 countries, find that the size effect appears to be reversed in the period after which an academic study on the size effect in that country appeared.

Regarding the growth premium, to our knowledge this is the first work to document that high B/M firms underperform low B/M firms. The next section discusses in more details reasons why the spread might emerge.

## C. Discussion

The common presumption in the finance literature is that the B/M ratio is a measure of a firms future growth opportunities relative to its accounting value. In other words, a low ratio of book equity relative to market value suggests that investors expect high future growth prospects compared to the value of assets in place.

The finding of the value premium in the asset pricing literature is considered puzzlingly as growth firms are considered riskier. Zhang (2005) describes the value premium as a troublesome anomaly for rational expectations, because according to conventional wisdom, growth options hinge upon future economic conditions and must be riskier than assets in place. The work of Gomes et al. (2003) also predicts that growth options are always riskier than assets in place, as these options are "leveraged" on existing assets. Growth stocks, which derive market value more from growth options, must therefore be riskier than value stocks, which derive market values more from assets in place.

Literature has looked for rational explanations to answer the question why high B/M firms present a risk premium. Fama and French (1996) contend that HML is a risk factor that represents distress of weak firms with low earnings that tend to have high B/M ratios. They argue that stocks with high ratios of book equity to market value are more prone to financial distress and hence riskier. Hence, the value premium is a compensation for this risk. The work of Zhang (2005) challenges the presumption that growth options are riskier and present some fundamentals to assets in place being riskier. Zhang argues that due to costly reversibility and the countercyclical pricing of risk, disinvestment of assets-in-place is difficult. Therefore, firms with a high proportion of physical assets are riskier than those with a high proportion of growth options, especially during economic contractions when the price of risk is high.

The spread of low B/M firms can arise because of different reasons. First, as a compensation for the riskiness of growth opportunities in this industry. Several papers value resources companies in a options framework where the option becomes in-the-money when the price of oil increases (see Pindyck, 1990). Litzenberger and Rabinowitz (1995) state that under uncertainty, ownership of oil reserves may be viewed as holding a call option whose exercise price corresponds to the extraction cost. So the evidence is consistent with the rational argument that investors percept growth options as riskier than assets in place (e.g. Gomes et al., 2003), and the spread arises as a compensation for risk.

A second possible explanation is maybe firms with low B/M in this industry are "typical" growth firms. The impact of current profitability in B/M ratio is present in the model of Gomes et al. (2003) that shows a negative relation between the B/M ratio and firm profitability. Also Hou and Robinson (2006) contend that the same level of book-to-market are fundamentally different from one another depending on the market structure of the industry in which they operate. They state a low book-to-market firm in a concentrated industry is not well described as a "growth firm", because *"This firm operates in an industry with a large asset base, high unit profitability, and low R&D, and subsequently has high capitalized future profitability. Its book-to-market is low not because its growth prospects are high, but because its current and expected future profitability is high"*(Hou and Robinson, 2006, see pag. 1951-1952). Conversely, a low book-to-market stock in a competitive industry is indeed better characterized as a growth firm. These firms engage in more R&D on average and are less profitable, and thus the low market-to-book is not a reflection of high capitalized profitability, but rather of expected growth.

The key question is still why low B/M firms are percept as riskier and provide a premium? In a risk priced framework, the plausible answer seems again the riskiness of growth options of the industry.

Still, another view is to assume that the HML factor really proxies for distress risk, raising the question why it is not relevant in this industry? A first hypothesis can be because distress risk is not relevant. Because demand for oil and its derived products is quite inelastic, firms tend to be insulated for oil price shocks, and oil price hikes are not likely to decrease substantially revenues. However, oil price decreases might jeopardize current investments and future growth. Early work like Pindyck (1990) assumes that production permanently stops as soon as the price falls below extraction cost. When this occurs, the reserves which are not yet extracted are lost and the producers do not have the option to resume production in the future. A second hypothesis drives on the structure of this industry. Hou and Robinson (2006) analyze whether distress risk is likely to vary with the market structure. They advocate that barriers to entry in industries insulate some firms from aggregate demand shocks, while exposing others. They posit that industries with high barriers to entry are associated with lower equilibrium stock returns. The oil industry has strong entry barriers starting with the scarcity of resources like oil fields, state and governmental licences, environmental licences among others, and to large scale up-front investments. Accordingly, distress risk could be less relevant in this industry, and no risk premium for it.

Last but not least important are behavioral explanations. The systematic mispricing of securities can be originated by non-rational investor behavior. Lakonishok et al. (1994) suggest investors incorrect extrapolation of the past earnings growth of firms as the source of the value premium. Chan et al. (2003) support this view and find that the association between B/M ratios and future growth is weak.

To distinguish the hypothesis of misvaluation explanation and risk based explanation we follow Daniel and Titman (1997) that argue that the value premium is due to the value characteristic of the stock and not for proxying for risk. They point out that in tests where factors are constructed from characteristics that are known return predictors, factor loadings can be found to predict returns even if risk is not priced. In other words, since the $HML$ factor is constructed based on B/M sorts, the $HML$ factor loadings and the original characteristic (B/M) are likely to be highly correlated. If markets are inefficient and investors misprice B/M, then the factor loadings can pick up the mispricing that is correlated with B/M. The problem is further worsened by employing portfolios that are formed based on B/M.

Daniel and Titman (1997) suggest triple-sort stocks into portfolios to distinguish between the rational risk explanation and the misvaluation explanation. First, to identify variation in the $HML$ factor loading unrelated to the B/M characteristic and then test whether the independent variation in $HML$ loading is associated with spreads in average returns. The risk explanation predicts that $HML$ loading continues to predict returns after controlling for B/M, while the mispricing theory predicts that $HML$ loading has no incremental predictive power after controlling for variation in B/M.

Thus stocks are triple-sorted into portfolios based on size, B/M and $HML$ loading. The portfolio-level factor loadings are calculated as follows: two size groups (S and B) and three book-to-market groups (H, M, and L) based on the 33th and 67th percentile breakpoints for the oil/gas firms. The six portfolios are formed as the intersections of these two size and three B/M groups. Each of the six portfolios are then divided into two portfolios (H and L) based on $HML$ factor loading estimated with monthly returns over the previous 36 months (i.e. rolling regressions of 36 months). Then, we use the following equation to perform our time series regression:

$$R_{it} = \alpha_i + \beta_{0i} market_t + \beta_{1i} SMB_t + \beta_{2i} HML_t + \beta_{3i} HML(beta)_t + \varepsilon_{it}. \tag{13}$$

The resulting three subportfolios within each of the size, B/M category thus consist of stocks of similar size and B/M characteristics, but different levels of $HML$ loading. The correlation between their $HML$ loading and B/M characteristic should be sufficiently low. We use these portfolios to test whether $HML$ factor loading can predict returns after controlling for variation in B/M.

Table X presents the results of the time series regressions. We separate the results of portfolios with a low and high sensitivity to the $HML$ factor to highlight the differences. The coefficients of $HML$ loadings are negative because the factor is defined in a negative way (note that the growth premium is the symmetric of the value premium). Coefficients of low loadings are all very similar and very distinct of high $HML$ loadings, which seems to support a risk based explanation. The coefficient on low $HML$ loading is lower than the coefficient on high $HML$ loading. We also note that the coefficient of B/M still shows dispersion.

Moreover, the patterns of the intercepts seem also consistent with a risk based explanation. The behavioral alternative contends that average returns are determined by the B/M characteristic irrespective of the $HML$ factor loading. In the context of the regression framework here, it implies that the intercepts of the low $HML$ loading portfolios should be positive whereas the intercepts of the high $HML$ loading portfolios should be negative. The evidence is not supportive of this claim, all intercepts are positive. The GRS test does not reject the null hypothesis that all pricing errors are equal to zero, which it is not opposite to rational factor pricing. We also note that the $R^2$ is substantially higher for firms with low loading on $HML$ factor.[9]

# VI. Robustness

In this section we check the robustness of the risk premium finding on low B/M firms. The evaluation of cross-sectional results are based on asset pricing tests that suffer from low power, such that, high explanatory power in cross-sectional regressions does not often imply a strong support for the model (see Lewellen et al., 2010).

To circumvent some of these problems and increase the robustness of results, Lewellen et al. (2010) have prescribed several remedies such as to expand the set of test portfolios beyond size

[9]Fama-Macbeth goes in the same direction of time series analysis. Both coefficients of $HML$ and the $HML$ loading are statistically significant, supporting the risk explanation.

and B/M portfolios. According, we repeat the estimations using different portfolios sortings: six portfolios based on size and B/M ratio; twelve portfolios based on size, B/M and oil sensitivity and twelve portfolios based on size, B/M and HML loadings. The cross section regressions using the different portfolio construction confirm the risk premium on low B/M firms.[10]

As also prescribed by Lewellen et al. (2010) we compute GLS for cross sectional regressions because the cross-sectional regressions can suffer from the error-in-variables problem given that the betas are estimates obtained from the time series analysis, but results are kept.

To further check the validity of results, we do a horse race with $SMB$ and $HML$ mimicking factors and the Fama and French factors from Prof. Kenneth French web page. The factors have a positive mean for the period, 0.011% and 0.527% respectively, meaning that a portfolio of small firms and value firms has provided on average higher returns than large and growth firms respectively. We repeat cross sectional regressions and the result on HML mimicking factor is kept, while the Fama and French HML factor has a negative risk premium which is not consistent with the positive mean of the factor, so the distress explanation seems to not to be supported empirically.

# VII. Conclusion

A recent strand of literature has addressed how industry features are related with asset pricing. Works seem to concur that standard asset pricing models fail to explain the cross section of returns of industry portfolios (Lewellen et al., 2010; Chou et al., 2012) and other factors are relevant to industries (Viale et al., 2009; Zeng et al., 2010).

This paper analysis the case of a commodity dependent industry, the oil industry, and whether the price commodity risk might affect the cross section of returns. Commodity dependence creates a strong link between firm profitability and the price of the commodity, and we analyze the hypothesis that price commodity risk might have an impact on the cross section of returns.

We follow previous asset pricing approaches and construct portfolios sorted on previous-month

[10]Results are available from authors upon request.

oil sensitivity. We find that raw value-weighted (VW) portfolio annualized returns for firms in the lowest oil beta decile are on average 0.914% monthly, while VW returns for firms in the highest oil beta decile are on average higher 2.018% monthly. The spread between high and low oil sensitivity portfolios is 13.24% annually, in the EW portfolio 14.97% annually. Analyzing the features of the oil portfolios, we confirm an inverse relation between oil sensitivity and the B/M ratio. To gauge the robustness of our results, we repeat our analysis across different grouped portfolios. We find that the oil premium dilutes when we control for market capitalization and the B/M ratio. In fact, we find that the spread is positive for low B/M firms and negative for high B/M firms. To understand the anomaly, we construct factor mimicking portfolios on the characteristics that seem to be related with abnormal returns: size, B/M and oil loadings.

The oil mimicking portfolio performs well in the time series analysis, but in the cross section the estimation confirms that low B/M firms provide a risk premium. The risk premium is only statistically significant for the $HML$ factor whether we add the oil mimicking portfolio into the model or not. In addition, the coefficient of OIL is positive but not statistically significant, thus commodity risk is not a priced factor and reflects market mispricing. In contrast, the risk premium on low B/M firms is pervasive. Additional tests dismiss a behavioral explanation for the anomaly, favoring a risk based explanation.

Features of the industry are likely to support the result. First, the presence and riskiness of growth of options in this industry. Second, low B/M firms are not typical 'growth' firms, low B/M ratios arise because firms are highly capitalized return firms. Third, large entry barriers in this industry do not create distress risk, and the value premium does not emerge as a compensation for distress risk.

Overall, our evidence supports that commodity price risk creates market mispricing and is in accordance with the views that that advocate that industry features affect asset pricing. The evidence supports that *"the structure of product markets affects asset prices, then either market structure affects risk directly, or else it is somehow correlated with investor perceptions in a way that links it to behavioral phenomena"* (Hou and Robinson, 2006, pag. 1930).

# Appendix

## A. 2x3x2 portfolio construction procedure–factors SMB, HML, and $OIL$

After merging the data obtained from Computstat, CRESP and Datastream, we delete the securities with missing observations from our final sample. The total number of observations (firm*month) after this first filter is 45781.

**Building portfolios for security analysis** Each security is assigned to one of the six portfolios that are formed based on the book-to-market and firm size. First, we split our sample into two groups. The first group includes the observations that are below the median of the firm size values and the second includes the observations that are above the median of the firm size values. Once we obtain this two groups we split the observations of each group into three groups formed based on the values of the book-to-market values. For this we consider the observations of book-to-market below the 30th percentile, between the 30th percentile and the 70th percentile and above the 70th percentile.

Finally, we sort securities in each of the six portfolios into two subportfolios formed based on their oil beta coefficient.

# References

Al-Mudaf, A. and T. H. Goodwin (1993). Oil shocks and oil stocks: an evidence from 1970s. *Applied Economics 25*, 181–190.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*, 31–56.

Ang, A., J. Chen, and Y. Xing (2006). Downside risk. *The Review of Financial Studies 19*, 1191–1239.

Asness, C., R. Porter, and R. Stevens (2000). Predicting stock returns using industry-relative firm characteristics. *Working Paper*.

Ball, R. (1978). Anomalies in relationships between securities' yields and yieldsurrogates. *Journal of Financial Economics 6*, 103–126.

Banz, R. (1981). The relationship between return and market value of common stock. *Journal of Financial Economics 9*, 3–18.

Basu, S. (1977). Investment performance of common stocks in relation their price-earnings ratios: A test of the efficiency market hypothesis. *Journal of Finance 32*, 663–682.

Basu, S. (1983). The relationship between earnings yield, market value and return for NYSE common stocks: Further evidence. *Journal of Financial Economics 12*, 129–156.

Bhandari, L. (1988). Debt-Equity ratio and expected common stock returns: Empirical evidence. *Journal of Finance 43*, 507–528.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business 45*, 444–454.

Boyer, M. M. and D. Filion (2007). Common and fundamental factors in stock returns of Canadian oil and gas companies. *Energy Economics 29*(3), 428–453.

Chan, L., J. Karceski, and J. Lakonishok (2000). New paradigm or same old hype in equity investing? *Financial Analysts Journal 56*, 23–36.

Chan, L., J. Karceski, and J. Lakonishok (2003). The level and persistence of growth rates. *Journal of Finance 58*, 634–684.

Chen, N.-F., R. Roll, and S. Ross (1986). Economic forces and the stock market. *Journal of Business 59*, 383–327.

Chou, P.-H., P.-H. Ho, and K.-C. Ko (2012). Do industries matter in explaining stock returns and asset-pricing anomalies? *Journal of Banking Finance 36*, 355–370.

Cochrane, J. (2001). *Asset Pricing*. Princeton and Oxford.

Cohen, R., C. Polk, and T. Vuolteenaho (2003). The value spread. *Journal of Finance 58*, 609–641.

Daniel, K. and S. Titman (1997). Evidence on the characteristics of cross sectional variation in stock returns. *Journal of Finance 52*, 1–33.

De Bondt, W. and R. Thaler (1985). Does the stock market overreact? *Journal of Finance 40*, 793–805.

Demsetz, R. and P. Strahan (1995). Historical patterns and recent changes in the relationship between bank size and risk. *Economic Policy Review 1*, 13–26.

Demsetz, R. and P. Strahan (1997). Diversification, size, and risk at bank holding companies. *Journal of Money, Credit, and Banking 29*, 300–313.

Dichev, I. (1998). Is the risk of bankruptcy a systematic risk? *Journal of Finance 53*, 1131–1147.

Dimson, E. and P. Marsh (1998). Murphys law and market anomalies. *Journal of Portfolio Management 25*, 53–69.

Dimson, E., P. Marsh, and M. Staunton (2002). *Triumph of the Optimists: 101 Years of Global Investment Returns*. Princeton University Press.

Driesprong, G., B. Jacobsen, and B. Maat (2008). Striking Oil: Another Puzzle. *Journal of Financial Economics 89*, 307–327.

El-Sharif, I., D. Brown, and B. Burton (2005). Evidence on the nature and extent of the relationship between oil prices and equity values in the U.K. *Energy Economics 27*, 810–830.

Eleswarapu, V. and M. Reinganum (1993). The seasonal behavior of the liquidity premium in asset pricing. *Journal of Financial Economics 34*, 373–386.

Elyasiani, E., I. Mansur, and M. Pagano (2007). Convergence and risk-return linkages across financial services firms. *Journal of Banking and Finance 31*, 1167–1190.

Faff, R. and T. Brailsford (1999). Oil price risk and the Australian stock market. *Journal of Energy Finance and Development 4*, 69–87.

Fama, E. and K. French (1992). The cross-section of expected stock returns. *Journal of Finance 47*, 427–465.

Fama, E. and K. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*, 3–56.

Fama, E. and K. French (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance 51*, 55–84.

Fama, E. and J. MacBeth (1973). Risk, return, and equilibrium: empirical tests. *Journal of Political Economy 71*, 607–636.

French, K. (1980). Stock returns and the weekend effect. *Journal of Financial Economics 8*, 55–69.

Gibbons, M., S. Ross, and J. Shanken (1989). A test of the efficiency of a given portfolio. *Econometrica 57*, 1121–1152.

Gomes, J., L. Kogan, and L. Zhang (2003). Equilibrium cross section of returns. *Journal of Political Economy 111*, 693–732.

Hamao, Y. (1989). An empirical examination of the arbitrage pricing theory using Japanese data. *Japan and the World Economy 1*, 45–61.

Hamilton, J. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy 91*, 228–248.

Hammoudeh, S., S. Dibooglu, and E. Aleisa (2004). Relationship among US oil prices and oil industry equity indices. *International Review of Economics and Finance 13*, 427–453.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *The Journal of Finance 56*, 1533–1597.

Hong, G. and S. Sarkar (2008). Commodity betas with mean reverting output prices. *Journal of Banking and Finance 32*, 1286–1296.

Horowitz, J. and N. Loughran, T.and Savin (2000a). The disappearing size effect. *Research in Economics 54*, 83–100.

Horowitz, J. and N. Loughran, T.and Savin (2000b). Three analyses of the firm size premium. *Journal of Empirical Finance 7*, 143–153.

Hou, K. (2003). Industry information diffusion and the lead-lag effect in stock returns. *Working paper, Ohio State University*.

Hou, K., D. Hirshleifer, and S. Teoh (2011). The accrual anomaly: Risk or mispricing? *Management Science, forthcoming*.

Hou, K. and D. Robinson (2006). Industry concentration and average stock returns. *The Journal of Finance 61*, 1927–1956.

Jaffe, J., D. Keim, and R. Westerfield (1989). Earnings yields, market values and stock returns. *Journal of Finance 45*, 135–148.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance 45*, 881–898.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance 48*, 65–92.

Knez, P. J. and M. J. Ready (1997). On the robustness of size and book-to-market in cross-sectional regressions. *Journal of Finance 52*, 1355–1382.

Lakonishok, J., A. Shleifer, and R. Vishny (1994). Contrarian investment, extrapolation, and risk. *Journal of Finance 49*, 1541–1578.

Lewellen, J., S. Nagel, and J. Shanken (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial Economics 96*, 175–194.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics 47*, 13–37.

Litzenberger, R. and N. Rabinowitz (1995). Backwardation in oil futures markets: Theory and empirical evidence. *Journal of Finance 50*, 1515–1545.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica 41*, 867–887.

Miller, M. (1999). The history of finance. *Journal of Portfolio Management 25*, 95–101.

Moskowitz, T. J. and M. Grinblatt (1999). Do industries explain momentum? *The Journal of Finance 54*, 1249–1290.

Oberndorfer, U. (2009). Energy prices, volatility, and the stock market: Evidence from the Eurozone. *Energy Policy 37*, 5787–5795.

Park, J. and R. A. Ratti (2008). Oil price shocks and stock markets in the U.S. and 13 European countries. *Energy Economics 30*, 2587–2608.

Pindyck, R. (1990). Uncertainty and exhaustible resource markets. *Journal of Political Economy 88*, 1203–1225.

Ramos, S. and H. Veiga (2011). Risk factors in oil and gas industry returns: International evidence. *Energy Economics 33*, 525–542.

Reinganum, M. R. (1983). The anomalous stock market behavior of small firms in january: Empirical tests for tax-loss selling effect. *Journal of Financial Economics 12*, 89–104.

Roll, R. (1983). On computing mean returns and the small firm premium. *Journal of Financial Economics 12*, 371–386.

Rosenberg, B., K. Reid, and R. Lanstein (1985). Persuasive evidence of market inefficiency. *Journal of Portfolio Management 11*, 9–17.

Sadorsky, P. (2001). Risk factors in stock returns of Canadian oil and gas companies. *Energy Economics 23*, 17–21.

Schwert, G. (2003). *Handbook of the Economics of Finance*, Chapter Anomalies and market efficiency. Amsterdam, North Holland.

Shanken, J. (1992). On the estimation of beta-pricing models. *Review of Financial Studies 5*, 1–33.

Sharpe, W. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance 19*, 425–442.

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: A Journal of Selected Papers 4*, 25–45.

Viale, A., J. Kolari, and D. Fraser (2009). Common risk factors in bank stocks. *Journal of Banking and Finance 33*, 464–472.

Zeng, L., H. H. A. Yong, S. Treepongkaruna, and R. Faff (2010). Is there a banking risk premium in the US stock market? *SSRN working paper*.

Zhang, L. (2005). The value premium. *The Journal of Finance 60*, 67–103.

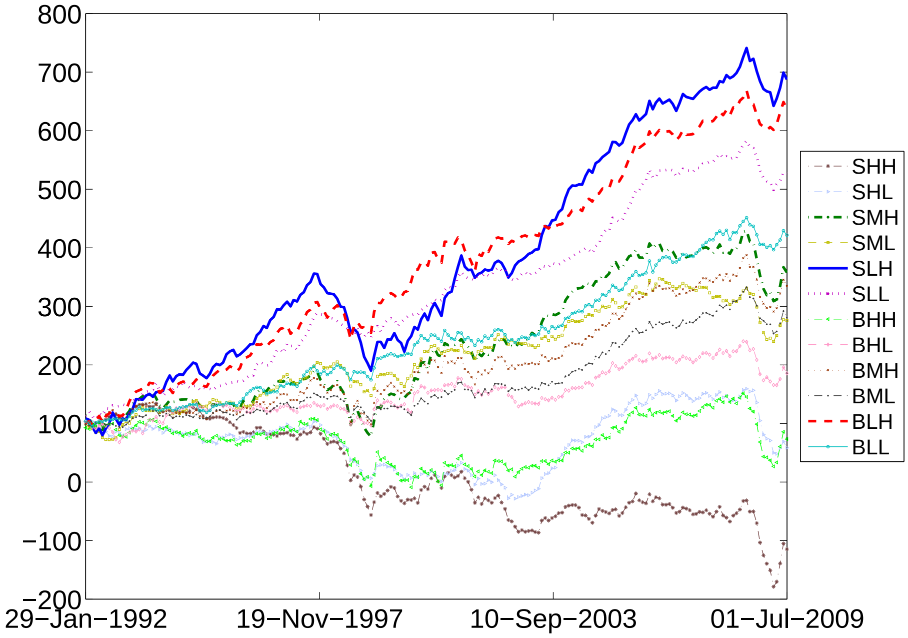


**Figure 1.** Portfolios cumulative returns.

## Table I: Summary statistics of firms by SIC code

This table reports summary statistics of the sample firms: the number of firms, market capitalization, B/M ratio and raw returns. Sample is from December, 1988 to June, 2009. Values are winsorize at 1% and returns are in percentage.

| SIC | | **Firms** | | | **M.Cap** | **B/M** | | | **Raw Return (%)** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CODE | Description | min | max | mean | Median | Mean | Median | sd | Mean | Median | sd |
| 1311 | Crude Petroleum & Natural Gas | 81 | 148 | 108 | 291,166 | 1.62 | 0.61 | 5.14 | 1.08 | 0.00 | 16.47 |
| 1381 | Drilling Oil & Gas Wells | 14 | 22 | 17 | 589,566 | 2.78 | 0.57 | 9.11 | 1.36 | 0.07 | 15.11 |
| 1382 | Oil & Gas Field Exploration Services | 5 | 20 | 11 | 198,522 | 1.92 | 0.68 | 5.65 | 1.07 | 0.00 | 16.44 |
| 1389 | Oil & Gas Field Services, Nec | 8 | 21 | 13 | 676,602 | 1.14 | 0.50 | 3.43 | 1.55 | 0.74 | 17.41 |
| 2911 | Petroleum Refining | 17 | 32 | 23 | 1,930,909 | 2.31 | 0.69 | 5.98 | 1.07 | 0.68 | 11.07 |
| 2990 | Miscellaneous Products of Petroleum & Coal | 1 | 1 | 1 | 73,760 | 0.49 | 0.12 | 1.03 | -2.21 | -5.75 | 30.29 |
| 3533 | Oil & Gas Field Machinery & Equipment | 3 | 12 | 8 | 747,738 | 0.47 | 0.42 | 0.27 | 1.60 | 1.25 | 15.07 |

## Table II
## Portfolio returns sorted on oil returns sensitivity

This table reports excess returns of portfolios formed on $\beta_{oil}$ using equation (2). $\beta_{oil}$ are estimated using 36 months rolling windows. Stocks are sorted into five portfolios according to their $\beta_{oil}$. The portfolios are held for one month then rebuilt. Panels A and B report value- and equal-weighted portfolio returns, respectively. Panel C shows the average market capitalization and B/M ratio by quintile portfolio. Returns are in percentage.

| Panel A: Value Weighted Portfolios | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Quintile** | **20** | **40** | **60** | **80** | **100** | **High-Low** | **t-Stat** |
| Return | 0.914 | 0.907 | 0.825 | 1.165 | 2.018 | 1.104 | 1.270 |
| $\beta_{oil}$ | -0.063 | 0.196 | 0.339 | 0.482 | 0.730 | | |
| Panel B: Equal Weighted Portfolios | | | | | | | |
| **Quintile** | **20** | **40** | **60** | **80** | **100** | | |
| Return | 0.576 | 0.781 | 0.849 | 0.947 | 1.823 | 1.248 | 1.470 |
| $\beta_{oil}$ | -0.063 | 0.196 | 0.339 | 0.482 | 0.730 | | |
| Panel C: Averages Values | | | | | | | |
| Market Capitalization | 479,887 | 1,360,270 | 1,723,191 | 1,433,370 | 575,087 | | |
| B/M ratio | 0.74 | 0.63 | 0.62 | 0.60 | 0.59 | | |

## Table III
## Triple sorted portfolio returns

This table reports the mean excess monthly returns for 12 portfolios formed on market capitalization, B/M ratio and the estimated factor loading on the oil factor. First, we rank firms by their market capitalization (size) and B/M ratio, based on 50 percent breakpoints for market capitalization and 30 and 70 percent breakpoints for B/M. Secondly, stocks are further sorted into two subportfolios based on their $\beta_{oil}$ coefficient in the regression (2). Columns present the average returns of the 12 portfolios and the spread on a portfolio with high oil loading minus low oil loading (High-Low). Returns are in percentage.

| | | Oil Loading Portfolio | | |
|---|---|---|---|---|
| **size** | **BM** | **H** | **L** | **High-Low** |
| S | H | -0.408 | 0.118 | -0.525 |
| B | H | 0.200 | 0.472 | -0.272 |
| S | M | 1.164 | 1.066 | 0.098 |
| B | M | 1.000 | 0.731 | 0.268 |
| S | L | 3.031 | 2.573 | 0.458 |
| B | L | 1.876 | 0.994 | 0.882 |

**Table IV**
**Summary Statistics of Factors**

This table reports summary statistics of the market and the mimicking portfolios used in time-series and cross-section regression. *market* represents the market excess return and $SMB$, $HML$ and $OIL$ are zero investment portfolios formed on market capitalization, B/M ratio and oil loading. Returns are in percentage.

| | market | SMB | HML | OIL |
|---|---|---|---|---|
| Mean (%) | 0.370 | -0.113 | -2.465 | 0.180 |
| Std. dev. (%) | 4.415 | 3.535 | 3.284 | 4.011 |
| Minimum (%) | -18.540 | -11.067 | -12.668 | -12.054 |
| Median (%) | 0.985 | -0.057 | -2.475 | 0.282 |
| Maximum (%) | 11.040 | 12.054 | 6.658 | 17.482 |

## Table V
## Correlation of the factors

This table reports Pearson correlation coefficients of factors: market(market excess return), $SMB$, $HML$, and $OIL$. $market$ represents the market excess return and $SMB$, $HML$ and $OIL$ are zero investment portfolios formed on market capitalization, B/M ratio and oil loading. The *** means rejection of the hypothesis $H0 : \rho = 0$ at 0.1%.

| | market | $SMB$ | $HML$ | OIL |
|---|---|---|---|---|
| market | 1 | | | |
| $SMB$ | -0.019 | 1 | | |
| $HML$ | 0.158*** | 0.010 | 1 | |
| OIL | 0.256*** | 0.012 | -0.092*** | 1 |

## Table VI: Time series regressions for portfolios formed from sorts on size, B/M and $\beta_{OIL}$–Panel A

This table presents the coefficients and t-statistics of a three factor model. Factors are: *market*, *SMB*, and *HML*. Dependent variables are 12 portfolios sorted by market capitalization (size), book-to-market ratio and $\beta_{OIL}$. The $R^2$ values from each time series are reported after t-statistics. The last row reports the adjusted p-value from GRS test.

| Panel A: Three Factor Model | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Low Low $\beta_{OIL}$ | | | | t_statistic | | | | |
| (SIZE,BM,$\beta_{OIL}$) | alpha | market | SMB | HML | alpha | market | SMB | HML | $R^2$ |
| SHL | 0.271 | 0.860 | 0.638 | 0.290 | 0.545 | 9.570 | 5.755 | 2.403 | 0.402 |
| SML | 0.304 | 0.835 | 0.566 | -0.116 | 0.568 | 8.624 | 4.734 | -0.892 | 0.316 |
| SLL | 0.134 | 0.793 | 0.531 | -0.676 | 0.260 | 8.487 | 4.610 | -5.378 | 0.344 |
| BHL | 0.636 | 0.798 | -0.364 | 0.229 | 1.223 | 8.478 | -3.136 | 1.810 | 0.311 |
| BML | 0.060 | 0.738 | -0.249 | -0.203 | 0.126 | 8.524 | -2.327 | -1.743 | 0.278 |
| BLL | 0.095 | 0.792 | -0.367 | -0.447 | 0.207 | 9.475 | -3.565 | -3.979 | 0.349 |
| | High $\beta_{OIL}$ | | | | t_statistic | | | | |
| (SIZE,BM,$\beta_{OIL}$) | alpha | market | SMB | HML | alpha | market | SMB | HML | $R^2$ |
| SHH | -0.788 | 1.020 | 0.716 | 0.215 | -1.166 | 8.335 | 4.747 | 1.309 | 0.322 |
| SMH | 0.401 | 1.076 | 0.370 | -0.190 | 0.524 | 7.766 | 2.166 | -1.022 | 0.238 |
| SLH | 0.216 | 0.991 | 0.995 | -0.944 | 0.276 | 6.986 | 5.690 | -4.951 | 0.314 |
| BHH | 0.230 | 1.008 | -0.271 | 0.309 | 0.329 | 7.979 | -1.738 | 1.816 | 0.272 |
| BMH | -0.385 | 1.127 | -0.491 | -0.418 | -0.543 | 8.769 | -3.100 | -2.418 | 0.301 |
| BLH | -0.098 | 1.111 | -0.441 | -0.891 | -0.148 | 9.290 | -2.986 | -5.540 | 0.356 |
| p-value (GRS) | 0.307 | | | | | | | | |

## Table VII: Time series regressions for portfolios formed from sorts on size, B/M and $\beta_{OIL}$–Panel B

This table presents the coefficients and t-statistics of a three factor model. Factors are: $market$, $SMB$, $HML$ and $OIL$. Dependent variables are 12 portfolios sorted by market capitalization (size), book-to-market ratio and $\beta_{OIL}$. The $R^2$ values from each time series are reported after t-statistics. The last row reports the adjusted p-value from GRS test.

| Panel B: Four Factor Model | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Low $\beta_{OIL}$ | | | | | t_statistic | |
| (SIZE,BM,$\beta_{OIL}$) | alpha | market | SMB | HML | OIL | alpha | market | SMB | HML | OIL | $R^2$ |
| SHL | 0.461 | 0.710 | 0.625 | 0.389 | 0.593 | 1.011 | 8.287 | 6.156 | 3.476 | 6.339 | 0.500 |
| SML | 0.522 | 0.663 | 0.552 | -0.003 | 0.682 | 1.078 | 7.277 | 5.105 | -0.024 | 6.861 | 0.444 |
| SLL | 0.264 | 0.690 | 0.523 | -0.608 | 0.406 | 0.528 | 7.351 | 4.694 | -4.963 | 3.957 | 0.391 |
| BHL | 0.831 | 0.644 | -0.377 | 0.330 | 0.610 | 1.735 | 7.147 | -3.528 | 2.811 | 6.205 | 0.420 |
| BML | 0.307 | 0.544 | -0.265 | -0.075 | 0.770 | 0.763 | 7.181 | -2.947 | -0.760 | 9.315 | 0.492 |
| BLL | 0.303 | 0.627 | -0.381 | -0.339 | 0.649 | 0.745 | 8.193 | -4.194 | -3.394 | 7.769 | 0.497 |
| | | | | | High $\beta_{OIL}$ | | | | | t_statistic | |
| (SIZE,BM,$\beta_{OIL}$) | alpha | market | SMB | HML | OIL | alpha | market | SMB | HML | OIL | $R^2$ |
| SHH | -0.288 | 0.626 | 0.684 | 0.474 | 1.558 | -0.681 | 7.863 | 7.249 | 4.566 | 17.942 | 0.736 |
| SMH | 0.959 | 0.637 | 0.334 | 0.098 | 1.739 | 1.955 | 6.905 | 3.057 | 0.818 | 17.285 | 0.690 |
| SLH | 0.771 | 0.553 | 0.959 | -0.656 | 1.732 | 1.481 | 5.645 | 8.261 | -5.136 | 16.202 | 0.699 |
| BHH | 0.717 | 0.624 | -0.303 | 0.561 | 1.519 | 1.513 | 7.014 | -2.865 | 4.827 | 15.632 | 0.668 |
| BMH | 0.150 | 0.705 | -0.526 | -0.141 | 1.668 | 0.347 | 8.703 | -5.473 | -1.331 | 18.862 | 0.745 |
| BLH | 0.381 | 0.734 | -0.472 | -0.643 | 1.494 | 0.894 | 9.153 | -4.961 | -6.146 | 17.075 | 0.734 |
| p-value (GRS) | 0.9832 | | | | | | | | | | |

**Table VIII**
**Cross sectional regression for portfolios formed from sorts on size, B/M and $\beta_{OIL}$**

This table reports the coefficients of second-stage cross-sectional regression results for a three-factor model (Panel A), and four-factor model (Panel B). The sample means of the monthly portfolio excess returns are regressed on the betas without the intercept. Individual t-statistics and p-values are reported next the coefficients. Adjusted t-statistics and adjusted p-value are reported by using Shanken's correction.

| Panel A: Three Factor Model | | | | | |
|---|---|---|---|---|---|
| | Estimate | Standard t-stat | Adjusted t-stat | p-value | Adjusted p-value |
| $\lambda_{market}$ | 0.454 | 0.839 | 1.488 | 0.007 | 0.126 |
| $\lambda_{SMB}$ | -0.112 | -0.449 | -0.459 | | |
| $\lambda_{HML}$ | -2.414 | -10.408 | -10.630 | | |

| Panel B: Four Factor Model | | | | | |
|---|---|---|---|---|---|
| | Estimate | Standard t-stat | Adjusted t-stat | p-value | Adjusted p-value |
| $\lambda_{market}$ | 0.918 | 1.737 | 3.005 | 0.008 | 0.152 |
| $\lambda_{SMB}$ | -0.104 | -0.416 | -0.426 | | |
| $\lambda_{HML}$ | -2.451 | -10.635 | -10.791 | | |
| $\lambda_{OIL}$ | 0.258 | 0.914 | 0.928 | | |

**Table IX**
**Cross sectional regressions - GLS- for portfolios formed from sorts on size, B/M and $\beta_{OIL}$**

This table reports the GLS cross-sectional regression results for a three-factor model (Panel A), and a four factor model (Panel B). The sample means of the monthly portfolio excess returns are regressed on the betas without the intercept. Individual t-statistics and p-values are reported near the coefficients. Adjusted t-statistics and adjusted p-value are reported by using Shanken's correction.

| Panel A: Three Factor Model | | | | | |
|---|---|---|---|---|---|
| | Estimate | Standard t-stat | Adjusted t-stat | p-value | Adjusted p-value |
| $\lambda_{market}$ | 0.502 | 1.014 | 0.896 | 0.006 | 0.066 |
| $\lambda_{SMB}$ | 0.2812 | 0.546 | 0.470 | | |
| $\lambda_{HML}$ | -2.0708 | -4.084 | -3.499 | | |

| Panel B: Four Factor Model | | | | | |
|---|---|---|---|---|---|
| | Estimate | Standard t-stat | Adjusted t-stat | p-value | Adjusted p-value |
| $\lambda_{market}$ | 0.794 | 1.095 | 0.919 | 0.005 | 0.072 |
| $\lambda_{SMB}$ | 0.1685 | 0.320 | 0.270 | | |
| $\lambda_{HML}$ | -2.1072 | -3.229 | -2.682 | | |
| $\lambda_{OIL}$ | 0.1036 | 0.233 | 0.204 | | |

## Table X: Four factor regressions for portfolios formed from sorts on size, B/M and $\beta_{HML}$

This table presents the factor loadings and t-statistics on the $market$, $SMB$, and $HML$ and $\beta_{HML}$ computed from the first stage time series regressions for 12 portfolios. The last column presents the $R^2$ for each portfolio. The last row reports the adjusted p-value from GRS test.

| | Low $\beta_{HML}$ | | | | | t_statistic | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (SIZE,BM,$\beta_{HML}$) | alpha | market | SMB | HML | $\beta_{HML}$ | alpha | market | SMB | HML | $\beta_{HML}$ | $R^2$ |
| SHL | 0.329 | 0.741 | 0.871 | 0.425 | -1.343 | 0.448 | 6.453 | 4.896 | 2.289 | -8.160 | 0.509 |
| SML | 1.026 | 0.742 | 0.716 | -0.022 | -1.378 | 1.446 | 6.685 | 4.164 | -0.122 | -8.663 | 0.511 |
| SLL | 0.943 | 0.758 | 1.342 | -0.621 | -1.299 | 1.328 | 6.829 | 7.805 | -3.458 | -8.169 | 0.554 |
| BHL | 0.227 | 0.706 | 0.021 | 0.410 | -1.367 | 0.273 | 5.424 | 0.104 | 1.948 | -7.332 | 0.406 |
| BML | 0.592 | 0.836 | -0.206 | 0.005 | -1.297 | 0.802 | 7.243 | -1.155 | 0.024 | -7.840 | 0.512 |
| BLL | 0.336 | 0.849 | 0.143 | -0.607 | -1.152 | 0.494 | 7.980 | 0.867 | -3.526 | -7.560 | 0.560 |
| | High $\beta_{HML}$ | | | | | t_statistic | | | | | |
| (SIZE,BM,$\beta_{HML}$) | alpha | market | SMB | HML | $\beta_{HML}$ | alpha | market | SMB | HML | $\beta_{HML}$ | $R^2$ |
| SHH | 0.382 | 0.878 | 0.737 | 0.296 | -0.466 | 0.576 | 8.462 | 4.580 | 1.762 | -3.135 | 0.459 |
| SMH | 0.391 | 0.824 | 0.894 | -0.413 | -0.310 | 0.496 | 6.698 | 4.692 | -2.075 | -1.759 | 0.315 |
| SLH | 0.626 | 0.736 | 1.164 | -0.914 | -0.034 | 0.785 | 5.899 | 6.028 | -4.532 | -0.190 | 0.303 |
| BHH | 1.045 | 0.798 | -0.181 | 0.253 | -0.396 | 1.633 | 7.976 | -1.167 | 1.566 | -2.765 | 0.359 |
| BMH | 0.965 | 0.709 | -0.068 | -0.067 | -0.304 | 1.408 | 6.620 | -0.410 | -0.384 | -1.982 | 0.268 |
| BLH | 0.819 | 0.688 | -0.180 | -0.347 | -0.272 | 1.296 | 6.953 | -1.175 | -2.170 | -1.918 | 0.328 |
| p-value (GRS) | 0.628 | | | | | | | | | | |